Challenges and Opportunities for Tool Adoption in Industrial UX Research Collaborations

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UX research practitioners analyze qualitative data to comprehend users' needs and synthesize design implications for software systems. Collaborating with multiple stakeholders is inevitable for these professionals and adds additional pressure to their already laborious data analysis tasks. In this paper, we investigate how these practitioners' multi-stakeholder collaboration affects their data analysis practices. Specifically, we investigate the challenges qualitative UX research (QUXR) practitioners face, limitations of the current qualitative data analysis (QDA) support tools they use, and design implications for future QDA tools to address the limitations. Through semi-structured interviews combined with diagramming activities with thirteen industry QUXR practitioners, we have revealed that collaboration becomes a bigger challenge than data analysis and that it often leads to (1) preferring simple tools despite the QDA specialized tools' beneficial features and (2) wanting to triangulate their work to convince stakeholders. Finally, we have synthesized these results and suggest design implications for QDA support tools.

CCS Concepts: • **Human-centered computing** → **Human computer interaction (HCI)**.

Additional Key Words and Phrases: qualitative UX research practice, collaboration, industry, human-centered design

ACM Reference Format:
Daye Kang and Jeffrey M. Rzeszotarski. 2024. Challenges and Opportunities for Tool Adoption in Industrial UX Research Collaborations . *Proc. ACM Hum.-Comput. Interact.* 8, CSCW2, Article 443 (November 2024), 27 pages. https://doi.org/10.1145/3686982

1 Introduction

Qualitative user experience research (QUXR), widely adopted by software organizations in the industry, is essential for creating user-centered software products [22]. QUXR is crucial for these organizations to remain agile against rapidly changing user demands and avoid any wasted effort on unwanted software features. QUXR practitioners (henceforth referred to as *practitioners*) in these organizations analyze qualitative user data, mainly interview transcripts, to derive insights on user needs, typically within the early stages of product development. The practitioners then share the results with diverse stakeholders in the organization, including designers, software engineers, data scientists, and managers, to collectively make design decisions. The diversity of stakeholders in this process generates synergies for innovation, but it also entails coordination costs. While the benefits of QUXR often outweigh the cost of its establishment and maintenance within an organization, these coordination costs increase based on team size and product complexity.

Qualitative data analysis (QDA), central to QUXR, typically involves practitioners manually reading, labeling, categorizing, and interpreting 15 to 20 one-hour-long interview transcripts to

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ACM 2573-0142/2024/11-ART443
https://doi.org/10.1145/3686982

identify patterns in the text. Despite the seemingly small dataset size, the iterative nature of QDA leads to a notoriously lengthy analysis time [8, 13, 53].

The slow pace of QDA can pose serious challenges in collaborative product development within the fast-moving tech industry. Since QDA takes place during the early stages of the product development, its slow conduct can act as a bottleneck, impeding the progress. Furthermore, the slow pace of QDA creates questioning of its efficiency, and preference of quantitative analysis over QDA as a comparably faster technique [59, 66]. Consequently, practitioners hold lower persuasion power in collaborative product development [18]. Convincing members with diverse values can be challenging [52], and this becomes problematic, as failure to convince can lead to missing opportunities in innovation [22].

A number of prior efforts within human-computer interaction have sought to improve the QDA process. These include the development of tools that employ textual data processing techniques [32, 56, 68, 76], and facilitate collaborative modes of conducting qualitative analysis [30, 45]. Yet, adoption of these tools remains low in the industry [26]. Instead, practitioners prefer to use non-QDA-specific tools such as Google Docs and Excel [26]. This is curious given the clear benefits offered by specialized QDA support tools (e.g., Atlas.ti, NVivo) and these tools' higher levels of adoption in academic research [16, 43, 74, 80]. We argue that a key aspect of this issue lies in how tools do (or do not) consider the contextual, collaborative factors, such as heterogeneity among stakeholders in software organizations, which ought to be considered. However, there are not many prior work which a) delineates the issues related to collaboration in QUXR in software organizations in the industry, and b) identifies design implications for tools that support qualitative data analysis.

We aim to understand how multi-stakeholder collaboration in product development affects the QUXR practitioners' tool usage in QDA, and explore how to improve current QDA practices. Specifically, we intend to answer the following research questions.

RQ1) What challenges do industry QUXR practitioners face when collaborating with multiple stakeholders with varying expertise in product development?
RQ2) Considering the *present* state of QDA support tool usage:
- **A)** How do these challenges impact practitioners' use of QDA support tools?
- **B)** What are the benefits and limitations of the current state-of-the-art tools in addressing these challenges?
- **C)** What do QUXR practitioners need in QDA tools to overcome challenges not addressed by their current tools?

RQ3) With respect to *future* QDA support tools that might be used by QUXR practitioners, what are the potential implications of these tools when addressing their limitations?

To explore these questions, we conducted 90-minute semi-structured interviews with 13 UXR practitioners from different product development teams. As part of the interview, we conducted two diagramming activities to visualize these practitioners' workflows, which helped identify common patterns and contextualize challenges. We qualitatively analyzed the interview data using thematic analysis and identified the following main findings:

(1) Bringing multiple stakeholders to a common ground is more difficult than QDA itself, due to coordination costs and the diversity among stakeholders.

(2) Practitioners utilize simple collaborative tools over specialized QDA tools, despite tradeoffs in efficiency. This is a result of a need to share findings across multiple teams.

(3) Due to lack of specialized systems, QDA tasks are split across multiple tools for individual practitioners, hindering data provenance, data management and data-driven decision makings.

(4) Due to differences in priorities, not all stakeholders equally value qualitative analysis. Consequently, QUXR practitioners have difficulty selling research results to other stakeholders. To convince other stakeholders, they tend to triangulate their research with additional analysis, and in doing so, face technical barriers.

(5) Practitioners also express concerns about support tools, including 1) the ability of AI-based tools to understand the processes and goals of complex thematic analysis and 2) the potential for these tools to replace traditional practices like coding.

These findings highlight the significance of considering challenges and needs arising from multi-stakeholder collaboration when designing QDA tools for practitioners. They also reveal that existing QDA tools do not sufficiently support multi-stakeholder collaboration, and current tools adopted by practitioners miss opportunities for providing support and hold risk of hindering data-driven decision making. Synthesizing our findings, we identify three opportunities: 1) multi-stakeholder inclusive QUXR practice; 2) maintaining data provenance throughout the QDA process, and 3) triangulating QUXR findings through additional quantitative or qualitative data analysis.

2 Related work

2.1 Multi-stakeholder collaboration in industry qualitative user research

Collaboration among multiple stakeholders is common in product development, which combines technical, user, market, and business considerations. Relatedly, collaboration involves teams with specialized knowledge and skills of engineering, design, UX, marketing, and sales. For a successful QUXR process, it is important for QUXR practitioners to communicate their findings and establish consensus with these different stakeholders in product development [52].

Diversity of members and insights positively affects innovation in product development [57], however, it is also vital to acknowledge drawbacks in coordination between the members. Research suggests that the costs associated with coordination can sometimes outweigh the benefits [75]. As the size of a team increases, the overall workload also tends to increase [77]. In other words, coordination becomes more costly in larger teams with the task of aligning viewpoints, efforts, and communication among members. A major task of QUXR practitioners is generating consensus among different stakeholders at the planning stage (Figure 1, A) and at the end of QUXR (Figure 1, B). Throughout the process, they are often positioned at the center of these stakeholders [26].

Prior research has explored QUXR practice in collaborative settings. However, the studies mainly focus on the collaboration dynamics between researchers in academic settings, not those of diverse stakeholders in industry organizations [45]. For instance, Jiang et al. have investigated how researchers in Information Science and HCI collaborate as co-authors, and how the hierarchy among them affects their consensus-making processes [45]. The nature of multi-stakeholder collaboration in industry organizations is not necessarily compatible with the homogeneity commonly found in these academic research settings (i.e., researchers of similar backgrounds with similar goals). Differently in these organizations, multiple teams, including the ones focusing on QUXR, work as independent units for the most part of collaborations, and do not always have the expertise (or desire) to fully engage with other teams. In this paper, we examine the challenges QUXR practitioners face when collaborating with multiple stakeholders and how these challenges affect their qualitative data analysis practice.

2.2 Qualitative user experience research in practice

User experience refers to a “person’s perceptions and responses resulting from the use and/or anticipated use of a product, system or service" [28]. A primary goal of practitioners focusing on UX is to improve the users’ quality of life by delivering more pleasurable, holistic, and efficient user experiences [40]. User-centered design is a common approach that these practitioners follow in order to deliver such experiences, and it focuses on prioritizing users’ need while developing

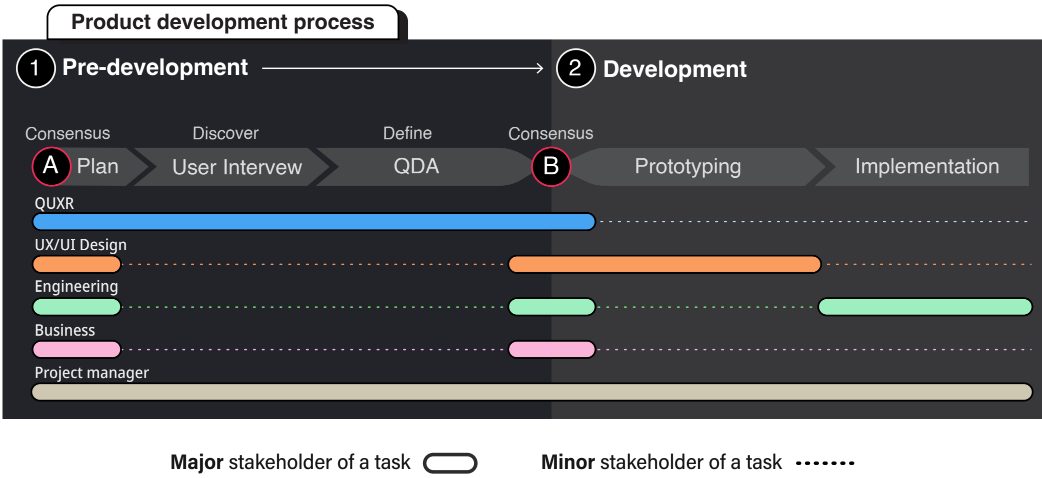


Fig. 1. **Product development process** The diagram offers a simplified product development workflow based on the key steps acquired from prior literature [72] (in practice the process can be iterative and not linear). QUXR practitioners take care of the pre-development stage. At the beginning of their research, they listen to multiple stakeholders' different needs to reflect them in the research (A). During QDA, they keep communicating with other stakeholders. At the end of their analysis, they put stakeholders on the same ground by making a consensus on what would be the core user needs and goals of a new product (B).

systems [2, 10, 49, 79]. Delivering such experiences is vital in the successful adoption of technology products [22], which makes UX practitioners key actors in product development.

Previous studies have examined how user experience methods are employed and perceived by UX practitioners in industries [35, 67]. These studies have emphasized the importance of understanding how human-centered design methods are used in corporate environments [21, 36, 42, 58, 78].

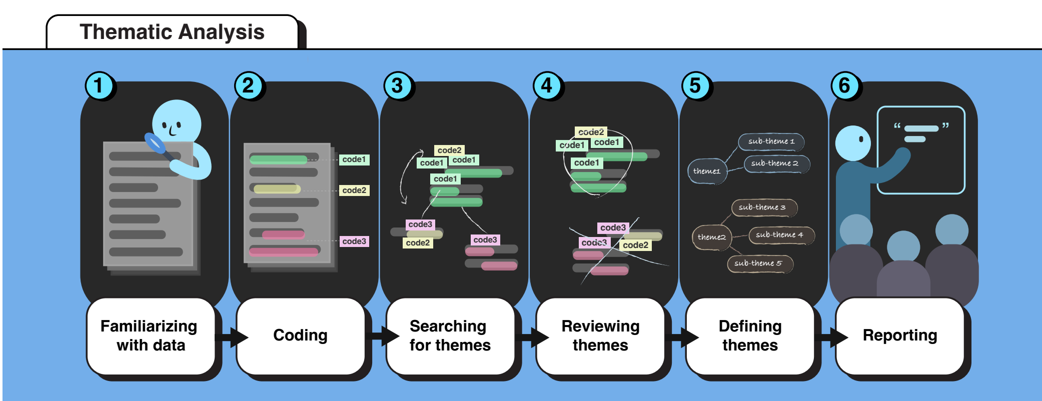
One stream of studies focuses on identifying areas where UX practitioners need more support and examining their current tool usage. For instance, a recent study by Lu et al. found that UX practitioners need more support with non-GUI tasks such as user interviews and brainstorming, which are vital for understanding user needs and creating usable, enjoyable designs [51]. This highlights that qualitative UX research practices like user interviews are relatively unsupported compared to user interface design. Another recent study explored the collaborative practices and tools (e.g., Figma) employed by user experience practitioners as well [26].

These prior studies offer valuable insights about UX practitioners and their work, however, they focus on issues at the cross-section of various UX specializations, such as designing user interfaces, designing user experiences, and researching users and needs. This overall coverage has so far missed a narrower focus on QUXR practitioners and practice in industry organizations. Distinct from UI/UX design, UX research or QUXR is a specialization in UX practice that uses qualitative data to investigate and understand target users' needs to provide guidelines at pre-development stage of product development [29, 46, 48, 59, 69, 70]. Without this essential starting point, the business team and engineers may have a flawed understanding of users, potentially leading to development failures [22]. Because of QUXR's significant role in the development of a product, understanding the issues and challenges in this practice is important.

As Figure 1 illustrates, QUXR in industry organizations generally begins with 1) data collection and 2) data analysis. Interviews are one of the most widely used means of data collection [7, 24], as they provide insights about the users' views, motives, or contexts, which quantitative data may not always capture [22, 59, 71], but the collected data may also be messy and effortful to interpret [50].

This has necessitated the development of various qualitative data analysis methods [61]. Thematic analysis is one of the commonly adopted ones within the HCI and CSCW community [12, 64]. Thematic analysis systematically reveals patterns (themes) based on commonalities among textual data, such as notes or interview transcripts [13, 14]. As shown in Figure 2, thematic analysis starts with carefully reading and re-reading raw textual data until a researcher fully understands it. Then, researchers assign codes (labels) to interesting segments of this data. After researchers complete coding, they derive broader themes from these codes and segments of the text that are linked. Researchers continuously refine themes until they make a consistent pattern. After creating a comprehensive thematic map, researchers construct narratives that highlight compelling findings, and communicate them to their audience through multiple mediums, including presentations and reports.

Thematic analysis is often considered laborious and painstaking [53] because not only the iterative reading and coding of textual data but also the inductive reasoning are all time-expensive and demanding [8, 13]. There has been much interest in improving the efficiency of this method through computer-aided data analysis tools utilizing techniques such as natural language processing [31, 47], which we call QDA support tools. In this paper, we investigate the challenges QUXR practitioners encounter in conducting thematic analysis as part of multi-stakeholder collaboration within product development in the industry. We reveal the limitations of the state-of-the-art QDA support tools,



Phase	Description of each phase	Common tasks
1	In this phase, researchers engage deeply with the data until they develop a comprehensive understanding of its content.	The process involves transcribing verbal data and repeatedly reading and re-reading the collected data.
2	Coding phase involves assigning labels (codes) to segments of qualitative data based on their meaningful aspects.	Identify noteworthy aspects and code text selections alongside the transcript.
3	Once initial codes are collected, researchers develop a broader level of theme (pattern).	Use visual representations such as mind-maps to sort the different codes and data extracts into potential themes.
4	Once candidate themes are set researchers refine those themes.	Check whether themes appear to form a coherent pattern and whether codes and data extracts fits themes.
5	Once satisfactory thematic map is made, identify the essence of what each theme is about.	Redefine themes until there is a narrative that can clearly identify the interesting results and explain why.
6	Write-up (or present) thematic analysis results that convince the reader of the value and validity of the analysis.	Deliver a succinct, cohesive, rational, non-repetitive, and captivating narrative conveyed by the data.

Fig. 2. **Six phases of thematic analysis** ([13] provides more detailed insights on this process)

Participants	Experience	Company size	Product
P1	3 years	100-999 people	Web/app applications
P2	5 years	100-999 people	Web/app applications
P3	2 years	0-100 people	Digital payment application
P4	1 year	0-100 people	Educational application
P5	1 year	0-100 people	Smart textile product design
P6	2 years	More than 10,000 people	Streaming service
P7	<1 year	More than 10,000 people	IT service management department
P8	5 years	More than 10,000 people	Cosmetic products / Digital contents
P9	2 years	1,000 - 10,000 people	Content platform using Voice AI
P10	1 year	More than 10,000 people	Smart home appliances
P11	2 years	100-999 people	Messenger services
P12	2 years	1,000 - 10,000 people	Educational application
P13	4 years	More than 10,000 people	Mobile Interface

Table 1. Demographics of study participants

and based on those limitations, provide implications for the design of these tools. We believe our study will contribute to a deeper understanding of QUXR practice in the industry as well as design of technologies to support it.

3 Method

To understand (1) the QUXR practitioners' challenges when collaborating with stakeholders in product development, (2) assess current QDA tools' limitations, and (3) propose design implications for future QDA tools, we conducted a two-step study including an exploratory and a main study (Figure 3).

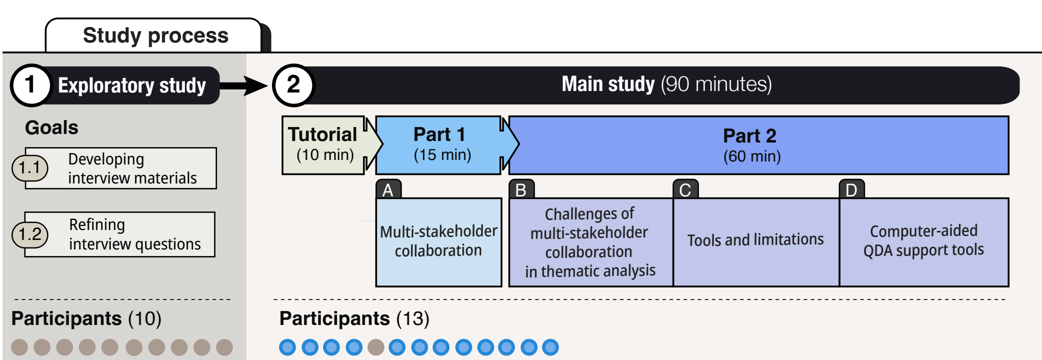


Fig. 3. We conducted an exploratory study (1) to develop interview materials and refine interview questions. Based on the materials developed in this exploratory study, we then conducted a main study (2) to understand the context of multi-stakeholder collaboration (A), thematic analysis practice (B), the limitations of current tools, and the needs of practitioners for computer-aided QDA tools. Each section (A,B,C,D) took approximately 20 minutes.

3.1 Exploratory study

We initially conducted a series of exploratory studies to learn about and diagram the QUXR workflow in the context of product development as well as to help design the main study interviews. We recruited an independent set of 10 participants who have qualitative UX research experience in the tech industry. Each pilot study lasted 60 minutes, and included a think-aloud diagramming activity followed by an interview with each individual participant. During the diagramming session, we asked each participant to create two visualizations: one depicting their entire product development process along with a verbalization of it, and the other illustrating their qualitative data analysis process, also accompanied by verbalization. Based on these visualizations, we then interviewed them about their thematic analysis practice. To create a final set of materials for the main study, we aggregated the diagrams of participants, and additionally, ones from sources in prior literature [13, 72]. Figure 4 displays the example diagrams synthesized from the aggregate.

3.2 Participants

Participants for the main study were recruited through open calls to popular UX research social media groups as well as through snowball sampling. Participants were required to have conducted qualitative research and exploratory interviews as a QUXR practitioner in a tech company. We ultimately recruited thirteen practitioners (6 female, 6 male, 1 non-binary). Three of them have worked on general web/app applications (3), others have worked on more specific products in the field of education (2), streaming (1), digital payment (1), content (2), smart home (1), messenger (1), IT management service (1) and smart textile (1). Participants self-reported an average of 2.3 years of UX research experience (SD = 1.5). They all have university-level UX research education and experience. As our exploratory and main study were significantly different, we did not filter the exploratory study participants. As a result, we had one participant (P5), who participated in both studies.

3.3 Main study

The main study involved thirteen ninety-minute interviews, consisting of a tutorial and two parts conducted on a web conference platform (Figure 3, ②). We started with a 10-minute tutorial session to get the participants familiar with Miro board [55], which is the app we used for online diagramming. In parts one and two, we asked participants to first complete a short survey and then create a diagram describing their usual work process—product development for part one and thematic analysis for part two—while verbalizing each step. After they finished creating the diagrams, we conducted a semi-structured interview with follow-up questions based on their diagrams. In part one, we focused on understanding the context of multi-stakeholder collaboration in product development (Figure 3, ②–A). In part two, we focused on understanding the thematic analysis process and challenges that come from multi-stakeholder collaboration within thematic analysis (Figure 3, ②–B) as well as the limitations of current tools adopted by practitioners (Figure 3, ②–C). We also asked participants to envision computer-aided QDA support tools that can help address challenges in the QDA process (Figure 3, ②–D).

Part 1) In part 1, we acquired an understanding of the participants' workplace context and collaboration process in product development. We first asked short survey questions such as, 'How many UX research collaborators do you usually work with?' Then, we provided the participants with the one example product development workflow diagram we synthesized from the exploratory study to provoke them to outline their product development workflow. We incorporated this diagramming activity into the interviews to understand how participants' environments affect their practice [39], while potentially reducing the risk of them revealing confidential information.

Although we acknowledge that participants may be primed by a diagram, we believe that it would help to establish common ground with them and work as a starting point for them to react [63]. In this diagramming activity, we asked participants to freely modify the example diagram to make it represent the product development work practice within their company. We then used their diagram to probe how their QDA practice is positioned within the context of product development involving multiple stakeholders in a semi-structured interview. The interview included questions such as:

- Do you collaborate with other stakeholders who are not qualitative UX researchers? At which stage does collaboration occur?
- How do you deliver your user research results to other stakeholders?
- How do other stakeholders at work affect your qualitative data analysis practice?
- What is challenging for you when conducting research at this stage?
- What do you do to address the challenges?

Part 2) In part 2, we obtained knowledge of the participants' thematic analysis practices, challenges in multi-stakeholder collaboration, limitations of current QDA support tools, and visions on the design of future tools through the same set of methods (survey, diagramming, and interview). As part of the survey, we asked questions related to thematic analysis practice, such as 'Do you use any computer-assisted qualitative data analysis tools? (e.g., NVivo, Atlas.ti, Dovetail).' During the interview, we first asked participants to diagram their process of exploratory thematic analysis and encouraged them to borrow from the example diagram synthesized in the exploratory study (Fig 4-B). We asked them to place stickers on the diagram they modified —based on the provided example diagram (Fig 4-B) — to better align with their workflow. These stickers should indicate two

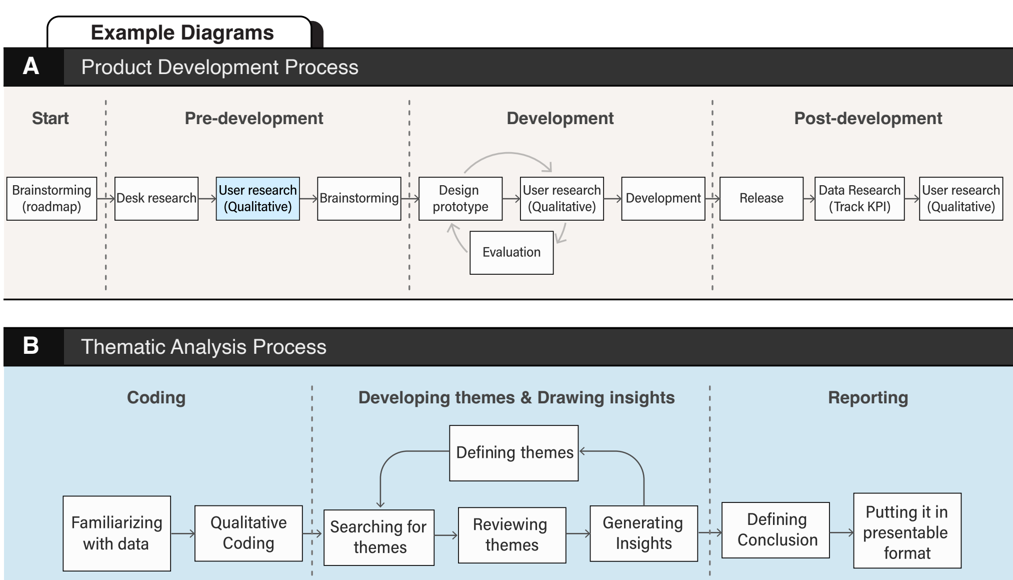


Fig. 4. **Example Diagrams** We collected and synthesized example diagrams from the exploratory study to be used in the main study. The top diagram (A) shows the product development process from the beginning to after product release. We intended to understand where qualitative UX research is located in this whole process. The bottom diagram (B) shows the thematic analysis process.

things: where their collaboration with other stakeholders occurs and which stage in the thematic analysis process they find most challenging. We asked follow-up questions such as:

- Why do you think these stages are challenging?
- What do you do to overcome those challenges?
- How does collaboration in this stage affect QDA practice?

We then asked questions about the tools they use in thematic analysis, how they use these tools, as well as the limitations of these tools:

- What are the tools and methods you use in the thematic analysis process?
- At which stage do you use this method and tool?
- Can you show me how you use tools?

Finally, we asked participants to envision digital tools that can help overcome the challenges they experience while working individually or collaborating with others in their organization. We probed participants to point out where and what kind of assistance they needed in their workflow diagram. We asked questions such as 'Can you tell me what kind of assistance you want to get and why?'

3.4 Analysis

We used thematic analysis as a method in our study, following the six phases outlined by Braun and Clarke [13]. The first author conducted all the interviews and created transcripts. Interview transcripts were then made available to both authors for review. As the one who was most familiar with the content, the first author conducted open coding on the transcripts. The first author then discussed these codes with the second author, who had also reviewed the transcripts. In several cases, the second author introduced new codes they had identified in their own review. We iteratively modified the codes to better describe the essence of transcripts. We condensed similar codes and discussed several cases where our interpretation of the transcripts differed. We developed a final code set as a result.

To develop themes, we collaborated using a digital whiteboard tool. After a preliminary session on the board, we worked independently to refine themes on the board by incorporating relevant data from the raw transcripts and codes to support and validate the newly revised themes. After the first round of theme development and refinement, we re-convened multiple times to make sure themes clearly explained the observed data and to verify that they were distinct from each other. After these discussions, we ultimately finalized two main themes, which we describe in the next section.

4 Results

We sought to answer the following questions in this study:

RQ1) What challenges do industry QUXR practitioners face when collaborating with multiple stakeholders with varying expertise in product development?

RQ2) Considering the *present* state of QDA support tool usage:

- **A)** How do the challenges from RQ1 impact practitioners' use of QDA support tools?
- **B)** What are the benefits and limitations of the current state of the art of tools in addressing the challenges uncovered in RQ1?
- **C)** What do QUXR practitioners need in QDA tools to overcome challenges not addressed by their current tools?

Two overarching themes emerged after the analysis of interviews: (1) the need for frequent communication in collaboration influences practitioners' tool choices and impacts data management;

(2) practitioners' challenges of advocating qualitative research to other stakeholders in product development, and the support needed to address the stakeholders' skepticism on QDA (Figure 5). In the following sections, we unpack these themes.

4.1 Collaboration affects tool choices

A variety of factors other than the performance of QDA tools affected the practitioners' tool preferences. For example, the majority of our participants gave up useful affordances of professional QDA tools because they lacked usability for non-QUXR stakeholders. We observed that eight out of thirteen participants were not using any tailored systems for thematic analysis, despite the benefits of these tools in dealing with complex textual data and awareness of these tools. Since many previous academic works [31, 45, 68] have attempted to facilitate faster and more effective analysis, it is unfortunate that industry practitioners may not see the benefits of such efforts. This disconnect between academic research and reality in practice suggests that a broader understanding of users' context is critical for adoption of research products.

4.1.1 Challenge of managing stakeholders and importance of frequent communication

One challenge practitioners highlighted when working collaboratively (**RQ1**) is the difficulty of managing stakeholders with different interests and building common ground. This challenge creates a dilemma in using QDA software due to non-QUXR coworkers' lack of access to these software when frequent sharing is crucial.

Participants believe "collaboration is the key" (P1) for success in product development, and it affects "every aspect of development" (P3). They prioritize tools that fit their needs less because they tend to be useful to their collaborators or in supporting collaboration. One key rationale is in building a common ground with non-QUXR stakeholders such as project managers, engineers, and designers. However, the need to consider different interests and motivations can feel like "herding cats" (P6):

> *The UX road map includes design, technical specs, and everything, but the problem is that each team has different opinions... Nevertheless, we have to draw a big picture from this situation, and it is the most challenging work for me. (P13)*

For instance P13 provided an anecdote, "when we envision a product in the early stage [of product development], we communicate and shape the vision together [with other teams]. However, by the time a consensus is about to be reached —if we all agree that a foldable phone should target

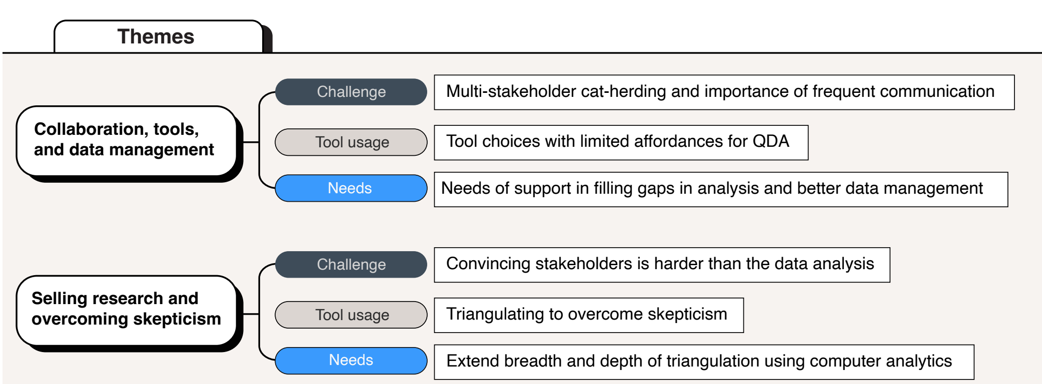


Fig. 5. **Themes** As a result of our thematic analysis, we developed two main themes and three sub-themes within each primary theme.

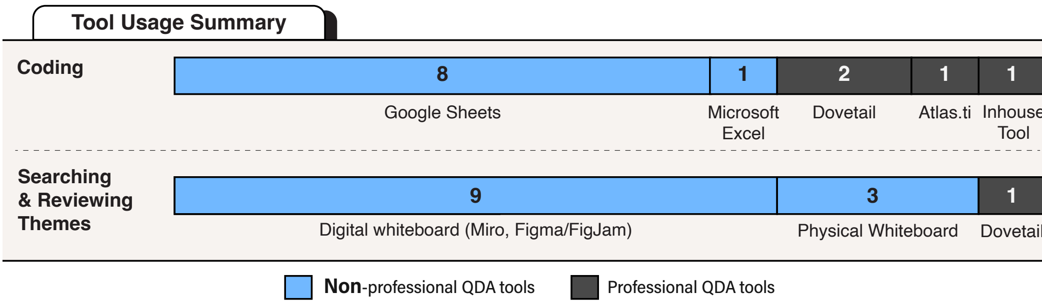


Fig. 6. **Tools usage summary** Breakdown of participant tool usage by two common QDA tasks.

middle-aged customers— suddenly, the marketing team suggests selling foldable phones to Gen Z, while the UX team argues that only middle-aged customers use foldable phones. Although both the marketing and UX teams conducted trend research [on the same population], they interpret the results differently." Because each team pursues independent agendas, building common ground can be especially challenging even when they are co-located and using the same resources.

To narrow this gap between different teams, practitioners use specific methods and tools. Some have tried "alignment workshop[s]" (P6), while others have tried to involve stakeholders in the "actual interview [with users]" (P9). The challenge is that any effort they took only magnified the already high costs of "herding cats." To build common ground with non-QUXR co-workers, practitioners attempted to "share data" (P4) in a "simplified summary" (P4) format with a bit of "raw data [from interview transcripts]" (P8) as frequently as possible. The tools practitioners use should be accessible to non-UX coworkers. When they use QDA tools, the non-QUXR co-workers need to download the software that they would not use otherwise. This creates additional burden for those workers during collaboration. To prioritize building common ground and consensus, practitioners deliberately avoided using QDA software.

4.1.2 Oldies but goodies – "boring" tool choices with limited affordances for QDA

In section 4.1.1 we underscored the challenges in herding multiple stakeholders and the challenges that come from a lack of professional QDA tools that are accessible to non-QUXR coworkers. We now turn specifically towards how these issues affect their use of present tools (**RQ2-A**).

Nine out of thirteen participants do not use any computer-aided QDA software for coding (see Figure 6). Among four participants who use these tools, two people use 'Dovetail'[23], one uses 'Atlas.ti', and the other uses an 'in-house developed tool.' The majority of the participants choose simple cloud-based tools such as 'Google Sheets' [73] because these tools provide essential features — reading transcription and coding — for coding, along with collaborative features, for instance, synchronized editing. P10 uses Microsoft Excel (an offline tool) because cloud-based tools' IP addresses are blocked due to their company's strict security. They wish 'collaborative editing' feature to have.

The main reason why most practitioners choose "boring" (P12) but "good" (P12) cloud-based tools like 'Google Sheets' [73] is because they value collaboration more than the efficiency that professional QDA tools bring. One participant said:

> *I want to use tools like Atlas.ti but, I have to see data with other people, and the aspect of sharing is important. So, to make it easier to share, I just organize everything in Google Sheets. (P4)*

Cohesiveness provided by simple tools outweigh the costs of deploying more complex tools in P12's team. The affordances of simple cloud-based tools (e.g., Google Sheets) for collaboration come at the cost of inefficiency at the coding and theme development stages. P4 complained that they were unable to use convenient features of Atlas.ti in spreadsheets, such as sorting by code. They said, "it's a bit difficult to see all the related quotes under the code at once." Although spreadsheets enable practitioners to label sentences and share the raw data with their stakeholders easily, the limitations in supporting reorganizing and grouping of codes become a burdens.

4.1.3 Practitioners lose data provenance by involving different tools

In previous sections, we have reported the **1)** challenge of QUXR practitioners and their non-QUXR coworkers meeting on a common ground (Sec.4.1.1) and **2)** how such challenges led practitioners to use simple and general tools (e.g., Google Sheets) over professional QDA tools (Sec.4.1.2). In this section, we delve into the limitations of current state-of-the-art tools **(RQ2-B)**. While general tools like Google Sheets have the benefits of easy collaboration, fall short in supporting various stages of thematic analysis. Consequently, practitioners are forced to use different tools for different stages of thematic analysis. This leads to rough transitions between tools and the loss of data provenance, which ultimately hinders collaboration between practitioners and their non-QUXR coworkers.

As previously mentioned, thematic analysis involves the iterative interpretation of data based on coding and deriving themes. To categorize codes and develop themes, participants use tools such as Miro [55], FigJam [27], or a "physical whiteboard with sticky notes" (P1). These tools are more specialized to the task at hand, but are still general enough for the whole product development team to collaborate. About using a digital whiteboard, P12 said, "...you create on your own way of doing the analysis. It is not like you have to get used to the platform." Moving from a text-based tool to a visual tool is "definitely not the most seamless [process]" (P6), and lots of "jumping between [applications]" (P6) occur. This challenge of transitioning between different applications is evidenced in this comment:

> *I'm going through and highlighting things in my Google doc and making my inline tags and all of that. Then I've probably got that on one screen and then I've got Miro on the other and I'm writing the themes out or copy-pasting sticky notes, or maybe I'm cross-referencing between the spreadsheet and Miro. (P6)*

One key aspect of transitioning between multiple tools for participants is the loss of data provenance (e.g., copying a quote from one program to another). Data provenance, or information about the source and context of data [15], is essential in collaborative decision-making. If only one stakeholder knows the origin and details of a data element, then there is a risk that the context to that data may possibly be lost. P10 said, "when I am discussing [interview results] with my co-workers [and they mention what participants said], if I can't recall the details, I quickly refer to the transcript to catch up ... Sometimes, someone might make an incorrect statement, like saying, 'I think only a few users said it' without thoroughly reviewing the [transcript] data." Lost provenance affects not only ongoing research but also previous user research conducted within the company. While past research results could potentially be reused, the difficulty in finding data from earlier studies leads to a lack of "reusable knowledge" (P9). P9 reports:

> *People often ask me, 'There was someone who said 'blah blah' in the last research. Where can I find that data?' Also, when one year passes, they ask,'What was the framework that we made last time?'...as the team grows in size and the process becomes long, it's difficult to remind them all the time. (P9)*

When practitioners move to a different stage of thematic analysis and switch to a different tool designated for that stage, they continue to lose data provenance. For example, codes get disconnected from quotes that the practitioners derive them from. Lack of support in managing provenance reduces efficiency and causes redundant labor.

4.1.4 Idealized technical support for curation and collection

Within the previous section, we discussed how practitioners' fragmented tool usage affects the loss of data, and hinder collaboration between co-workers. In this section, we outline practitioners' needs for future tools that could potentially tackle such limitations **(RQ2-C)**.

As mentioned earlier, a single practitioner cannot keep track of all the history of a UX research process. Furthermore, QUXR practitioners work in an environment with a "short timeline" (P5) and team management demands that put significant strain on their memory and attention. It may be more practical to delegate some of the provenance tracking to computational tools that can detect similarities in text and track changes made during analysis, such as updates to codes or themes. In our interviews, participants frequently envisioned a tool or digital assistant that could provide timely feedback when they lose track of important aspects of the analysis, helping them get back on course. They also imagined receiving guidance on overlooked connections in data during the thematic analysis process, similar to an "analysis of the analysis" (P6). Participants envisioned responses such as: "we've seen this theme as a pain point and it affected these five people" (P6), "chronological order is not important. How long it takes is the most important thing we need to know. Did you forget it?" (P9), or "okay look this group of codes are pretty close to these ones. But no one is paying attention to it. Let's talk about this one" (P12).

Aside from these more futuristic scenarios, a simple tag- or heuristic-based provenance system might be helpful enough to connect disparate pieces of information and enhance practitioners' ability to track data during analysis. There is a long history of such tools in the CSCW domain for developing folksonomies [37] and collective knowledge bases [41]. In addition to these possibilities, participants also raised questions about the adaptability of a potential AI-based support agent, particularly its ability to help practitioners identify missing data connections and provide appropriate feedback tailored to different contexts within the complex analysis process. P13 said, "It would be great if it could process [the] data I need at the right moment. However, how does AI know what data I need and at what point?" (P13). Ultimately, participants questioned whether such an agent would have the capabilities to comprehend the complex process of thematic analysis, which requires not only an understanding of the standard procedures and goals at each stage but also a clear grasp of the overarching research objectives.

4.2 Presenting research and overcoming skepticism in organizations

In section 4.1, we reported the first theme: the need for frequent communication with stakeholders *during* the research process influences practitioners' tool choices and impacts data management. In this section, we report the second theme with respect to the *end* of the research process, where practitioners have to sell their research and develop plans for action. We describe the practitioners' challenge of selling research results to their non-QUXR coworkers (RQ1) and how this challenge affects their tool usage. We will outline the practitioners' descriptions of the benefits and limitations of current QDA tools (RQ2) and their needs that future tools may address (RQ3).

UX research studies are often published in academic venues directly oriented towards qualitative work and reviewed by researchers who value qualitative data. However, in industry organizations, we observed that QUXR practitioners deal with coworkers (e.g., engineers, and business managers), and not all of them understand the language of qualitative research. Practitioners shared that reporting is more challenging than the data analysis (e.g., qualitative coding and searching for themes) itself (Figure 7). In the following section, we report in detail why QUXR practitioners find reporting challenging, how practitioners use triangulation to mitigate the reporting challenge, and the difficulty of triangulation in practice.

4.2.1 "Selling" is harder than the research itself

Participants experience challenges associated with reporting QDA results to non-QUXR coworkers. For some practitioners, "making a presentable report is more difficult than the analysis" (P11). To deliver insights to non-QUXR coworkers, participants need to consider: "What are the insights we need to convey, and how does it need to be conveyed? ... What is the story that's going to best convey that so that it lands" (P6). However, even with such thorough thinking, delivering insights "with clear evidence so even people who attend the presentation with zero context can understand" (P11) is considered difficult. P1 said even with a "fantastic job" in presenting data, there would still be "complaints." P10 explains such difficulty of communicating with stakeholders can derive from differences in "background, knowledge and priority," of different teams. They said, "product managers prioritize timelines; developers care about program functionality. For designers, it is important their design is implemented as designed; for UX researchers, insights and features derived from research should be implemented in the products. We all make the same product, but each team's priority is different."

Competing values and priorities among stakeholders make the reporting of insights and design suggestions more challenging for practitioners, as the decision to implement these suggestions affects large-scale production directions that involve other teams. In addition to that, "[what] UX team wants may differ from what is achievable" (P1) from other teams' perspectives. Therefore, participants mention that complex social dynamics such as "selling research" (P7) and "making stakeholders believe it is their idea" (P12) are at play. Some participants commented that it is always difficult to find a way to "make stakeholders more empathetic" (P4) and to make the data "appealing" (P10) and "convincing" (P13). Relatedly, P9 emphasizes the importance of "understanding which decision-making processes [they are] involved in, who the decision maker is, and what their considerations are." He shares an anecdote that supports his claim:

> *... I did user testing once using heuristic research rules. The decision-maker at that time was a 'designer.' When we said we needed to change the design based on these rules, they said, 'It's not a real user.' Well, what they said is not wrong, but since it's against*

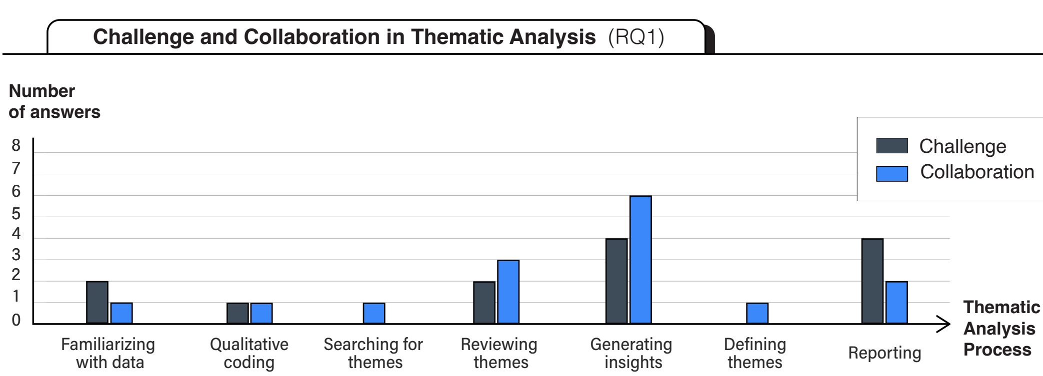


Fig. 7. **Challenge and Collaboration** QUXR practitioners find the 'reporting' and 'generating insights' stages relatively more challenging than others. Many of the participants chose the 'generating insights' stage as the most collaborative. Participants generally found collaborative stages to be more challenging compared to less collaborative stages, such as 'coding' and 'searching for themes.'

> *the UX rule, it [design] should be updated, but it was a junior designer who had little understanding of such rules. So, my job here is not to do better user research but to change that decision maker's decision. So, I brought one user. Then, I interviewed just one user. Then, the designer changed the design based on that one interview. (P9)*

This illustrates the importance of understanding the non-QUXR coworkers' expectations about the reporting they receive. Depending on which specific non-QUXR coworkers group they are reporting to, practitioners "adapt" (P2) that group's perspective. For example, the development team "cannot develop all features suggested by the UX research team, and they already have numerous products they need to develop" (P10). Furthermore, since "engineers often get involved in the later stages of product development" (P12), there are "risks" (P12) for them to try ideas which "seem too novel" (P8). Because if there are any "delays" (P11) in early phases, they would have "less time for development" (P12). P5 expressed a similar idea, which suggests offering "detailed and comprehensive use cases of the products" enables developers to estimate the time and resources needed for development. Others, like P3, emphasized the importance of convincing developers why a suggested feature is "essential" to users. For business-related teams, it is crucial for insights and suggestions to be aligned with the "business goal" (P7). Often business teams care for "market size" (P9), or "market success" (P4) with "measurable success indicators" (P8). Whereas the design team has a better understanding of UX research methods and the value of user-centered design, so practitioners found they "understand and emphasize" (P4) the qualitative data results. However, as P9 mentioned earlier, they might be against methods not involving actual user feedback.

4.2.2 Triangulating to overcome skepticism

In the previous section, we reported practitioners' challenges of selling research and convincing non-QUXR coworkers due to conflicts from different backgrounds and priorities. Here, we describe how this challenge creates doubts about QDA among non-QUXR coworkers, leading to great efforts spent on triangulating insights to overcome these doubts **(RQ2-A)**. Then, we outline the benefits and limitations of current QDA tools practitioners use **(RQ2-B)**.

One challenge that QUXR practitioners encounter when presenting their work is that they are often challenged by their non-QUXR coworkers about rigor. P4 said, "I show a lot of quotes and also show interview videos... but [stakeholders] keep asking if the result is generalized". This view is shared by other practitioners as well. P2 also said, "... although I believe insights [derived from qualitative data] is very meaningful, because the sample size is small, it is a big limitation. Convincing stakeholders is extremely difficult."

Some participants faced concerns about validity from non-QUXR coworkers. P4 believes convincing stakeholders only using qualitative UX research reporting methods such as "journey map" and "user persona" is hard. This is because "[non-QUXR coworkers] think a persona developed from rigorous research is [the] same as a persona made in 10 minutes from some side project." P10 confirmed this challenge. They said "... we [QUXR practitioners] use interviews to envision and suggest future products, and then report on them. But in our company, which operates in a top-down manner, I often hear things like, 'That's just based on what a handful of people said.'"

To overcome these doubts, UX researchers *triangulate* their research by "backing up qualitative data using quantitative data" (P4) and "collaborating with credible [outside] partners" (P10). For instance, P13 has access to the quantitative data of other non-QUXR teams in the same organization, so they ask for "app data such as how many times users opened an app and where they touched." They believe such data, which "represent[s] a few million actual users of the app," provides additional persuasive power. P11 also said analyzing external data such as "social media data" helps them to be a bit more "persuasive to others," because the data size is larger than 10-20 interviews. Similarly, P8 has access to "a predictive model to tell what features [among many potential features for the apps they are developing] were favored" (P8). For them, convincing non-QUXR coworkers using a predictive model is "easier" because "the novelty of the method appealed to [them]." To triangulate, P3 and P8 use larger text data gathered online (e.g., blogs, forums), then employ predictive models. Here, persuasion is provided, perhaps unjustifiably, by computational modeling.

However, such methods are not applicable to everyone. Nine of thirteen participants reported a desire to analyze larger text sources such as social media to triangulate their results. But only two of thirteen participants actually engage in this method, because it requires "tons of input" (P8) to "build necessary skills" (P8). To process a large volume of data, programming skills are needed. For many participants, "self-studying R or Python itself is very challenging" (P8). P11 gives credence to this:

> *... I stay away from using [programming languages] because, it takes more time and effort to use it since I am not used to writing code and pre-processing data. If there is a credible service that can do these tasks, then, I want to use it as a side tool, but I don't want to analyze data by myself. (P11)*

Even so, P3 argued that qualitative data from "forums" or "surveys" that are about "features that they[users] would like or what they[users] would like not to be included" provides a frank picture of user perceptions for UX research. They posit that if a potential QDA tool is designed in a way to minimize the necessity for coding through user-friendly graphical interfaces or facilitate simpler interactions with machine learning (ML) models, QUXR practitioners without programming skills may analyze big data:

> *The main idea behind creating the ML model was for it to be as simplistic as it can be so that anyone who's with the raw data can actually clean the data up and feed it to the model ... he or she does not need to have a software engineering background. (P3)*

4.2.3 Systems for scaling triangulation

In section 4.2.2, we described how practitioners aim to corroborate interview findings with quantitative data like user logs and additional textual data, but non-technical practitioners find scaling research with computational methods daunting. Here, we report practitioners' needs to diversify data sources more than interview data with the help of a system that reduces the burden of programming while adding statistical evidence **(RQ2-C)**. Yet, practitioners also shared their concerns about adopting technical solutions in their workflow.

While triangulation is helpful in convincing organizational stakeholders, participants have trouble collecting and processing data. Practitioners use data from online forums, "journals and industry reports" (P6) or "quantitative user log data [from other teams]" (P13) to get additional qualitative insights and back up their research. P2 considered social media to be more "honest" and "natural" than data they could get from interviews. P8 pointed out the importance of multiple data sources for generating ample insights. He said, "It seems like when I utilized data obtained from various channels, insights are richer than when I used only one data source." However, even with all these benefits, practitioners with no technical skills resorted to manually copying meaningful sentences into notes. While in an ideal situation, a data team may help in these efforts (especially if the organization gathers its own feedback), the reality of requesting and using data is less so:

> *When I want to see the data, I ask the data team. Asking once or twice is okay, but even during one working day, I want to see all sorts of data, and I feel a bit burdensome to ask every time... anyone should be able to access data easily. (P4)*

The ordeal of accessing and utilizing data does not end at requesting data from other teams. Even if participants get access to data from other teams, interpreting large volumes of raw data acted as a limitation, even for practitioners with quantitative data analysis experience. P13 said he used to conduct data analysis in graduate school, but he said the large volume of data was still overwhelming to manage. He reported:

> *... I got raw data [from non-QUXR teams] in an Excel file, but there was so much data with many conditions, so handling them was extremely difficult. I managed to analyze them, but if there had been more data, then I don't think it would have been possible to analyze them. (P13)*

A digital system may be an alternative for practitioners who need to access and analyze data independently without programming skills. For instance, a tool that utilizes a computational model [19] with a user-friendly interface (e.g., GUI) may help practitioners to collect qualitative data and analyze large volumes of text without the need for programming or manage raw data. Such tools can be particularly beneficial to participants who wish to analyze more data to add breadth and depth to the results. Participants felt that extended access to data would "add additional levels of statistical analysis" (P6) and "confirm and validate data in a wider range" (P7). Some participants envisioned "collaboration across [non-QUXR] departments" (P7) to bring in data "overlaps with UX research" (P7). For example, QUXR practitioners may access consumer research data from the marketing department, including complaints and feedback about the product, to further support their findings. Participants also believed that statistical analysis of additional qualitative data would be helpful because "not everyone understands the importance or the nature of the qualitative data analysis" (P12). One participant put quantitative reasoning in context with their workplace's decision-making:

> *...a really good idea perishes without turning into a product because we failed to persuade executives, then the same idea is realized from another company, then it is a huge success... I think [external data analyzed by an ML model] will be effective as an indicator to explain the significance when we bring a new idea. (P10)*

However, participants also raised concerns regarding adopting digital tools - especially AI - into QDA processes. They were concerned that AI tools might prioritize efficiency at the expense of traditional qualitative UX research methods, such as interviews and coding. Some practitioners expressed 'a little bit of distrust' (P11) regarding the quality of data from social media or online forums, particularly concerning the validity or the risk of fake reviews.

4.3 Summary of results

In this paper, we investigated the QUXR practitioners' challenges in multi-stakeholder collaboration in product development (RQ1), impact of these challenges on the use of QDA support tools (RQ2–A), benefits and limitations of these tools (RQ2–B), and practitioners' needs that future tools may address (RQ2–C). Table 2 summarizes our findings.

5 Discussion and implications

In this section, we provide the potential implications for design of future QDA tools based on our findings. To do that, we organized our findings using a persona [39] and a user journey map [39]. In the persona, we captured our participants' common motivations related to thematic analysis within the context of multi-stakeholder collaboration (Figure 8). In the journey map, we illustrated our participants' frustrations and identified leverage points for intervention (Figure 9)

QUXR practitioners are motivated to effectively coordinate with and convince stakeholders, often sharing their analysis process to foster understanding and facilitate consensus (Figure 8, G1). This frequent sharing leads them to incorporate simple collaborative tools into QDA, resulting in fragmented tool use and problematic transitions that compromised data management and the integrity of analysis history (Figure 9, A). This affects the 'generating insights' stage of QDA, where practitioners need to reach a consensus on themes or insights (Figure 9, Ⓑ). Additionally, practitioners tend to triangulate their QDA results to more effectively convince stakeholders (Figure 8, G2), they often face limitations in trying more advanced methods due to restricted time, inadequate technical skills, and a lack of understanding in quantitative analysis (Figure 9, Ⓒ). Based on these findings, we identified new design opportunities around (1) multistakeholder inclusive QDA tools; (2) data management; and (3) computer-aided triangulation of QUXR.

§ 4.1: Collaboration affects tool choices			
Section	**Summary**	**RQ(s)**	**Participants**
§ 4.1.1	Getting diverse stakeholders to meet on the same ground is extremely hard. QUXR practitioners address this challenge by frequently sharing bite-sized updates of their QDA with stakeholders.	RQ1	1,3,4,6, 8,9,13
§ 4.1.2	QUXR practitioners prefer to use simple collaborative tools over specialized QDA tools to share intermediate results easily during the QDA process.	RQ2-A	4,10,12
§ 4.1.3	Because simple tools do not fully support the QDA process, QUXR practitioners frequently alternate different tools, making it difficult to keep track of data provenance — the trail of where data originated and how it has moved.	RQ2-B	1,6,9, 10,12
§ 4.1.4	QUXR practitioners envision tool support to track changes made during thematic analysis and identify overlooked connections, such as missing themes, within the data. Yet, they also raise concerns about a potential AI-based tool's capability to understand the processes and goals of complex thematic analysis and its ability to provide timely and appropriate support within that process.	RQ2-C	5,6,7,9, 12,13
§ 4.2: Presenting research and overcoming skepticism in organizations			
§ 4.2.1	Delivering research results in a convincing and compelling way to sell research is sometimes considered more challenging than research.	RQ1	1,2,3,4,6, 7,8,9,10, 11,12,13
§ 4.2.2	QUXR practitioners use various methods to back up their QDA results. However, technical skills that some of these methods require (e.g., analysis using Python) are barriers for them.	RQ2-A,B	2,3,4,8, 10,11,13
§ 4.2.3	QUXR practitioners wish they have access to more data, such as social media data, in addition to interview data, to triangulate their UX research findings. They envision a digital tool that can assist in analyzing such data easily, without the need for programming. However, they are concerned that AI tools might replace traditional processes in thematic analysis, such as coding.	RQ2-C	2,4,6,7, 8,10,11, 12,13

Table 2. **Summary of results**

5.1 Towards multi-stakeholder inclusive QUXR practice

Our study reveals that collaboration between QUXR practitioners and their non-QUXR coworkers in industry organizations presents substantial challenges for practitioners. Often outnumbered, practitioners face difficulty in making consensus on the direction of product development with non-QUXR coworkers (4.1), and skepticism by non-QUXR coworkers about QDA methods and results (4.2). Despite these issues, practitioners engage stakeholders through frequent updates (4.1.1), using simpler tools like Google Sheets and Miro [55], sacrificing the advanced functionality of specialized QDA tools [5, 54, 60] to maintain collaboration (4.1.2).

Therefore, it is worth considering the specific aspects of tools such as Sheets and Miro that support collaborative exchange to a degree that they are prioritized over specialized systems. One aspect cited by participants is that individuals across their organization had general competency with such tools (Sec.4.1.2 – P12, P4). Another aspect at play is the flexible nature of these tools for supporting many users collaborating at once with little latency or barriers to entry. Users could share links and immediately bring in others. Finally, the familiar and easily navigable interfaces of these tools presented the QDA results in a favorable light for non-experts (a sort of social proof). A well-filled Miro board or a dense Sheet can signal rigor to an audience that otherwise may not be able to identify diligence in QDA.

Multi-level interface for different stakeholders On a basic level, there is an opportunity to tailor QDA support tools to the needs of all stakeholders in a product development team. One possible avenue would be adopting a multi-level interface [20] (Figure 10). A multi-level interface refers to a user interface that presents information across at varying amounts of sophistication and gives users an ability to access detailed or simple options while maintaining an intuitive user experience. This might enable QUXR practitioners to analyze data utilizing appropriate support while non-QUXR coworkers to see the necessary information without being hindered by complex features designed for the QDA. Coupled with other tools for easy sharing of QDA results, this interface might enable practitioners to quickly offer proof of their labor and create opportunities for teammates to offer feedback on the shared data. Moreover, a multi-level interface might also help to reduce fragmentation across the team, centralizing resources and potentially resolving issues related to data provenance.

However, the design of such an interface would need to be handled with care, since we do not know the level of detail and data representations that are required for different stakeholders. For instance, business-related stakeholders might want a quantitative representation of qualitative

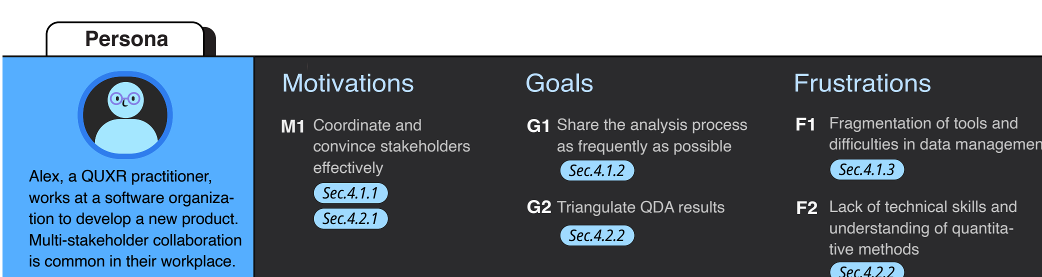


Fig. 8. **Persona** A key motivation for QUXR practitioners is effectively coordinating and convincing stakeholders (M1). To facilitate consensus, they frequently share analyses to help stakeholders understand users (G1) and aim to triangulate findings to increase persuasiveness (G2). However, this reliance on tools lacking data management support (F1) and limited technical skills (F2) frustrate practitioners.

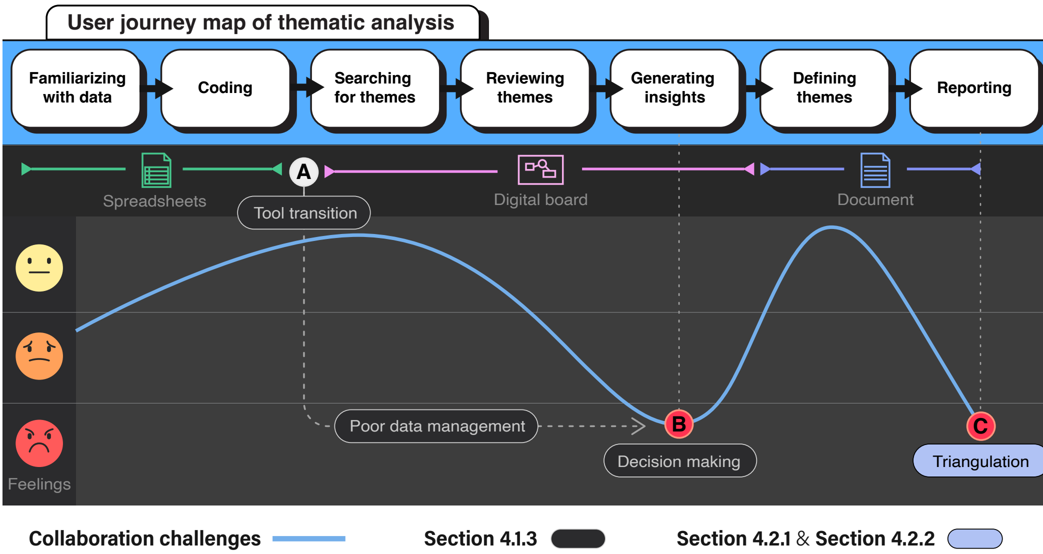


Fig. 9. **Journey Map** We identified two major frustrations within the collaborative context. One exists in the 'generating insights' stage (B), and the other exists in the 'reporting' stage (C). Practitioners' fragmented tool choices in the analysis phases (A) caused data management issues, and it influenced data-driven decision-making in the 'generating insights' stage.

data with simple summary views. Designers may want to examine individual interview comments to find nuances. This sort of flexibility may be hard to establish, especially given that the roles and expectations likely vary from organization to organization. Recent studies in the field of AI-mediated communication [38], commercial tools [11, 34], and language models using deep learning such as ChatGPT [62] hint at the possibility of AI-mediated communication with stakeholders by adjusting the tone of the language for a different audience. Researchers may be able to reformat or manipulate the outcomes of their process with the help of AI, offloading much of the harder data work and only providing guiding insights. Figure 10 illustrates one such scenario, where codes are presented at varying levels of detail and stakeholders can interrogate the model to re-adjust the presentation or answer questions.

Yet, there is also a growing current of skepticism and concern in HCI related to AI that may impact such potential tools. As the origins and copyright status of content produced by models such as ChatGPT may be unknown, organizations may be uncomfortable implementing them into workflows. Likewise, it is unclear how much these commercial models ingest from their input. Providing them with confidential user interview data may pose ethical or trade secrets concerns that would be hard to overcome given such uncertainty. Finally, there also exist concerns related to the accuracy of models and their tendency to hallucinate. While a model may be able to provide flexible levels of feedback for all sorts of users, it would be useless if the feedback it provided was seemingly accurate but completely groundless in ten percent of cases. Thus, while we see exciting possibilities to help QDA tools interact with more kinds of users through AI mediation, the risks also merit future investigation and consideration.

5.2 Data provenance and management

Our findings suggest that when QUXR practitioners move from the 'coding' step to the 'theme development' step of thematic analysis, they lose the context associated with the data, because they move snippets of quotes from the text-based tool they use for coding to a visual tool they use to build themes. Due to frequent switching between tools, practitioners have difficulty keeping track of data provenance: the origin of a piece of data. Data provenance is crucial because practitioners often must go back to the original script to see nuances and discover related materials that did not initially seem relevant. Furthermore, data provenance affects both current and future decisions regarding the finalization of themes and product development (Sec.4.1.3).

Our findings suggest that when practitioners move from the 'coding' step to the 'theme development' step of the analysis, they lose the context associated with the data because they move snippets of quotes from the text-based tool they used for coding to a visual tool they use to build themes. While tailored tools may perhaps help to smooth this transition, the mixture of ill-suited tools mentioned in the previous subsection causes these losses. Due to frequent switching between tools, practitioners had difficulty keeping track of data provenance: the origin of a piece of data. Data provenance is crucial because practitioners often must go back to the original script to see nuances and discover related materials that did not initially seem relevant. Furthermore, data provenance not only affects decision-making on the current research but also future decision-making (Sec.4.1.3).

Previous research that sought to support QDA focused on a single stage of the process, such as coding or theme development [31, 33, 45, 68]. However, it does not consider the broader problem of supporting barriers in the 'transition' between steps. Designing a tool that supports coding and theme development simultaneously is a potential avenue to enhance data provenance (Figure 10, Ⓐ, Ⓑ). When a researcher transfers a text segment between platforms, such as from a spreadsheet to a digital board, the data provenance is easily lost. Establishing a connection between the original raw text and the text segment can help keep the segment grounded in the raw text, even during a messy and iterative theme development process (Sec.4.1.4).

5.3 Bolstering UX research findings with triangulation

Our study highlights the difficulties QUXR practitioners face in convincing non-QUXR coworkers with QDA results (Sec.4.2.1). They often face skepticism regarding generalizability and validity (Sec.4.2.2), which aligns with related prior research [18, 25]. Despite aiming to increase research credibility through triangulation with diverse data sources, practitioners are hindered by technical barriers, limited access to resources, and tight schedules (Sec.4.2.3).

5.3.1 Triangulating qualitative data with quantitative analysis of textual data. One avenue for improvement is simply to better connect resources within an organization. As some participants noted, other teams in their organization gather measurements, such as customer feedback submissions, but these were not accessible to them. However, as P13 highlighted, because of the challenges of handling large volumes of raw data, accessing that additional data is also not sufficient, especially for those who are not familiar with quantitative or statistical analysis (4.2.3). Quantitative analysis demands proficiency with statistical analysis software and numerical data interpretation. Practitioners inexperienced with these methods may make misinterpretations.

Therefore, analyzing additional qualitative data from various sources like news articles, academic journals, social media, and online reviews may be easier for QUXR practitioners who are accustomed to working with textual data. Using computational methods such as topic modeling, sentiment analysis, and text classification would help practitioners to scale up their research. Especially, topic modeling has been shown to be similar to QDA methods such as grounded theory [9]. In this way, practitioners would be able to maintain the depth of understanding that comes from user interviews and support it with the breadth that comes from additional textual data analysis. However, it is also important to note that computational methods are not the definitive answer. Analyzing textual data computationally has its own conundrum, such as the difficulty of capturing sensitive meanings of words [4] and bias in embeddings [3]. Therefore, practitioners should be aware of these potential risks when adopting computational methods.

We believe there is a special opportunity at this moment in time for large language models to assist in analyzing vast amounts of additional textual data. Practitioners might use natural language prompts on models fine-tuned for their market to analyze interview comments, web posts, and other textual data. This may empower practitioners to analyze large volumes of textual data without the need for coding. On the other hand, scraping is currently an ethically complex issue due to issues related to platform content ownership and user consent. Furthermore, utilizing data from online forums or social media comes along with a risk of using data with low credibility [1, 17, 44]. The anonymity of users enables them to leave free thoughts, but it also enables them to exploit this anonymity to their own benefit, such as by leaving fake reviews. Issues related to the general use of AI tools mentioned in section 5.1 also apply here. Despite these notable caveats, we find that recent leaps forward in language processing abilities may be able to provide useful benefits to practitioners which would also help to boost their reach and credibility in their organizations.

5.3.2 Triangulating qualitative data with numerical data analysis. Qualitative researchers often place value in the contextual and nuanced insights that participants provide, as reflected by the researcher's perspective. On the other hand, quantitative researchers might view this approach as non-generalizable, and value more highly the idea that the same numerical analysis will deliver similar results. As we have found in our study, there is a greater interest among participants in convincing non-QUXR coworkers through complementary sources of data. This provides a unique opportunity to combine both qualitative and quantitative analysis to triangulate QDA findings [65].

For QUXR practitioners who develop digital products, one way to support their claims from user interviews is to adopt methods such as web analytics. Web analytics methods (e.g., event tracking) help researchers track specific interactions with website elements like clicks on buttons, video plays, or downloads of a file to understand how users engage with content and features on the site. It is noteworthy that web analytics provide granular feedback on a particular aspect of UI or UX. Yet, practitioners can utilize these kinds of methods to highlight the user needs, challenges, and motivations discovered from user interviews. For instance, in addition to quoting several participants who mentioned the challenge of finding a button on the website, showing web analytics results where only 5 percent of users used a button can add persuasive power to the remarks.

To maximize these benefits, instead of asking practitioners to analyze large volumes of raw log data, providing them with such information in a *consumable* format with room for *interpretation* is important. The reason is that if practitioners receive only raw data, it would be overwhelming to analyze and interpret the data because of the difficulty of utilizing programming languages as mentioned by participants (P8, P11) in section 4.2.2. Furthermore, as P4 mentioned in section 4.2.3, practitioners want to explore all aspects of data. If they only have access to fully analyzed results with static graphs, there would be no space for another interpretation and autonomy. We envision a visual dashboard for qualitative researchers that summarizes user behaviors while letting researchers investigate data on their own using interactive features [6]. It may help them incorporate quantitative data into their work more effectively.

Combining qualitative and quantitative data, such as sharing insights from qualitative data supported by social media trends or user log analysis, enhances QUXR practitioners' persuasiveness. However, heavy reliance on quantitative data analysis at the outset of product development can obscure opportunities for innovation because innovation may not emerge from visible trends within large crowds. Instead, it may stem from a small group of pioneering technology users, who can be difficult to identify. Conducting in-depth interviews with such individuals could unveil

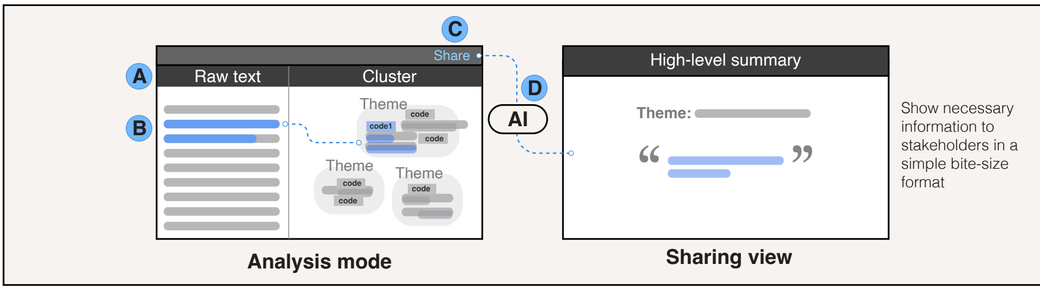


Fig. 10. **Prototype Multi-level Interface A)** Coding and theme development are supported in the same platform. **B)** Raw data and data extracts are linked together to prevent the loss of context. **C)** Sharing allows practitioners to show their analysis process to multiple stakeholders. It can also let users choose the level of complexity when they are sharing. **D)** To simplify the process and alleviate the burden of selecting and formatting data, generative AI might aid in reformatting the data into a presentable format.

their motivations for using technology in unconventional ways. Therefore, it is crucial to find a balance and maintain rigor in both methods to convince stakeholders. Future research can assess the persuasive power of methods on non-QUXR stakeholders, aiding QUXR practitioners in conducting mixed-method work.

5.4 Limitations

QUXR practices can vary depending on company culture. Although we worked with participants from start-ups and big multinational companies, our study does not cover aspects or issues that may exist in QUXR practices in other work settings. Likewise, while we adopted measures to improve participant comfort, not all details may have been shared with us due to non-disclosure agreements or other related concerns. Though we saw convergence in our results as we approached 13 full participant transcripts, we also acknowledge that this sample size may not offer coverage on all styles of work. In addition to that, we did not cover all types of UX tasks. We focused on understanding how practitioners analyze interview data using thematic analysis. Although this was our chosen focus, we acknowledge it can be a limitation since we did not explore other research methods (e.g., diary studies) used by practitioners. We hope that future research can extend our findings using different methods, such as large-scale surveys or ethnographic observation of QUXR practices.

QDA for product development is a complex task that involves inducing meaning from a disordered text, generating innovative yet realistic findings, and communicating these findings to diverse stakeholders. While we revealed the competing interests that affect QUXR in the industry, and produced some provocative suggestions concerning how future QDA tools might be developed, we acknowledge that our perspective is not the only one on this issue. As a field, QUXR places high value on human judgment and authenticity in the process. For example, P5 referred to AI-based approaches as "dehumanizing" and data cleaning as "taboo" because QUXR practitioners value low- and high-frequency words that may be eliminated during the pre-processing stage of computational text analysis. They believed that these words also add value in understanding the context and characteristics of verbal descriptions. In thinking about how our findings might be applied more broadly, we urge readers to consider the tension between technological solutionism and effective technological interventions when developing new systems in this space.

6 Conclusion

In this paper, we investigated challenges faced by QUXR practitioners when collaborating with diverse stakeholders in industry organizations, impact of these challenges on their use of QDA support tools, limitations of existing QDA support tools, and practitioners' needs that future QDA tools may address. We finally provided design considerations for future QDA tools. Based on semi-structured interviews with QUXR practitioners in the industry, our results suggest that QUXR is more than just understanding the potential users of a product better. It requires coordination skills to establish consensus with non-QUXR coworkers during product development. We identified two main challenges practitioners face in collaboration. The first challenge is meeting with non-QUXR coworkers on the same ground. The second challenge is convincing non-QUXR coworkers about the validity of QDA methods and results. Based on these challenges, we suggested technical support opportunities around (1) multi-stakeholder inclusive UX practice; (2) supporting data provenance and management throughout the QDA process; and (3) triangulating research findings through additional quantitative or qualitative data analysis.

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Received July 2023; revised January 2024; accepted March 2024