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Mind the Gap Between UX Data and Visualization Proposals: Analyzing User Dissatisfaction and Driving Interactive System Improvements

Maylon Macedo [**Aeronautics Institute of Technology (ITA)** | ***maylon@ita.br***]
Luciana Zaina [**Federal University of São Carlos (UFSCar)** | ***lzaina@ufscar.br***]

Department of Software and Information Systems (IEC-I), Aeronautics Institute of Technology (ITA), São José dos Campos, São Paulo - Brazil.

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Abstract Software professionals typically analyze user experience data (i.e., UX data) to identify positive and negative aspects of user interactions with software. While the scientific literature has proposed various UX data visualization approaches, these methods are rarely evaluated by software professionals (i.e., designers and developers) to determine their practical effectiveness in understanding user satisfaction and dissatisfaction. Moreover, professionals often adapt visualization techniques based on their own practical experiences, contributing to a wealth of informal knowledge published in UX blogs and websites (known as grey literature). To consolidate this dispersed knowledge, we conducted an analysis of 144 grey literature articles that discussed UX data definitions and visualization techniques. Our findings revealed three key components that support the investigation of user dissatisfaction: the visualization approach, the purpose of using the visualization, and UX data definitions. To validate the relevance of this three-leg approach, we conducted a study with 31 software professionals, using five UX data visualizations focused on a mobile airline ticketing application. We selected this domain to ensure familiarity and minimize the need for contextual interpretation. Through an online questionnaire, participants provided insights on how well the visualizations helped them identify aspects of the application contributing to user dissatisfaction. The results confirmed the practical value of the three-leg approach, with 78% of positive feedback regarding its effectiveness in UX data analysis. Additionally, 84% of participants acknowledged that the proposed visualizations could be integrated into their daily workflows. In this extended study, we introduced a new research question (i.e., RQ3) to investigate how UX data visualizations can support system improvements beyond identifying dissatisfaction. To address this, we conducted a new analysis of the grey literature, focusing on the potential benefits that UX data visualizations can bring to interactive systems. We also reanalyzed the collected study data, incorporating participant comments on how UX data visualizations could enhance software development processes. The comparison between the new findings and participant feedback highlighted four key themes: understanding users, improving system interaction, fostering self-knowledge about the system, and handling development resources efficiently. These insights reinforced the role of UX data visualizations in bridging the gap between theoretical models and practical applications for software professionals. Our findings update prior conclusions and discussions, demonstrating the broader impact of UX data visualizations beyond dissatisfaction analysis, extending to strategic decision-making, usability improvements, and software evolution.

Keywords: User eXperience, UX data, Visualization, IHC

1 Introduction

Design focused on User eXperience (UX) improvements can create intuitive interfaces to meet user needs and preferences Norman and Nielsen [2018]. The UX encompasses the quality of human interaction with products and services, going beyond mere usability to include emotional aspects before, during, and after usage Hassenzahl [2018]. The evolution of UX has influenced technology development, leading to the emergence of related subjects like UX Research and UX data. UX research plays a crucial role in understanding how users interpret and interact with digital products and services to develop digital products user-friendly and aligned with user expectations Martinelli *et al*. [2022].

Analyzing UX data generated by the practice with users is crucial to avoid superficial insights in UX research Convertino and Frishberg [2017]. UX data refers to information that allows mapping users' interactions with interactive systems and can be analyzed to enhance user experiences and optimize products Luther *et al*. [2020]; Tong *et al*. [2022]. The literature points out that UX data is generated during UX research Zaina *et al*. [2021] and is also crucial for fueling analyses that help create successful, user-centered design solutions Koesten and Simperl [2021]. Software professionals can apply different techniques to analyze UX data to gain meaningful insights into user behavior and preferences, ultimately leading to enhanced user satisfaction Fritz and Berger [2015].

Visualizations are a suitable approach to help software professionals break through the barrier of UX data abstraction and obtain relevant insights from the data Buono *et al*. [2020]. The InfoVis area covers aspects related to the design and functionalities of visualizations; this area assists in developing visualizations that are more in line with the users' needs Munzner [2014]. In parallel with the HCI area, the InfoVis area aims to provide the user with visualizations that facilitate understanding of data that can be complex, abstract, and large Ware [2012]. The use of visualizations has the function of expanding human perception capabilities, facilitating interpretation and decision-making Card *et al*. [1999].

Based on the grey literature research (i.e., UX websites and blogs), we selected 144 articles that contained definitions of UX data and visualizations used to explore it. During the qualitative analysis of these materials, we identified recurring patterns in how software professionals approached the analysis of UX data in practice. Specifically, we observed that their reasoning processes often combined three complementary dimensions: the visualization approach adopted (e.g., chart formats or tools for visualization), the purpose of the visualization (e.g., identifying usability issues, supporting design decisions, or communicating findings), and the definition of the UX data (e.g., behavioral, attitudinal, qualitative, or quantitative). These three dimensions, which emerged inductively from the data, formed the basis of what we termed the three-leg approach for UX data analysis.

To illustrate its applicability, we selected four dissatisfaction reports and constructed five visualizations to explore UX data related to a mobile app for airline tickets. We then evaluated these visualizations with 31 software professionals to assess how effectively they could identify insights about events that triggered the users' dissatisfaction reports.

Our primary concern was to collect the participants' interpretations of the UX data available from the five visualizations to evaluate how well the visualizations helped participants identify aspects of the mobile application that resulted in reports of user dissatisfaction. The participants evaluated the use of visualizations positively, and a good number of participants (i.e., 84%) pointed out that the proposed visualizations could be appropriated to support their daily work.

This study's innovative idea is the methodology to explore UX data using visualizations developed based on a closed-loop study focused on the software professionals. The visualizations and data definitions were developed based on the investigation of grey literature (i.e., practical knowledge published by software professionals, mainly UX blogs); then, they were evaluated by software professionals to understand the suitability of the visualizations to get insights into UX issues and also the applicability of the visualizations in software practitioners work.

The results are considered emerging, as the data used and the research questions discussed are excerpts from a PhD research focused on building a taxonomy on UX data. We expected that with this approach, software professionals, regardless of their affinity with UX, can explore the potential of available data in their daily work, focusing on recognizing available data and applying visualizations to obtain insights that ultimately improve the user experience.

This article is an extended version of a paper published in the XXIII Brazilian Symposium on Human Factors in Computing Systems Macedo and Zaina [2024], which received an honorable mention. Following this recognition, we were invited to submit an extended version in which we expand our investigation by introducing a new research question, additional data, and extended analyses and discussions. The new research question (i.e., RQ3) focuses on identifying the potential improvements that UX data visualizations can bring to the design and development of interactive systems. RQ3 is further detailed in subsection 3.5, where its findings are discussed in depth. To address RQ3, we conducted a new round of analysis on the grey literature articles, emphasizing how visualization practices contribute to enhancing interactive systems. Additionally, we integrated more data collected from the study and performed an extended examination of participant comments. These comments were compared with the findings from RQ3, allowing us to explore how UX data visualizations can be effectively leveraged within software companies. Consequently, the discussion and conclusions were updated to reflect these new insights, and adjustments were made throughout the text to ensure consistency with the expanded analyses and findings presented in this extended version.

The sections are organized as follows: related work is discussed in section 2; section 3 presents the methodology, execution, and results of the research carried out in grey literature; the visualizations developed for the evaluation are presented in section 4; section 5 presents the organization, apparatus and ethical aspects of the study; section 6 presents the results; the discussion is presented in section 7; and section 8 summarizes the conclusions.

2 Related work

Buono *et al*. [2020] developed four visualizations to help visualize the paths followed by test participants while navigating websites to perform specific tasks, highlighting areas where users may face difficulties or where usability issues may arise. The goal is to provide a tool for novice evaluators to identify usability problems and understand their causes more effectively during usability evaluations. The results suggest that using visualizations as a tool to explore UX data is relevant. However, the evaluation showed that the visualizations developed focused on only one type of analysis (i.e., navigation data), while common industry practices involve different data sources and analyses.

UXmood Da Silva Franco *et al*. [2019] is a tool for integrating different data types (e.g., audio, video, text, and eye-tracking) into a dashboard with coordinated visualizations synchronized with a temporal slider. The tool allows replay test sessions while offering real-time sentiment analysis feedback, enabling UX specialists to focus freely on specific moments of user tests. The tool aims to help UX specialists solve the problem of synchronizing data from different sources, and it relies on UX professional experience to select what data to see and to do the analyses.

UXSENSE Batch *et al*. [2023] is a visual analytics system that utilizes machine learning (ML) techniques to extract user behavior from audio and video recordings as parallel timelines in a web-based interface. The tool uses ML to extract user sentiment, actions, posture, and spoken words from audio and video recordings; then, it uses the parallel timelines visualization to allow UX researchers to search, filter, and annotate the extracted data. The tool focuses on data preparation and leaves the professional to select the relevant data.

InteracDiff Dittrich *et al*. [2019] is a UX visualization tool to interpret and understand UX data after testing and evaluation sessions. The tool uses interactive charts and game-like features to make the data analysis process more enjoyable to users outside the UX research community. The tool proved adequate in tests to help novices digest collected UX data. However, its interactions may present a high cognitive load for professional use.

Each related work discussed above contributes to UX data exploration through visualization techniques and data integration methods. However, they each have distinct limitations. Buono *et al*. [2020] tool effectively highlights user navigation issues but is restricted to navigation data alone. UXmood Da Silva Franco *et al*. [2019] offers a comprehensive integration of various data types but focuses primarily on data synchronization rather than UX analysis. UXSENSE Batch *et al*. [2023] focuses on user behavior extraction using machine learning and applying parallel timeline visualizations to explore the data but only caters to professional researchers. InteracDiff Dittrich *et al*. [2019] introduces gamified interactions to make UX data analysis more accessible to novices, although it might impose a high cognitive load on experts. These insights underscore the need for a more versatile approach to support software professionals in tasks involving UX data. That approach must integrate diverse data sources, provide both broad and deep analyses, and cater to both novice and expert users.

3 UX data in practice according to grey literature

To publish a scientific article, authors must follow a rigorous methodological process, report relevant findings, and undergo peer review. However, software professionals often produce practical insights and innovative visualization strategies that remain undocumented in academic publications, as the traditional publication process is labor-intensive and not well suited for reporting smaller-scale or practice-driven contributions [Glass and DeMarco, 2006]. In contrast, grey literature consolidates valuable, experience-based knowledge that emerges directly from professional practice, including UX blogs, online communities, professional networks (e.g., LinkedIn), Q&A platforms, and personal pages [Adams *et al*., 2017]. Considering that UX data visualizations are frequently created, adapted, and refined in everyday design and development contexts, analyzing grey literature becomes essential to capture these real-world practices and lessons learned. This approach provides a broader and more authentic view of how software professionals interpret and apply UX data visualizations beyond the boundaries of academic research Garousi *et al*. [2016].

To understand how UX data visualizations support software professionals, we systematically analyzed grey literature, identifying common practices, challenges, and conditions necessary for integrating UX data analysis into the development workflow. To ensure methodological rigor in conducting and reporting the grey literature review, we followed the guidelines proposed by Garousi *et al*. [2019], which provide a structured process for systematically identifying, selecting, and analyzing grey sources in software engineering research. These guidelines recommend defining clear research objectives, establishing inclusion and exclusion criteria, and iteratively refining the search strings based on related works. They also emphasize transparency in the search process, such as: documenting search engines, search strings, the number of retrieved and selected items, and the application of a reproducible data extraction procedure. By adhering to these principles, we ensured that the grey literature analysis was both systematic and replicable.

Our primary goal was to identify **definitions of UX data, the visualizations used to explore it, and benefits to use these visualizations**. To structure our investigation, we formulated three research questions: *RQ1. What are the visualizations that help developers in the task of exploring UX data?*, *RQ2. What are UX data characteristics, and how is it used in visualization approaches?* and *RQ3 - How can UX data visualizations improve the design of interactive systems?*. The following sections detail the method adopted to conduct a grey literature review and discuss our findings in relation to these research questions.

3.1 Conduction

For a grey literature search, the researcher needs to define the search string by an iterative process, first exploring the related works and then defining the relevant terms for the search Garousi *et al*. [2019]. We defined eighteen search strings based on the most cited keywords in related works; each search string was composed of two terms (see Table 1). The configuration of two terms avoids using logical operators, as they are not common in internet search engines. Each of the eighteen search strings was manually entered into Google (i.e., one at a time) and all the results returned for each query were considered during the inclusion and exclusion process. Google was chosen as the search base due to its popularity in studies involving grey literature and because it is a general internet search engine Garousi *et al*. [2019]. The defined search strings, the number of results returned, and the number of grey articles selected for the extraction step are presented in Table 1.

The search process returned 2262 grey articles. However, 183 grey articles were unavailable (i.e., broken links or return errors). Each available grey article was downloaded as a PDF and registered in an electronic spreadsheet. For organization, each grey article received a unique ID respecting the template "*n1-n2*", where *n1* represents the ID of the search string and *n2* the sequential ID that identifies the result. The selection of articles was carried out by the first author with the support of three exclusion and one inclusion criteria. Table 2 presents the criteria and number of articles excluded after applying each criteria. After applying all inclusion and exclusion criteria, 144 grey articles were approved.

ID	Search string	Results	Selected
1	"quantitative UX"	99	14
2	"UX" + "data"	195	35
3	"UX" + "Data Analysis"	130	11
4	"UX data" + "analysis"	195	18
5	"UX data" + "charts"	67	4
6	"UX data" + "dev"	119	4
7	"UX" + "data-driven"	229	27
8	"UX data" + "evaluation"	124	3
9	"UX" + "data extraction"	164	4
10	"UX data" + "information visualization"	28	0
11	"UX data" + "InfoVis"	32	0
12	"UX data" + "patterns"	119	5
13	"UX data" + "platform"	130	6
14	"UX data" + "product development"	135	4
15	"UX" + "data scientist"	183	8
16	"UX data" + "software development"	138	0
17	"UX" + "information visualization"	93	0
18	"UX" + "InfoVis"	82	1
-	Total	2262	144

Table 1. Search strings and the number of articles returned and articles selected for the extraction stage. The ID also represents the order in which the strings were executed.

ID	Criteria	Articles removed
CE1	Content is duplicated	406
CE2	It's just advertising content	241
CE3	Not in textual format (i.e., videos or podcasts)	85
CI1	The grey article needs to describe something related to the use of UX data	1203

Table 2. Inclusion and exclusion criteria and the quantity removed from the total number of articles by each criteria | CEn means Exclusion, CIn means Inclusion

3.2 Extraction

To establish a systematic extraction process, we explored the scenarios and guiding questions proposed by Lam *et al.* [2012] for evaluating visualization-based approaches to information processing. These questions are categorized into four key scenarios: UWP (Understanding Environments and Work Practices), which focuses on understanding information processing practices; VDAR (Visual Data Analysis and Reasoning), which examines how visualizations support data analysis; CTV (Communication Through Visualization), which assesses the communicative effectiveness of visualizations; and CDA (Collaborative Data Analysis), which evaluates whether visualizations facilitate collaborative work. Based on these scenarios, we selected three questions from Lam *et al.* [2012] as our "extraction questions" to guide our analysis. The questions chosen are related to the UWP scenario. The extraction questions and their relationship with the research questions are presented in Table 3.

EQ	Question	RQ
EQ1	What types of visualizations are currently in use?	[RQ1]
EQ2	What data is currently used and what tasks are performed on it?	[RQ2]
EQ3	What is the context of use of visualizations?	[RQ3]

Table 3. Extraction questions (EQ) adapted from the Lam *et al.* [2012] proposal. The RQ column represents the intersection between the extraction question and the research questions.

In the extraction step, each approved grey literature article was fully read. We created a structured form to guide the extraction process, which was based on the extraction questions. The form included a dedicated field for each question (i.e., see the questions in Table 3). The extraction process resulted in 165 relevant excerpts used to address the research questions (see section 3). The number of excerpts extracted per question was as follows: EQ1 (53), EQ2 (112), and EQ3 (111). Due to limited space, citations to grey articles will be made using the "ACn" format (i.e., Article Citation), and the bibliographic information of grey articles can be consulted in this electronic spreadsheet.

Figure 1 presents an example of extraction carried out on the grey article AC53. All the extracted excerpts are available in a spreadsheet in Google Drive. Considering the grey literature analysis, we could answer three RQs. We discuss the results per RQs in the following sections.

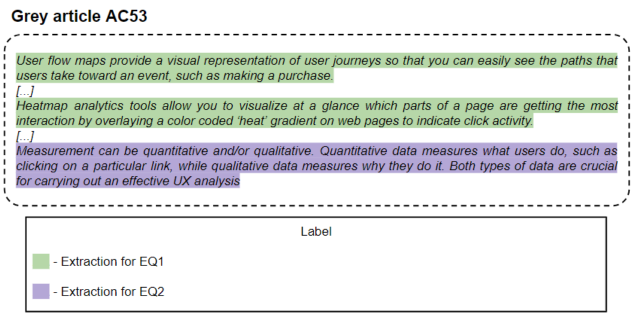

Figure 1. Example of extractions from grey article AC53, data relating to extraction questions EQ1 and EQ2 (see Table 3).

3.3 RQ1. What are the visualizations that help developers in the task of exploring UX data?

The most reported visualization in the grey literature is the table visualization. This visualization format (i.e., table) is easy to read and organizes information into lines and columns [AC1, AC2, AC3]. The table visualization gives rise to other visualizations, such as UX scorecards and Personas [AC70, AC132]. UX scorecards use tables to present user experience metrics over time [AC132], while Personas use this visualization format (i.e., tables) to list user needs, motivations, and behaviors [AC91].

There are visualization models that are present in many tools for analyzing UX data, for example, bubble charts [AC42, AC123], scatter plots [AC34], bar charts [AC123], bubble charts [AC123], and tree diagrams [AC141]. These visualizations are generally associated with tasks such as monitoring performance metrics, tracking user navigation in software, identifying behavioral patterns, and analyzing usability test results, among other applications [AC37, AC82, AC101, AC125, AC138].

Considering the variety of visualization formats available, dashboards are the common approach used to aggregate several visualizations into the same system [AC116]. Dashboards are customized according to the professional's needs and generally include visualizations such as heat maps, similarity matrices, and dendrograms [AC82, AC87, AC116, AC120, AC125, AC126, AC138]. The authors of the grey articles point to the heat map as an essential visualization to be added to dashboards, as it makes it possible to obtain an overview of user behavior in the system and identify areas of most significant interest or recurring interaction [AC40, AC42, AC54, AC57, AC65, AC71, AC120].

Some visualizations are customized to serve the purpose of organizing and structuring non-standardized UX data (i.e., like the UXmood tool Da Silva Franco *et al*. [2019]). Non-standardized UX data involves a mix of data that cannot be expressed only with numbers and texts, for example, videos recorded of user interaction with a system, click sequence in a mobile application interface, answers to open questions in questionnaires and user feedback [AC35, AC41, AC63, AC101, AC116, AC125, AC138]. Some examples of popular visualizations to show this data are affinity diagrams, empathy maps, and user flow maps [AC71, AC98, AC131]. A common approach to building a personalized visualization is to associate quantitative and qualitative data to achieve a more comprehensive view of the software's performance in terms of user experience. This approach encourages the engagement of the different professionals involved in the project because personalized visualizations serve multiple purposes (i.e., bring insights into various aspects of the product) [AC19, AC23, AC64, AC136, AC140].

3.4 RQ2. What are UX data characteristics, and how is it used in visualization approaches?

UX data is gathered from information collected and analyzed to understand how users interact with software, as in general, approaches that use UX data are focused on user-centered design [AC1, AC40, AC88, AC92, AC102, AC110, AC121, AC127, AC130, AC131, AC139]. To generate valuable UX data, software professionals needs to define a tracking plan that details which events and data should be monitored, how they are aligned with business objectives, and the goals of improving the user experience [AC80, AC99, AC135]. A point highlighted in the grey literature is that UX data must be interpreted in conjunction with other research methods [AC108, AC120, AC129].

The first emerging characteristic of UX data is its general classification, divided into behavioral and attitudinal data [AC25, AC32]. Behavioral data refers to information about users' real behavior and involves interactions with interfaces, task time, abandonment rate, and error rate [AC32, AC82]. Attitudinal data provides information about the user's subjective perception and attitudes, which involves users' opinions, feelings, and perceptions about the software [AC63, AC79].

A relevant approach is the combination of attitudinal data and behavioral data to mitigate limitations, as attitudinal data helps to understand the user's subjective perception that may not be evident with behavioral data alone [AC25, AC66, AC86]. Some of these approaches that stand out in the grey literature are creating personas and empathy maps to gain insight into user motivations [AC98], assembling a user journey map to identify interfaces that represent bottlenecks and have opportunities for improvement [AC98, AC142], and combine performance metrics with user feedback to understand behavior patterns when using the system [AC92, AC131].

Considering the nature of behavioral data and attitudinal data, both can be qualitative or quantitative [AC16, AC40, AC96]. Quantitative data reveals interaction patterns and trends, while qualitative data helps understand user attitudes' reasons [AC85, AC99]. Qualitative data is related to users' qualities and feelings regarding the product and may include data from user feedback and user interviews [AC57, AC89], usability tests [AC48, AC50], and observations that help understand the user's motivations and expectations [AC85]. Quantitative data is related to numerical and measurable values, allowing a more objective view of user behavior, such as conversion rate, session time, and pages visited [AC99]. A common approach to using UX data is to combine qualitative methods (e.g., interviews, usability testing, and diary studies) with quantitative methods (e.g., analytics, A/B testing, and surveys) to analyze the events that triggered the users' dissatisfaction reports [AC13, AC62, AC77, AC138].

3.5 RQ3 - How can UX data visualizations improve the design of interactive systems?

The integration of UX data visualizations into the design of interactive systems facilitates a data-driven methodology characterized by continuous iteration and validation. This approach ensures that development strategies remain aligned with end-user needs, fostering refinement throughout the design process [AC2, AC80, AC142]. By systematically collecting UX data over time, professionals can employ metrics to validate development progress [AC5], generate innovative, user-informed ideas [AC51], maintain alignment between user experience and software professionals objectives [AC53], and mitigate discrepancies between envisioned and actual user interactions [AC13].

Informations gathered from UX data visualization enables the creation of products that are not only aesthetically refined but also highly functional [AC17]. Grey literature articles highlight that the primary motivation behind leveraging UX data visualizations in user behavior analysis is to deepen the understanding of how individuals interact with software [AC51, AC59, AC5, AC54, AC53, AC65, AC133]. Additionally, these visualizations fosters a more empathetic, user-centered design approach by bridging the gap between software professionals and their target audiences [AC23, AC81]. The synergy between UX data insights and the expertise of software practitioners leads to more effective design solutions, aligning products more closely with market demands, thereby benefiting users [AC100].

Furthermore, UX data visualizations enables professionals to explore usability challenges, identify improvement opportunities, and understand user preferences trhought qualitative and quantitative analyses [AC65, AC69, AC64]. Qualitative data can be gathered through methods such as interviews and user testing, and uncovers the motivations behind observed behaviors [AC49, AC19, AC78], while quantitative data can be gathered through key performance metrics like abandonment and conversion rates, and provides insights into behavior patterns [AC4, AC92, AC19, AC13, AC62].

By analyzing both quantitative and qualitative data during the UX research, professionals can compare the effectiveness of different interfaces [AC52, AC38, AC60] and assess the impact of specific modifications on user navigation and overall product performance [AC126, AC120]. These visualizations provide detailed insights into user navigation patterns, viewed content, and in-software actions [AC125, AC37, AC126].

These analyses using both quantitative and qualitative data also contribute to practices, such as performance and success measurement [AC40, AC105, AC132]; understanding user behavior [AC26, AC9, AC131, AC18, AC111, AC76]; optimizing products and user experiences [AC1, AC130, AC139, AC132, AC85, AC100]; identifying usability issues and opportunities [AC4, AC92, AC102, AC42, AC100]; supporting decision-making processes [AC85, AC96]; and supports the development of user personas (e.g., with demographic and behavioral insights) [AC34, AC98, AC65].

UX data visualizations contribute significantly to enhancing the understanding of user experience. They facilitate usability improvements, feature prioritization, and stronger connections between software practitioners and end users [AC25, AC32, AC38, AC66, AC86]. Using UX data visualizations during the design processes requires a user-centered approach [AC120, AC122, AC124, AC129], and combining UX data with other methodologies further strengthens outcomes related to user satisfaction, engagement, and overall experience quality [AC120, AC124, AC129].

3.6 Reports of dissatisfaction

When analyzing UX data visualizations discussed in grey articles, we found an implicit development pattern (i.e., the three-leg approach) where the UX data definition is combined with a visualization format to accomplish a specific data analysis purpose. A common purpose of the reported UX data visualizations was to identify insights about events that triggered users' dissatisfaction reports [AC120]. We wrote four reports of dissatisfaction (RD) based on the most common issues in the grey literature (i.e., summarized in article AC120) to support our three-leg approach application to develop the study visualizations.

Our reports of dissatisfaction did not directly represent users' dissatisfaction; they were written to represent dissatisfaction on the part of the management team about the health of the mobile application that was receiving users' dissatisfaction reports. The first report (i.e., RD1) was developed using three quantitative metrics — the percentage of users who complete a task (i.e., success rate), the percentage of users who encounter a blocker and fail to complete the task (i.e., error rate), and the average time users take to complete their task. While several other quantitative indicators could have been considered, these metrics were selected for RD1 as they provide a clear and objective overview of user performance in the system tasks. The report was written as: *RD1 - Many people access the mobile application, but few complete the purchase*.

The RD2 report aims to find the issues that users are facing by organizing UX data around data that represents system events. The report was written as: *RD2 - The reason for the decrease in sales after February 2022 is unknown*. The RD3 report relies on tracking search usage and user search terms to find particular trending material to engage new users. The report was written as: *RD3 - Users who like discounts cannot find the mobile application in internet searches*. The RD4 report is focused on analysis that highlights patterns to identify recurring issues and users experiencing identical or close interaction problems. The report was written as: *RD4 - People say they do not understand how the cashback policy works*. Figure 2 shows an example of the extractions from grey literature that were used to develop the reports of dissatisfaction.

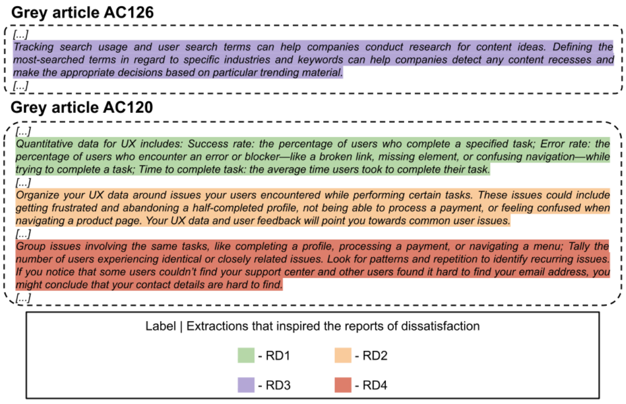

Figure 2. Example of extractions from grey article AC120 and AC130 relating to reports of dissatisfaction.

4 Visualizations to explore UX data

To develop the visualizations, we applied the three-leg approach by matching the reports of dissatisfaction (RD) with the purposes discussed in the grey literature. This alignment guided the selection of suitable visualization types and the corresponding UX data required. The UX data were generated using artificial intelligence, based on the common UX data definitions identified in the grey literature, the reports of dissatisfaction, and the fictional company scenario (i.e., TecFlyFind) developed for the study. Consequently, the visualization examples presented in the following sections were built using UX data contextualized for TecFlyFind. All details about TecFlyFind are presented in section 5.

To generate the UX data, we used ChatGPT-4o, providing it with a structured description of the study context, including the defined interfaces, the common UX data definitions extracted from the grey literature, the reports of dissatisfaction, and the TecFlyFind scenario. The model was instructed to produce a CSV dataset simulating realistic user navigation patterns across the application interfaces, particularly reflecting behaviors related to the dissatisfaction reports. This process ensured the creation of coherent and contextually relevant data for constructing the study's visualizations.

The visualizations developed for this study were made as medium-fidelity prototypes. A prototype is a candidate solution to a specific problem; the prototype's fidelity level (i.e., low, medium, high) means how close it looks to a working solution from the user's point of view Norman and Nielsen [2018]. We developed one visualization to assist in analyzing each of the four dissatisfaction reports (i.e., RD1 to RD4) explained in subsection 3.6. Due to the comprehensive scope of the RD1, we decide to develop two visualizations for it. The following sections present the visualizations developed and discuss the rationale for using the visualization format, the objective of the proposed UX data visualization, the purpose of the analysis, and the contribution of each one to reports of dissatisfaction analyses.

4.1 Last pages visited

We chose the user flow chart and thumbnails of the application interfaces to develop a personalized visualization that relates the number of users with the last interface viewed before leaving the application. **Rationale:** Visualizing how the users use the product (i.e., user flow visualization) can help identify potential weak areas, providing a starting point for further UX investigation [AC16]. **Objective:** to overview the number of users who abandon the application in each available interface. **Purpose:** to help software professionals identify whether there is an interface that has a higher occurrence of abandonment. **Dissatisfaction report:** to collaborate in analyzing the report *RD1 - Many people access the mobile application, but few complete the purchase*, Through this visualization, we can see that the warning page regarding the cashback policy was the last interface viewed by the majority of users who abandoned the application. Figure 3 presents the visualization made available to participants.

4.2 Time in the system

Based on a severity matrix, we built a visualization that groups the number of users who interacted with the product (i.e., the value within the cells) according to the progression achieved in the purchase process (i.e., X-axis) and the time spent on interaction (i.e., Y-axis). **Rationale:** A severity matrix visualization simplifies the analysis of how often each event occurred and enables the researcher to evaluate how bad it was [AC123]. **Objective:** to observe the grouping of users according to the time spent to complete the steps necessary to complete a purchase. **Purpose:** to see the concentration of users who abandon the application without completing the task. **Dissatisfaction report:** to assist in the analysis of the *RD1 - Many people access the mobile application, but few complete the purchase* because through this visualization, we can observe that the interaction time spent in the purchase task is linear in relation to the number of steps to complete the task, suggesting that there are no interaction problems. Figure 4 presents the visualization made available to participants.

4.3 Interaction with specific user interface

We apply a heatmap over an image representing the homepage interface to determine the areas where users are clicking. **Rationale:** Heatmaps visualization is a popular method that software professionals count on to discern how users spend time; this visualization makes it possible to visualize users' undesirable actions, such as rage clicks, incomplete scrolls, and confusing mouse movements [AC65]. **Objective:** to summarize data on the journey of all users that interacted with the homepage. **Purpose:** presenting the most and least "pressed" areas of the interface through a color scale without presenting the absolute quantity of interactions. **Dissatisfaction report:** to get insights into the report *RD4 - People say they do not understand how the cashback policy works*, because through visualization it is possible to notice that users rarely click on the link with information about the cashback policy. Figure 5 presents the visualization made available to participants.

4.4 Calendar of events

We take advantage of a calendar's structure with tag functionality to insert textual information that represents infrastructure events. **Rationale:** Software professionals needs to visualize system-level key performance indicators (e.g., bugs count, usage frequency, up-time) to avoid the narrow vision only in the user data and understand more about the system context [AC59]. **Objective:** overview the relationship between events that affect the mobile application infrastructure and data about the sales department. **Purpose:** to enable software practitioners to directly observe whether variations in access and sales data occur in conjunction with events that affect the product's functioning (e.g., updates, instabilities, reported bugs). **Dissatisfaction report:** to assist in the analysis of the report *RD2 - The reason for the decrease in sales after February 2022 is unknown*, as the drop in access and sales numbers occurred after the inclusion of the warning about cashback policy (Figure 8-D). Figure 6 presents the visualization made available to participants.

4.5 Most searched terms

We developed a custom visualization composed of a word cloud and a table of baseline terms. **Rationale:** The Search Terms used by users to find your product deserve a more extensive analysis to turn your content into user-centered language [AC30]. **Objective:** to compare the baseline terms used by the team to promote the product with the word cloud highlighting the most used terms for a particular subject in internet search engines (e.g., Google). **Purpose:** to facilitate the analysis of the representativeness of the terms chosen to promote TecFlyFind in relation to the most searched terms on the internet for purchasing airline tickets. **Dissatisfaction report:** to assist in the analysis of the report *RD3 - Users who like discounts cannot find the mobile application in internet searches*, showing that the keywords chosen for promotion are not the ones most used by users. Figure 7 presents the visualization made available to participants.

5 The study

This study was a proof of concept of the relevance of the three-leg approach (i.e., visualization, purposes, and UX data) to develop visualizations (see section 4) to support the investigation of causes of users' dissatisfaction reports (see subsection 3.6). We aimed to evaluate how well the visualizations helped software professionals identify aspects of the mobile application that resulted in users' dissatisfaction reports. We developed some apparatus to support the study: (i) the airline ticket company scenario; (ii) a fictional mobile app (i.e., TecFlyFind) with app interfaces and usage flow; and (iii) a questionnaire to collect participants' interpretations of the UX

Figure 3. Visualization representing the total amount of access and what was the last interface seen by users before leaving the APP.

Time spent by the user in the system	15 minutes	0	0	0	0	12
	12 minutes	0	0	0	14	3
	10 minutes	0	5	9	19	38
	7 minutes	0	1	23	101	46
	5 minutes	6	2	65	15	23
	2 minutes	2	0	0	0	0
	< 1 minute	2	0	0	0	0
TecFlyFind		20%	40%	60%	80%	100%
		Homepage	List	Cart	Warning	Finishing
		Steps to finalize the purchase				

Figure 4. Visualization representing the user's progression in the task and the time spent on the APP - Only users in the 100% column completed the task, the others are dropouts.

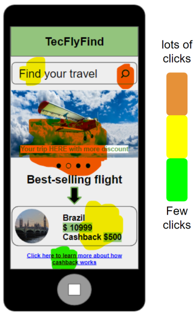

Figure 5. Visualization showing which areas are most clicked on the TecFly-Find homepage.

data available on the visualizations. The following sections describe the apparatus. We chose the airline tickets domain because it is a common sense domain that avoids the effort of the participant to interpret the application domain.

5.1 Ethical aspects

Our study considered the regulation document 510/2016 of the Health National Board in Brazil and was approved by the ethical committee of the Federal University of São Carlos (UFSCar) under the process number 68524023.0.0000.5504. About the collection, processing, and availability of data: We prepared an invitation message to the participants informing them who the researchers in charge of the study, the study's aim, and how data collection would happen, and we explained that the data would be strictly used for scientific purposes; we developed and delivered to participants the Term of Informed Consent took into account the recommendations of regulation document 510/2016; we also make clear that our evaluation focused on the visualizations and not the participants' exper-

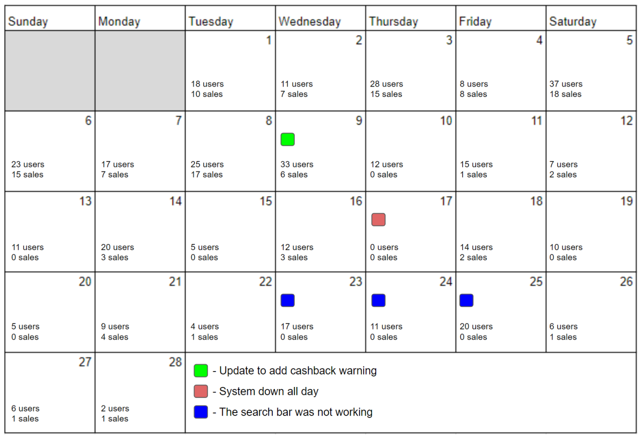

Figure 6. Calendar-shaped visualization representing the number of accesses, the number of sales and events in relation to the TecFlyFind infrastructure.

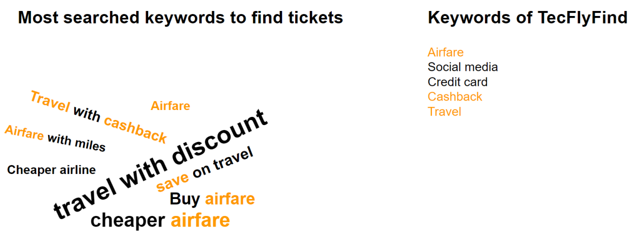

Figure 7. Visualization representing the relationship between the terms most used on the internet to find airline tickets (word cloud) and the terms used to promote the app (table).

tise; we provided the authors' contact details to participants and informed them that they could request the data at any time.

Regarding care for possible impacts arising from research and its conduct, we invited participants to the study and made it clear that participation was free and they could withdraw at any time; to mitigate participants' fatigue and stress, the ideal time to complete the questionnaire was thirty minutes. We reduced the time needed to complete the questionnaire by presenting the five visualizations and the ten questions (see subsection 5.4) on the same page of the questionnaire. Additionally, we decided to use only the homepage in the *Interaction with specific user interface* visualization to reduce the study time. The participant was free to choose when to respond to the questionnaire, and we did not make any demands on where the participant should be. We allowed participants to pause their responses and come back to respond later if they felt tired.

Concerns about transparency, auditability of results, dissemination, and use of research products: The Term of Informed Consent clarifies that all the data used in publications would be anonymized and made available to allow the reader to replicate the analysis presented; the raw data would only be accessed by researchers; after the end of data collection all identity information would be erased from the raw data; and all participants can have access to data and research results.

5.2 The company scenario

The fictional company aims to be the largest airline ticket seller on the internet. The company's difference is that it provides cashback on airline tickets through disclosure agreements with the ticket buyer. The target audience is people who are active on social media and want to travel by plane at a cheaper price. The company works as follows: (i) The company offers a mobile application (i.e., named TecFlyFind) to search for airline tickets; (ii) The customer who publishes on their social networks that they purchased an airline ticket using the TecFlyFind app is entitled to cashback; and (iii) After the company analyzes the publication on the social network, the cashback will be credited to the customer's account.

5.3 TecFlyFind application

The purpose of the mobile application is to search for airline tickets, inform about the company's cashback policy, and finalize the purchase. The application has six interfaces, with the main flow that directs the user through the process of purchasing tickets consisting of five interfaces; the sixth interface explains the rules of the cashback program, and access is optional. Figure 8 shows the interfaces and usage flow of TecFlyFind.

The application developed for this study was a medium-fidelity prototype created collaboratively by the authors through a brainstorming process. Its design was inspired by the interfaces and purchase flows of commercial airline ticket applications (e.g., Booking). The prototype was not interactive or navigable; however, it included detailed images of all interfaces accompanied by a document describing the main user flow as well as possible secondary interaction paths. This approach ensured consistency in participants' understanding of the system context.

The homepage (Figure 8-A) features an advertising banner, the best-selling flight, and the option to search for a destination. After searching for a destination, the application lists prices and the amount of cashback offered (Figure 8-B). After selecting a flight, the application adds it to the shopping cart (Figure 8-C). After proceeding through the cart, a warning is displayed that the cashback will only be credited after analyzing the publication on the social network (Figure 8-D). After closing the warning, the purchase confirmation interface (Figure 8-E) is displayed. On the homepage (Figure 8-A) and in the confirmation interface (Figure 8-E), there is a link that redirects to the explanation of the cashback policy (Figure 8-F).

5.4 Questionnaire

We developed a questionnaire to collect data and guide participants through the study's steps. To reach the largest and most diverse pool of participants, we chose an online questionnaire format. The questionnaire was divided into five sections: (i) Informed Consent Form (ICF) for academic purposes, (ii) profile questions, (iii) presentation of TecFlyFind, (iv) gathering perceptions about visualizations, and (v) collecting participants' feedbacks on the relevance of the visualizations.

The *profile section* included questions about the participant (e.g., age, years of experience, position), the company (e.g., type, segment, year of foundation, whether it allows access to customer feedback), interests related to the study (e.g., InfoVis, UX, Analytics, visualizations), and personal knowledge about UX data and software used to visualize UX data. In the *TecFlyFind section*, we presented information about the fictional company (detailed in subsection 5.2) and the mobile application (described in subsection 5.3).

For gathering data on participants' interpretations of the UX data available in the visualizations, we presented each of the five visualizations (described in section 4) and asked two questions per visualization (ten questions in total). The questions were identical for each visualization: participants were asked to identify, for each visualization, (1) which reports of dissatisfaction could be analyzed using that visualization, and (2) what insights they identified from interpreting the visualization. For the first question, participants had the option to select from the four dissatisfaction reports described in subsection 3.6, with the addition of an option for "none" and a free-text field. In the second question, participants could choose from ten predefined options describing UX-related insights (see Table 4 for the list of options) to capture their interpretation of the data displayed in the visualization.

ID	Information
IE1	I see reasons why the user cannot complete the purchase
IE2	I see parts of the system that the user is having difficulty with
IE3	I see opportunities to improve access to the system
IE4	I see functions that can be added to the system
IE5	I see opportunities to improve the usability of the system
IE6	I see who my main users are
IE7	I see reasons for users not to use the system
IE8	I see errors/crashes in the system
IE9	I see opportunities to improve access to system information
IE10	I don't see any useful information

Table 4. Pre-defined options to collect the participant's perception of what information they were able to extract from the study visualizations.

At the end of the questionnaire, two additional questions were included to assess the relevance of the visualizations for participants' daily work. The first question (discussed in subsection 6.3) was multiple choice, asking participants to identify the most appropriate target audience for each visualization: (a) Not useful; (b) Appropriate for designers; (c) Appropriate for developers; or (d) Appropriate for stakeholders. The final question (discussed in subsection 6.4) was open-ended, allowing participants to describe the potential benefits and usefulness of applying the UX data visualizations in their daily work.

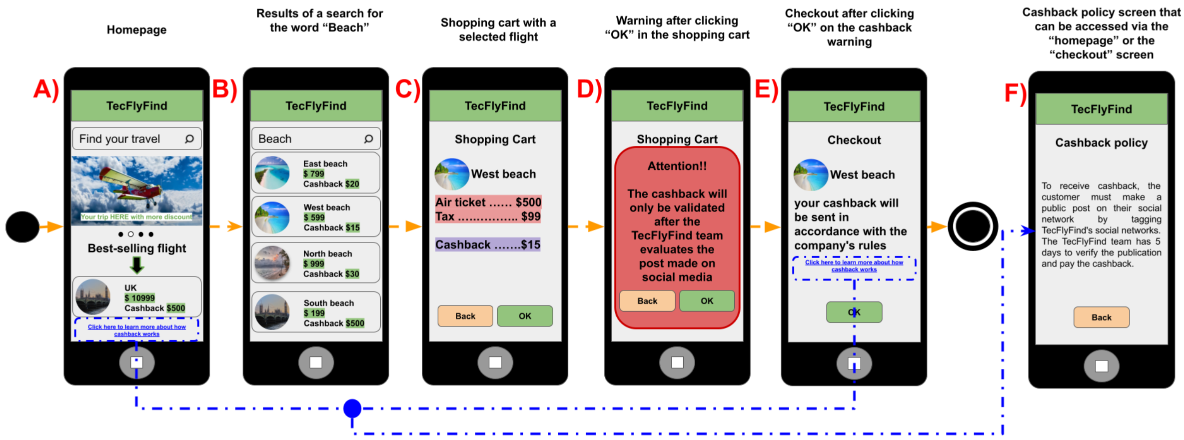

Figure 8. User flow of TecFlyFind to contextualize participants - Arrows with orange dashes represent the main flow - Arrows with blue dashes and dots represent the flow to read the cashback policy page.

5.5 Study conduction

The invitation to participate in the study was made through social networks and email lists of the authors' research group network. In total, 31 participants answered the questionnaire. While filling out the questionnaire, the researcher was available via an instant messaging application to answer any participant's questions if necessary. In addition to the questionnaire, participants also had access to the PDF with the TecFlyFind interfaces.

5.6 Threats to Validity

We considered the conclusion, construct, internal, and external validity threats following the recommendations of Wohlin *et al*. [2012].

To address conclusion validity, we ensured consistency in data analysis by applying a systematic coding procedure both for the grey literature and for participants' open-ended comments. The coding process was performed by multiple researchers who discussed and refined the extracted themes and categories to mitigate individual interpretation bias. In addition, the inclusion of the new research question (RQ3) was grounded in the results of the previous study phase, ensuring theoretical alignment and coherence between the old and new analyses.

Regarding construct validity, we employed a structured set of artifacts (i.e., the scenario of the airline ticket mobile application, the visualizations, and the online questionnaire) to ensure that all participants interpreted the tasks within the same context. The participants were presented with a clear description of the study goals, the definitions of UX data, and examples of visualization use to minimize misunderstandings about the constructs being evaluated. Moreover, the extraction process from the grey literature followed methodological rigor according to Garousi *et al*. [2019], reducing potential bias in identifying and interpreting practical evidence from non-scientific sources.

For internal validity, we considered possible influences related to participants' engagement and fatigue during the study. The online questionnaire was designed to be concise and straightforward, taking no more than one hour to complete. Participants were guided through the same visualizations and tasks, which reduced inconsistencies caused by variation in exposure or task complexity. Since participation was voluntary and without compensation, motivation was primarily intrinsic, linked to professional interest in UX and data visualization topics.

Concerning external validity, our sample included 31 software professionals with varied backgrounds in UX, software development, and data analysis. While this diversity strengthens generalizability within software team contexts, we recognize that the results may not fully extend to teams operating in significantly different domains or organizational cultures. Nonetheless, previous studies indicate that both professionals and advanced students tend to perform similarly in exploratory design and reasoning tasks Salman *et al*. [2015], supporting the relevance of our results for practical settings. The addition of RQ3 and its associated analyses further broadened the study's external perspective by connecting empirical findings from practitioners with evidence extracted from grey literature.

6 Results

The majority of responses originated from Brazil, with 30 participants based there and 1 Brazilian participant living and working in Malta, Portugal. The Brazilian participants were from São Paulo (27), Paraná (1), Alagoas (1), and Santa Catarina (1). Our participants were members of software teams and had roles as designers, software developers, software engineers, product managers, and UX researchers. Participants had relevant professional experience, with more than 80% (N = 25) declaring working in a big company and 21 participants with more than four years of experience. Regarding the participants' interest in topics related to the research, it was noted that the average indicates that everyone has a reasonable interest in the topics covered. Table 5 and Table 6 presents the data collected about the participants' profiles. In the following sections, we present the results organized based on the focus of the questions presented in the questionnaire:

Profile			Company	
ID	**Age**	**Experience**	**Type**	**Explore UX data?**
P1	27	+ 4 years	Company	Sometimes
P2	28	+ 4 years	Company	Always
P3	42	> 2 years	Startup	Sometimes
P4	27	+ 4 years	Startup	Always
P5	28	+ 4 years	Company	Always
P6	27	+ 4 years	Company	Sometimes
P7	27	+ 4 years	Company	Sometimes
P8	29	+ 4 years	Startup	Always
P9	34	+ 4 years	Startup	Never
P10	26	> 2 years	Company	Always
P11	26	+ 4 years	Company	Sometimes
P12	22	> 1 year	Startup	Always
P13	25	> 2 years	Company	Sometimes
P14	30	+ 4 years	Company	Always
P15	27	+ 4 years	Company	Never
P16	27	+ 4 years	Company	Sometimes
P17	27	+ 4 years	Company	Always
P18	33	+ 4 years	Company	Always
P19	31	< 1 year	Company	Always
P20	23	> 1 year	Company	Sometimes
P21	32	+ 4 years	Company	Rarely
P22	27	+ 4 years	Company	Sometimes
P23	27	> 2 years	Company	Always
P24	24	+ 4 years	Company	Always
P25	33	< 1 year	Company	Always
P26	26	+ 4 years	Company	Sometimes
P27	27	> 2 years	Startup	Sometimes
P28	32	+ 4 years	Company	Sometimes
P29	31	+ 4 years	Company	Always
P30	30	+ 4 years	Company	Always
P31	45	> 2 years	Company	Always

Table 5. Profile data of participants.

ID	InfoVis	UX	Analytics	Charts
P1	3	2	2	2
P2	3	3	3	3
P3	3	4	4	3
P4	4	4	4	4
P5	4	3	3	3
P6	3	2	1	2
P7	4	4	4	4
P8	4	3	3	3
P9	3	3	2	3
P10	4	3	3	3
P11	4	4	3	3
P12	3	3	2	4
P13	4	3	3	4
P14	4	4	4	4
P15	4	4	3	4
P16	4	3	3	4
P17	3	2	2	2
P18	2	4	2	2
P19	4	2	4	3
P20	3	4	3	3
P21	3	2	1	1
P22	3	3	3	3
P23	4	4	4	4
P24	4	4	4	4
P25	4	4	3	3
P26	3	4	3	3
P27	4	3	2	3
P28	3	4	4	3
P29	4	4	4	4
P30	3	4	3	4
P31	4	4	4	4

Table 6. Interest data of participants | Label: 1 - No interest, 2 - Little interest, 3 - Reasonable interest, 4 - A lot of interest.

6.1 Participants knowledge about UX data

As previously discussed (see section 1), the definition of UX data is not yet well defined among software developers. In our evaluation, in the profile questionnaire, participants were asked about their personal knowledge about UX data considering their daily work context (see subsection 5.4). For this question, there were five pre-definitions answers for UX data (i.e., D1 to D5) and an open text field where participants could enter their own definition (i.e., D6). The pre-defined answers were related to the use of the product (i.e., D2), the target audience (i.e., D5), the application's context (i.e., D4), and collection from the user (i.e., D1 and D3). Participants were free to select as many definitions as they wanted. Table 7 presents the answers that participants could choose and the number of votes each received.

ID	Definition	Votes
D1	Data produced by a UX professional	9
D2	Data collected regarding product use (e.g. logs, screen recording)	26
D3	Data collected through an instrument (e.g. questionnaire)	14
D4	System performance data (e.g. processor and memory usage)	3
D5	Data about the user (e.g. name and age)	4
D6	My own definition	4

Table 7. Pre-defined options that participants could choose to define UX data.

We noticed that participants were confident in choosing only the definitions directly related to the product and its use (i.e., D1, D2, and D3). In contrast, less than 15% (N = 4) of participants chose options related to the user and the context of use (i.e., D4 and D5). Only four participants (i.e., P12, P14, P24, and P29) used the field to inform their own definitions of UX data (i.e., D6). Participants P12 and P29 pointed out that UX data can have origins external to the user's interaction with the product, such as the company's business rules [*"P12 - both business and functional data that impact the customer experience user"*], and the user's interest and satisfaction with the use of the product [*"P29 - Set of metrics and indicators, I can mention here CSAT [Customer Satisfaction Score], CES [Customer Effort Score], summed with usage and engagement metrics"*].

According to P14, UX data can be *"user behavior data such as usage tracking"* and can be *"produced with qualitative and quantitative collection methods"*, while the responsibility for generating this data can be attributed to *"designer/researcher/cx/or another area of the company"*. P14's answer shed light on the practical definition of UX data and also brought definitions about its origin and those responsible for the data. Finally, participant P24 selected only definition D1 and used the free text field to inform that UX data is *"data collected to improve UX in products"*.

6.2 Using the visualizations to get insights

Based on the data from the question about which reports of dissatisfaction could be analyzed using the observed visualization, we observe that most votes align with the key answers (i.e., answers considered correct by the authors). These results suggest that participants were confident in extracting insights into the reports of dissatisfaction that the visualizations were designed to meet. However, we noticed that participants found new meanings for three of the five visualizations presented: the case of *Last pages visited* and the *Time in the system* visualizations, where participants pointed out that they can also help analyze the RD4 report that talks about *people say they do not understand how the cashback policy works*; and the visualization of *Calendar of events* which was highlighted as relevant to analyze the RD1 report that talks about *Many people access TecFlyFind, but few complete the purchase*. Table 8 summarizes the results and presents the key answer for each visualization.

Chart	RD1	RD2	RD3	RD4	None	Key answer
Last pages visited	25	1	2	21	0	RD1
Time in the system	20	0	4	13	4	RD1
Interaction with specific user interface	5	1	3	27	0	RD4
Calendar of events	11	20	3	9	2	RD2
Most searched terms	1	1	29	2	0	RD3

Table 8. Quantitative of participants' responses regarding which report of dissatisfaction (explained in subsection 3.6) benefited most from the observed visualization.

Considering the question of what insights the participants identified when interpreting the observed visualizations, we noticed in the *last pages visited* visualization that the participants pointed out that it was possible to extract insights about reasons for the user not to complete the purchase (i.e., IE1) and that it was also possible to find opportunities to improve the usability of the system (i.e., IE5) and access to information (i.e., IE9); the *Time in the system* and *Interaction with specific user interface* visualizations contributed to finding opportunities to improve the usability of the system (i.e., IE5), improve access to system information (i.e., IE9), and also helped participants see parts of the system where the user was having difficulties (i.e., IE2).

The visualization of *Calendar of events* was the most highlighted by participants to help in the search for failures and errors in the system (i.e., IE8) and also to clarify reasons for users not completing the purchase and not using the system (i.e., IE1, IE7). Finally, the visualization of *Most searched terms* was highlighted as relevant to discover who the main users are (i.e., IE6) and to find ways to improve access to the system and system information (i.e., IE3, IE9).

6.3 Applying visualizations in participants daily work

Considering the context of the company where they worked, participants should list which professionals could obtain meaningful insights using the study's visualizations or whether the visualizations would not be helpful. All the visualizations received at least one vote as not applicable. In this question, participants should choose only one option. The data shows that in three of the visualizations, the participants were divided into two roles as being those most interested in using the visualization as a helpful tool; this division only did not occur in the *Interaction with specific user interface* visualization (i.e., which had the majority of votes directed to designer) and in the *Most searched terms* visualization (i.e., which was understood as useful to stakeholders). Designers and stakeholders were chosen as preferred for the *Last pages visited* and *Time in the system* visualization, while developers and stakeholders were appointed for the *Most searched terms* visualization.

6.4 What improvements could UX data visualizations bring to company's work?

As discussed in subsection 5.4, we proposed an open-ended question for participants regarding the improvements that the use of general UX data visualizations (i.e., not just the visualizations presented in this study) could bring to their work in software development. Twenty-one out of the thirty participants provided contributions. We then compared their responses with the findings of *RQ3 – How can UX data visualizations improve the design of interactive systems?* (see section 3). Through a qualitative analysis of participants' responses, we categorized their contributions into four themes (see Table 9 for the themes and their definitions), which highlight improvements in UX data utilization related to the development of interactive systems.

Theme	Definition
Understand users	leveraging UX data visualizations to support the creation of more empathetic, user-centered designs, ensuring that products align with actual user needs rather than assumptions.
Self-knowledge about the system	UX data visualizations to tracking feature usage, aligning product vision with user expectations, and assessing system-wide interactions to enhance functionality and business alignment.
Handling development resources	UX data to identifying performance gaps, tracking user engagement, and justifying development investments.
Improve system interaction	focuses on analyzing qualitative and quantitative data to uncover critical touchpoints, assess feature effectiveness, and enhance the overall user experience through data-driven design decisions.

Table 9. Themes and definitions derived from participant comments about using UX data visualizations in their company.

The first theme was about Understanding users (see participants comments on this theme in Table 10), and the participants' comments aligned closely with the research findings. Several participants emphasized the role of UX data visualizations in understanding users' pain points and behavioral patterns, which resonates with the notion that these visualizations deepen insights into user interactions with software [AC5, AC51, AC53, AC54, AC59, AC65, AC133]. For instance, P2 highlighted that this process helps companies empathize with users, reinforcing the idea that UX data fosters a more user-centered design approach [AC23, AC81]. Additionally, participants P9 and P31 pointed out that UX data helps in better understanding user profiles, aligning with findings that such data supports persona development through demographic and behavioral insights [AC34, AC65, AC98]. Furthermore, P10's comment on prospecting new users suggests that UX data visualizations not only aid in refining existing experiences but also in identifying opportunities for expanding user engagement, which is consistent with the research's emphasis on using these tools to enhance user satisfaction and interaction quality [AC120, AC124, AC129].

Participants' comments also reinforced the research findings about Self-knowledge about the system (see participants comments on this theme in Table 11). P2 highlighted that UX data visualizations facilitate the understanding of the purpose of the application, which aligns with the idea that systematically collecting UX data helps mitigate discrepancies between

ID	Participant comment
[P2]	This process helps to *understand the user's pain*, allowing the company to put itself in the user's shoes
[P9]	Better *understand the user's profile*
[P10]	Help to *prospect new users*
[P31]	help us to better *understand the profile* of those who access the system and we can (or not) associate them with a persona

Table 10. Participants comments aligned with theme Understand users. Words in italic represents the rationale to be select on the actual theme.

envisioned and actual user interactions [AC13]. Similarly, P6 mentioned that such tools provide a better view of the product we sell, supporting the notion that UX data insights enable professionals to refine both functionality and market alignment [AC17, AC100]. P20's remark on the importance of aligning the key words of the business resonates with the research's emphasis on leveraging UX data to assess the impact of modifications on user navigation and overall product performance [AC120, AC126]. Finally, P27's comment about improving product visibility is consistent with findings that UX data visualizations help optimize products, prioritize features, and strengthen connections between software practitioners and end users [AC25, AC32, AC38, AC66, AC86].

ID	Participant comment
[P2]	facilitating the *understanding of the purpose of the application*
[P6]	I believe it would help our company to have a *better view of the product we sell*
[P20]	it would be *good to align the key words of the business*
[P27]	Improve *product visibility*

Table 11. Participants comments aligned with theme Self-knowledge about the system. Words in italic represents the rationale to be select on the actual theme.

We noted that Participants' comments also highlighted the ability of UX Data visualization in helping with Handling development resources (see participants comments on this theme in Table 12), reinforcing key findings from the research. P9 emphasized that these visualizations improve efficiency in managing product processing resources, aligning with the idea that UX data facilitates performance measurement and supports decision-making processes [AC40, AC85, AC96, AC105, AC132]. P20 noted that such tools could help developers take action more quickly in relation to a drop in users, which resonates with the role of UX data in validating development progress and ensuring strategies remain aligned with user needs [AC2, AC5, AC80, AC142]. P24 pointed out that using these resources in production systems enhances problem tracking and conversion into actionable tasks, supporting the research finding that UX data analysis enables professionals to compare interface effectiveness and optimize development workflows [AC38, AC52, AC60]. Additionally, P26 highlighted the challenge of tracking everything that happened in large companies, reinforcing the benefit of UX data in facilitating feature prioritization [AC25, AC32, AC38, AC66, AC86]. Finally, P30 emphasized that UX data helps justify the company's investment in user-centered development, which aligns with the research's emphasis on leveraging UX data insights to refine design decisions and improve financial outcomes for stakeholders [AC85, AC96].

Finally, the majority of the comments was about Improve system interaction (see participants comments on this theme in Table 13), which also was highlighted in grey literature. Several participants emphasized the importance of UX data visualizations in understanding and optimizing user interaction.

ID	Participant comment
[P9]	*Improve efficiency* in the use of product processing resources
[P20]	could help developers *take action more quickly* in relation to a drop in users
[P24]	Using these resources in production systems (or even approval), the problem *tracking process becomes more agile*, especially when converting these problems into actions to be performed by the development teams
[P26]	I thought the idea of the calendar showing everything, even product updates, was a great idea. It would help in many moments here at the company, we have a lot of difficulty *tracking everything that happened* in the products given that it is a very large company
[P30]	They can *justify the company's investment* in user-centered development, with more participatory dynamics that could provide a better financial return for stakeholders and the entire ecosystem

Table 12. Participants comments aligned with theme Handling development resources. Words in italic represents the rationale to be select on the actual theme.

P2 noted that these visualizations help improve navigation processes, aligning with research findings that UX data facilitates usability improvements and enhances user experience [AC25, AC32, AC38, AC66, AC86]. P6, P8, and P9 mentioned that UX data enables the identification of points of improvement, failures in the customer journey, and usability problems, supporting the idea that these tools help detect usability challenges and refine system functionalities [AC4, AC42, AC92, AC100, AC102]. Additionally, P10, P11, and P20 highlighted that UX data allows teams to map user interactions, identify critical paths in the system flow, and analyze the relevance of each screen, reinforcing research findings on how UX data visualizations provide insights into navigation patterns and software usage [AC37, AC126, AC125]. P17 and P18 pointed out that these insights reveal how users actually interact with the system, rather than relying solely on self-reported data, which aligns with the importance of combining qualitative and quantitative analyses to assess product performance [AC64, AC65, AC69, AC120, AC126]. Furthermore, P13, P15, and P16 mentioned the role of UX data in understanding past interactions, structuring optimal event sequences, and analyzing screen layout impacts on user decisions, which corresponds to research findings that UX visualizations support iterative product refinement and foster a more user-centered approach [AC120, AC122, AC124, AC129]. Finally, P30 emphasized that by providing clarification on how users interact, UX teams can strengthen or redesign user flows, reinforcing the grey literature's assertion that UX data helps bridge the gap between software professionals and end users to create more intuitive and effective interfaces [AC23, AC81].

7 Discussion

The first lesson learned that stands out is the participants' need for more confidence in defining UX data. According to reports in the grey literature, all definitions offered to participants are considered UX data; however, participants clearly only felt confident in stating that UX data is only data directly related to the use of the product, indicating a funneled view of the concept of "User eXperience" focusing only on the moment of interaction. Another point to highlight about the definition of UX data is that half of the participants supported the idea that UX data can only be generated and explored through the intervention of a UX professional. At this point, the three-leg approach (i.e., visualization, purposes, and UX data) proves to be a relevant solution because by establishing a purpose, the professional will be able to know the possible

ID	Participant comment
[P2]	Improve *navigation processes* [interaction with the system]
[P6]	It would make it easier to *identify possible points that could be improved*
[P8]	Identify *points of failure in the customer journey*
[P9]	Detect *usability problems*
[P10]	*Identify critical paths in the system flow*, identify strengths and weaknesses of use on specific screens
[P11]	*Mapping user interaction* with the product
[P12]	We could use it to collect information about the *acceptance and usefulness* of new features in our application
[P13]	I believe that the calendar of events and accesses is interesting for an organization and strategic review of *what happened previously*
[P13]	Interaction and permanence in the system also becomes useful to *discover possible screens or flows* that the user does not access or accesses and ends up leaving because they do not understand
[P15]	The flow would help designers and researchers *think about the best sequence of events*
[P16]	UX team understands *how screen layouts and screen order are influencing* purchases
[P17]	It is good for us to know *how the user actually uses the system*, and not what they answer in questionaires
[P18]	It provides useful *information about user behavior* that can help design screens that are more targeted to the information the user is looking for, and helps with the investigation of the root causes of a problem
[P20]	helps in a very visual way to *understand the complete user flow* to make a purchase and understand exactly what result each flow can lead to
[P20]	It helps to *know which are the most critical parts of a screen*
[P22]	to understand *how relevant each screen is to the user*
[P27]	In *identifying problems* in the functionalities
[P27]	In *analyzing the user's interaction* with the product and reaction to updates
[P28]	It could help in *identifying points of improvement in the system*, from the communication, usability and design aspects, to tracking failures that harmed sales conversion
[P30]	By providing *clarification on how the user interacts*, the design team can strengthen or redesign the user's intention of interaction

Table 13. Participants comments aligned with theme Improve system interaction. Words in italic represents the rationale to be select on the actual theme.

visualizations and the necessary UX data.

Participants felt motivated to use visualizations to seek insights into all reports of dissatisfaction provided. This motivation was perceived by the fact that participants consistently pointed out that the *Last pages visited* visualization and *Time in the system* visualization were also suitable for providing insights into the report *RD4 - People say they do not understand how the cashback policy works* (i.e., these visualizations was intended for RD1 report). The motivation of the participants in pointing out that these visualizations were suitable to get insights about the RD4 report is corroborated by the fact that in the question about insights identified in the visualization (see subsection 5.4) participants pointed out that visualization brought opportunities to improve the usability of the system and also improve access to information (i.e., IE5, IE9). Unlike what is pointed out in the grey literature, which states that a specific visualization serves one purpose, this observation shows that a visualization can be multipurpose even if it is not an overview visualization.

Similarly, participants pointed out the usefulness of the *Calendar of events* visualization for the report *RD1 - Many people access the mobile application, but few complete the purchase* (i.e., this visualization was intended for RD2 report). The participants' choice to point out contributions to RD1 is justifiable because when answering the question about insights present in the visualization, participants pointed out that through it, they were able to identify reasons for the user not to complete the purchase and not use the system (i.e., IE1 and IE7). We developed these visualizations to yield insights just for a report of dissatisfaction. However, this observation by participants to notice other contributions embedded in the visualizations shows that visualizations depend not only on the experience of the professional who develops them but also on the experience of the user who will use them.

Based on participants' comments about the exploration of UX data visualization to search opportunities to improve the product, we get valuable insights into the role of UX data visualizations in software development. First, UX data visualizations play a crucial role in understanding users, enabling professionals to identify pain points, refine user personas, and develop more empathetic, user-centered designs. Second, they are instrumental in improving system interaction, as they help detect usability issues, optimize navigation flows, and assess feature effectiveness. Third, UX data visualizations enhance self-knowledge about the system, allowing software practitioners to track feature usage, align product vision with user expectations, and improve internal communication about system performance. Finally, they support handling development resources by facilitating feature prioritization, validating design choices, and justifying investments in UX-driven development.

When exploring the study visualizations, participants felt confident in extracting insights to investigate the events that triggered the reports of dissatisfaction, including making recommendations that the visualizations would help analyze other reports of dissatisfaction and that they would be suitable for the work of other professionals such as designers, developers, and even stakeholders. This scenario suggests that software professionals (i) are aware of the existence of UX data but do not have the skills to characterize them; (ii) recognize that through visualizations of UX data, it is possible to obtain relevant information about product improvements; however, they trust only UX professionals to manage the data and build the visualizations; (iii) understand that UX data can yield varied insights according to the responsibilities of each position within the software development flow; however, they do not feel like protagonists in the process of collecting, managing, and analyzing UX data; and (iv) feel motivated to explore UX data in search of opportunities to improve the product; however, they are not always part of a company with a culture of access to UX data.

8 Conclusions

This study explored the relevance and applicability of the three-leg approach (i.e., visualization, purpose, and UX data) by analyzing UX data visualizations with 31 software professionals. The evaluation was grounded in the analysis of 144 grey literature articles discussing the practical use of UX data visualizations in software development practices. The research revealed that software professionals often have a narrow view of UX data, typically restricting it to product usage metrics generated by UX professionals. However, participants recognized the broader potential of the proposed visualizations, highlighting their applicability across various UX-related analyses. They acknowledged the adaptability of these visualizations, noting multiple utilities beyond their initial design purposes; Reinforcing the importance of the software professionals experience and interpretation in extracting meaningful insights from visualizations.

Our findings shed light on four key areas that professionals could benefit from using UX data visualization (i.e., Understanding users, Improving system interaction, Enhancing self-knowledge about the system, and Handling development resources) and the importance of fostering confidence among all software practitioners to effectively collect, manage, and analyze UX data. Participants acknowledged that UX data visualizations can bridge the gap between software professionals and end users, fostering a more user-centered design approach. In future work, we intend to further refine the three-leg approach by expanding the scope of visualizations and exploring their applicability in diverse domains. By bridging the gap between theoretical visualization methods and real-world applications, we aim to provide software professionals with practical tools (e.g., Taxonomys) that enhance user satisfaction and drive more effective UX-driven development processes.

Declarations

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The use of artificial intelligence

In this study, artificial intelligence was used to generate simulated UX data for the fictional application scenario, ensuring a realistic yet controlled dataset for analysis. Additionally, AI-based tools were employed to support minor language revision and proofreading of the manuscript, given that the authors are not native English speakers. The use of AI was strictly limited to these purposes and did not involve any content writing, conceptual development, or interpretation of results.

Authors' Contribution

Maylon Macedo: Conceptualization, methodology, software development, data curation, investigation, formal analysis, and writing – original draft. Luciana Zaina: Conceptualization, methodology, supervision, validation, and writing – original draft.

Conflicts of Interest

The authors declare that they have no competing interests.

Availability of Data and Materials

The datasets generated and/or analyzed during the current study are available in the paper.

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