Staring at Tables: Exploring Conceptual Data Modeling as a Rich Collaborative Activity

Laura Koesten
MBZUAI & University of Vienna & AIT
Abu Dhabi, UAE / Austria
laura.koesten@mbzuai.ac.ae

Daphne Miedema
University of Amsterdam
Amsterdam, the Netherlands
d.e.miedema@uva.nl

Hsiang-Yun Wu
University of Applied Sciences St. Pölten & TU Wien
St. Pölten / Vienna, Austria
hsiang-yun.wu@ustp.at

Mathias Funk
Eindhoven University of Technology
Eindhoven, the Netherlands
m.funk@tue.nl

Figure 1: Three examples of conceptual models resulting from our study (selected for diversity); Left: Style of an ER diagram (D2) ; Center: Informal style (D8) ; Right: Style of a star schema (D11)

Abstract

Conceptual data modeling is a central activity in data work, yet how such models are created remains understudied. While data attributes play a key role, modeling is also shaped by tasks, tools, developers' prior experiences, and often unfolds collaboratively between diverse stakeholders. In this study, we invited 22 participants with varying expertise in pairs to collaboratively sketch conceptual data models. We captured screen recordings, their evolving sketches, and conversations. Through a mixed-methods approach combining thematic analysis of dialogue with an examination of model artifacts, we identify how communication and collaboration patterns influenced the process. Our findings reveal a range of collaborative strategies and representations, as well as distinct ways dialogue shaped the emergence and expression of shared conceptual models. These insights deepen understanding of Human-Data Interaction in collaborative data work and point to design opportunities for tools that better support communication, negotiation, and sensemaking of data.

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CCS Concepts

• **Human-centered computing** → *Collaborative content creation*; *User studies*; • **Information systems** → *Database design and models*; • **Theory of computation** → **Data modeling**.

Keywords

Conceptual data modeling, Data abstraction, Collaborative sensemaking, Human-Data interaction

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1 Introduction

When we work with data, from simple end-user interactions with data to professional data work, we inevitably begin this process by organizing and structuring the data at hand–deliberately or unconsciously. The way we choose to arrange data is shaped not only by the data itself but also by the tasks we imagine, the tools we have at our disposal, the skills and experiences we bring, and the interfaces we (expect to) use to access the data. These data modeling decisions rarely occur in isolation: they emerge iteratively, often in conversation with teammates or under the influence of multiple stakeholders [22, 58]. As such, what may appear as an abstract modeling exercise is, in practice, a situated collaborative sensemaking and alignment activity.

Conceptual data modeling (CDM) has been described as the human act of constructing a data model [41], an abstraction of data to organize it in a meaningful way, so that, e.g., its real-world relationships are illustrated. It is a complex task that shapes how data can be used and requires both formal and practical knowledge. CDM is seen as a specific application scenario of data-centric sensemaking where practitioners must externalize and negotiate their assumptions through dedicated representational choices. At the heart of conceptual data models lie individual mental models, formed first in the mind, then reflected through real-world contexts or negotiation with others. This process is seldom straightforward. As prior work on sensemaking highlights [22, 38], individuals adopt diverse interpretive strategies, and the mental models they rely on are often tacit, difficult to externalize, and challenging to align. In CDM, however, these challenges surface explicitly: as disagreements about how to structure entities, how much detail to include, or what constitutes the "right" representation of data. This makes CDM a particularly rich and distinctive setting to study.

Understanding how to create meaningful conceptual models of data is important as they shape how we work with data or how we communicate about it, but also how we can form a critical stance. This positioning reflects one's background, values, and ethics. CDM helps us make sense of unfamiliar datasets and identify their structural properties, relations to real-world concepts and entities, and understand aspects of quantity and quality.Most importantly, we establish a connection that reflects the meaning behind the data. CDM plays a central role in supporting high- and low-level tasks such as querying [10], visualization [55], integration and system design [16]. This applies across disciplines and professions as data becomes increasingly embedded in our personal and professional digital environments. The data structures underlying the systems carry real-world consequences, influencing how people experience and are affected by data in everyday life [6]. Beyond professional data work, there is a growing need to examine how conceptual models support or constrain sensemaking across different contexts of data use, at a structural and systematic level. Previous work tends to examine data abstractions or simplified datasets, and studies of CDM often focus on individuals. Instead, we use a dataset modeled on real-world data in the domain of long-distance walking routes, to examine how the messy process of conceptual data modeling evolves in interaction with others.

1.1 Conceptual models, data models and mental models

The outcome of CDM is a conceptual data model, the most abstract form of a data model (see Figure 1 for informal examples). A conceptual data model focuses on the high-level structure and semantics of a dataset; it represents existing data and its relation to other data in the domain being modeled, without being tied to implementation details. In contrast, data abstractions allow to translate domain data into computationally usable forms. That means they map domain-specific data to an abstract data type, providing a bridge between the domain and its computational representation [5, 31, 55]. While both concepts operate at a level above "raw" data, conceptual data models emphasize the organization and meaning of the data within its domain. In contrast, data abstractions focus on how the data can be represented and manipulated computationally.

Conceptual data models are closely related to mental models: informal representations by the user of how a system works [33]. In the context of this work, they reflect how users think about organizing data and represent the user's internal cognitive framework and how data relates to existing knowledge. A user's mental model might include expectations about how entities are linked, such as when looking for all hiking trails of a certain length. Mental models guide not only how users interpret data, but also data operations.

Misalignments between users' mental models and conceptual data models can limit effective data use, such as when a user expects hierarchical relationships that the model does not reflect or represent [11]. The relationship between mental models and conceptual data models is central to this work. Mental models are informal, often tacit representations that users form about how a system works; here, they reflect how users think about organizing and relating data. For example, a user might expect all hiking trails of a certain length to be grouped, or assume that data is structured hierarchically, as in a family tree. These expectations influence how users interpret data operations and interact with data systems.

1.2 Challenges in collaborative conceptual data modeling

The process of creating conceptual data models is of particular interest, especially how people do this with others. While mental models are personal, idiosyncratic, and often not explicitly salient forms of cognition, their expression is particularly pronounced in collaborative settings. Collaboration on CDM occurs frequently, both in everyday human-data interactions and in professional contexts, such as designing databases and information systems. When two or more people articulate their mental models and begin forming proto-conceptual data models, processes of alignment and negotiation happen. Individual blind spots and biases are questioned, ambiguity is resolved through joint ideation and contextualization, and connections are made and characterized. This can be challenging. The difficulty lies not only in the technical complexity of the data to make sense of or in missing or ambiguous links to the real-world concepts the data represents. It also lies in the effort needed to abstract the right concepts and relationships, and in the collaborative discussions through which such models are developed.

This work presents an exploratory investigation of the challenges of conceptual data modeling. It focuses on how people interpret structured datasets and form mental models for data work. Because modeling typically involves discussion and negotiation rather than solitary work, we examine *collaborative* conceptual modeling for three reasons. First, it increases the ecological validity of the study, aligning with real-world modeling practices [19]. Second, constructing a conceptual model collaboratively requires the surfacing, discussion, and negotiation of decisions that are typically instinctive and internal, thus tacit and unobservable. Third, conceptual modeling is usually seen as something only technical experts do, even though including non-experts and domain stakeholders is an important part of data literacy and making sense of data. Hence, understanding conceptual modeling processes is essential for designing tools and interfaces that better support the creation and refinement of conceptual data models across stakeholders.

Although prior work has provided methods and tools to support conceptual modeling, less attention has been paid to the situated practices through which models are constructed and refined in collaborative settings. We still lack empirical accounts of how people, working together, move from encountering a dataset to articulating and aligning conceptual structures, a gap that constrains the design of more supportive interfaces for collaborative data work. Our study examines three guiding research questions across participants with different levels of expertise and in two different Central European countries:

- (1) How do participants collaboratively form, negotiate, and refine mental models during a conceptual data modeling task?
- (1.1) How does tool usage help shape conceptual modeling?
- (2) What collaboration practices help participants establish common ground and coordinate their modeling decisions?

We introduce a collaborative sensemaking task in which participants worked in pairs to create a shared conceptual data model. They were provided with a denormalized dataset in tabular form and asked to examine it to identify structural patterns. To support this process, they were allowed to use standard data manipulation functions. Based on their exploration, participants constructed a visual representation of the identified structure using a digital diagramming workspace. Each session was time-limited and recorded both in speech and in screen activity to capture participants' dialogue and their process, as well as their milestones and outcomes. We employed a range of analysis methods, including a cascade of qualitative analysis followed by quantitative and visual analysis, to obtain results pertaining to modeling activities, collaboration, and tool use.

Our study followed a decentralized design, with each author facilitating sessions in their own setting, introducing variation in location, participant experience, and background. We used a thematically neutral collaborative sensemaking task that was accessible to both experts and novices in data modeling.

The contributions of this paper are threefold. First, an empirical account of how 11 pairs of participants collaboratively construct conceptual data models from a structured dataset in a multi-lab study, showing how expertise, tool use, and dialogue shape this process. Second, we identify collaboration practices and challenges in reaching common ground during conceptual modeling, contributing to a deeper understanding of the dynamics of this activity. Third, we present narrative participant profiles that illustrate differences and similarities across participant pairs, offering situated process-focused insights into collaborative modeling practices.

This work contributes to HCI by framing conceptual data modeling as a collaborative sensemaking activity, highlighting how people negotiate, externalize, and align mental models, and negotiate when working with structured data in commonly available tools. By examining how people collaboratively make sense of structured data, we extend ongoing conversations in HCI on sensemaking, collaborative data work, and the design of tools that support complex *collaborative* data practices [23].

2 Related Work

We draw on literature from different but related communities, including databases, HCI, data visualization, and collaborative data work, to situate conceptual data modeling as an interaction-driven, data-centric, and socially embedded process.

2.1 Conceptual data modeling

Prior work has shown that even when people work with the same dataset, they often construct different personal mental representations, meaning their conceptual understanding can diverge [55]. This highlights the importance of tools that can surface underlying abstractions and help collaborators align their interpretations. At the same time, research has explored how conceptual reasoning can be embedded directly into statistical modeling systems. For example, the Tisane mixed-initiative authoring system enables researchers to specify statistical models through conceptual relationships between variables, which are then mapped to data structures and formal specifications [20]. In doing so, it illustrates how conceptual modeling can connect researchers' high-level reasoning with the abstractions required for computational analysis.

Research on expertise in data modeling has revealed important differences in how people construct conceptual structures. An experimental study comparing expert and novice database designers found that the two groups categorized problem elements differently and applied standard abstractions in distinct ways [2]. A follow-up empirical evaluation confirmed that experts tend to produce conceptual models that are more correct, complete, innovative, and flexible than those of novices [46]. Recent work has introduced the notion of abstraction moves as iterative automated operations such as revisualizing, simplifying, or annotating elements of a data structure to enable the construction and communication of higher-level conceptual views bridging raw data and shared understanding [17].

2.2 Database interaction

Research on data interaction has long highlighted the challenges of traditional database systems, where users must translate information needs into formal queries using relational models and SQL commands. This creates a tension between ease of use and the expressive capabilities of database systems [2, 50]. To address this, "knowledge-level" interfaces have been proposed that abstract away technical schemas and allow interaction through real-world concepts, drawing on work that bridges HCI and Knowledge Discovery [18]. The type of modeling formalism has also been shown to affect user performance. For example, Palvia and Liao [34] compared extended entity relational, object-oriented, and semantic object models, stating that the ability to capture domain semantics varied with both notation and training, a result echoed in related studies [59]. Other work has examined strategies to organize data in more constrained settings. Durding et al. [14], for instance, asked participants to structure small sets of words with inherent hierarchies, uncovering both conscious and unconscious strategies. Ionescu et al. [19] present a study on feature discovery, where they identify the following phases of the process: goal setting, hypothesis formulation, data exploration, and data integration. These works illustrate how interaction methods, representational choices, and user experience shape modeling outcomes. Our study builds on this tradition by examining how pairs collaboratively construct conceptual data models, highlighting the role of communication and negotiation in data interaction.

2.3 Data-centric sensemaking

Sensemaking, broadly defined, is the process of creating meaning by piecing information together [43]. Building on Pirolli and Card's sensemaking loop, it includes foraging for relevant information, structuring it into intermediate representations, and synthesizing insights [38]. This makes it an ongoing and layered process that has also been described to be shaped by context and personal experience [21]. Data-centric sensemaking has been shown to decompose into distinct activities connected to data-specific attributes, such as format, location, or dependencies [22].

The active and formative nature of data-centric sensemaking in data work has been described across different contexts. Muller et al. [30] show how data science experts develop an intuitive sense of their data and processes that actively shape their data. Sambasivan et al. [44] illustrate how data issues, including sensemaking failures that produce conceptual models misaligned with reality, can create harmful downstream effects. While they studied AI lifecycles and how practitioners conceptualized and navigated them, their work highlights how the quality of conceptual data models matters in shaping real-world outcomes. However, despite being integral to many professional work practices [3, 32], it remains underexplored how people who rely on data for their work make sense of it when creating conceptual data models.

Sensemaking has been studied as a process that concerns individual behavior, as a collective phenomenon, and as a practice between specific agents. Accordingly, prior work has employed different methodological approaches to study sensemaking of individuals, including interview studies [22, 24], and summarization tasks to surface sensemaking of data. Examinations of collaborative processes have been explored via online discussions [13], or pair-based reflections on personal data [56], discussed in the next Subsection 2.4. Few studies have explored how people negotiate shared understandings of data representations in situ, such as during the collaborative construction of conceptual models. In this work, we approach conceptual data modeling as a collaborative meaning-making process, reflecting the social dimension that has been recognized as central to sensemaking [42].

2.4 Collaborative nature of data work

Data work is increasingly recognized as a deeply collaborative and socially situated process, rather than an isolated technical activity. Zhang et al. [58] report that data science teams are "extremely collaborative" and engage multiple stakeholders across the data-science workflow, with collaboration patterns and practices shaped by the tools used. Ionescu et al. [19] highlight how data exploration is a collaborative activity, involving explorations with the client as well as consulting with colleagues. Koesten et al. [23] explore how structured data practices unfold in team contexts, highlighting that collaboration spans the creation, sharing, reuse, and analysis of data, and calling for tooling that supports these processes. Pedersen and Bossen [36] emphasize that data work is shaped by interdisciplinary collaboration, for example, between business-intelligence developers and healthcare professionals, showing how it depends on social negotiation and shared interpretation. In their work on collaborations between data scientists and domain experts, Mao et al. [27] show that tensions in building common ground, especially around content and process, can significantly shape collaboration dynamics and outcomes.

In workplace settings, Passi and Jackson [35] conducted ethnographic fieldwork with a corporate data science team, revealing how collaboration often involves negotiating trust through actions like questioning results, assessing credibility, and translating model outputs into understandable terms. Their findings emphasize that making sense of data in real-world settings is not only technical but also a deeply social process shaped by communication and context. Furthermore, effective collaboration relies on flexible role-switching and shared involvement, where the people working together take turns leading, supporting, and reflecting throughout the task.

Building on this, we reframe conceptual data modeling as a collaborative, socially situated process in which trust and confidence in the emerging model are built through interaction, explanation, and shifting roles, rather than residing in the final, static artifact (the completed conceptual model) itself.

3 Method

We conducted a collaborative sensemaking study in which pairs of participants worked together to construct and elicit a conceptual data model. Our method of using pairwise collaboration to surface sensemaking practices builds on prior work, such as Yan et al. [56]. Our study was distributed across two countries, Austria and the Netherlands, and four labs, with all authors facilitating the task under a shared protocol. All supplemental material for this study, including the data used in the study task, is published on Figshare[1].

Each pair participating in this multi-lab study received a denormalized dataset on the domain of long-distance walking routes. The dataset was in tabular form, and designed to support weak entities and subclass–superclass relationships with inherited attributes. The pairs were asked to explore the data to identify underlying structural patterns and create a shared sketch of their derived conceptual model. To support this process, participants used a spreadsheet tool with basic data manipulation functions such as filtering, sorting, and highlighting. They were asked to deliberate collaboratively, to think aloud while working, and to represent the identified structures visually in a shared diagramming workspace (e.g., using Miro.com or draw.io). Sessions were limited to approximately 50 minutes and were both screen- and audio-recorded to capture dialogue and interaction processes. The dataset was designed to include features relevant for conceptual modeling, such as graph-like relationships, weak entities, and hierarchical structures with sub- and super-classes. The dataset is available in the supplement (S.04).

[1] Supplemental material: https://doi.org/10.6084/m9.figshare.30093847

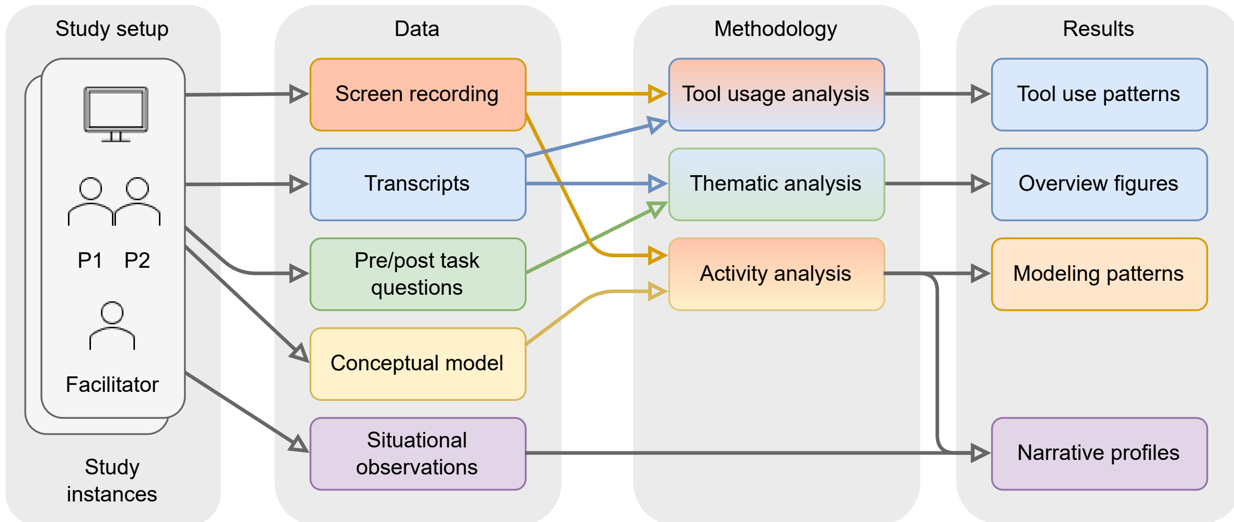


Figure 2: Schematic overview of study, from study setup in several instances to collected data, analysis methodology, and obtained results.

3.1 Participants

We recruited 22 participants (11 pairs) through purposive sampling in Austria and the Netherlands via the authors' local professional networks and snowball sampling. Participants were selected to represent diversity in age, gender, job level, data experience, and educational background. Their average age was 27.2 years (SD = 4.6), with 12 identifying as female, 10 as male, and none as non-binary/other. To reduce potential biases, most participant pairs were formed by the facilitators, who optimized pairings according to the criteria outlined above. Three additional pairs were formed through self-selection in coordination with a facilitator.

Participants were required to have basic digital literacy (e.g., navigating spreadsheets, creating simple diagrams with visual tools) and to share a common working language—either English or the primary language of the country in which the study was conducted. Participant data experience is self-reported and classified as basic, intermediate, or advanced (see Table 1). Basic experience reflects no formal background in data analysis, modeling, or interpretation, while intermediate indicates prior—but potentially outdated—coursework in these areas. Advanced experience denotes recent, specialized, and in-depth expertise in databases and data modeling. Recruitment stopped once we reached saturation.

Across our study data, we observe consistent and stable patterns, and the sample reflects diverse participant backgrounds in terms of data experiences, as outlined above [9, 45]. Participants received no compensation for this study.

3.2 Study task procedure

During each study session, the pairs were seated side by side in front of a shared computer. To ensure that participants could focus and communicate freely, the facilitator stayed nearby without engaging in direct observation. Before starting the collaborative modeling task, the participants received a study description, were able to ask questions, provided informed consent, and completed a short pre-task questionnaire covering demographics, prior experience with data and databases, visualization experience, and familiarity with data modeling. After a brief introduction to the tools, each pair worked collaboratively on the dataset to identify structures and construct a conceptual model. During the collaborative task, the facilitators provided timely interventions when participants needed additional guidance (i.e., to suggest checking unfamiliar terms). Additionally, they were reminded to keep verbalizing their thoughts if they fell silent for too long, following a think-aloud protocol. The modeling activity lasted approximately 50 minutes, after which the participants completed a post-task questionnaire that included closed-ended (for example, Likert scales on difficulty, confidence, satisfaction) and open-ended questions about their experiences. The study concluded with a short debrief and an opportunity for the participants to reflect on their experience. An overview of the study protocol is provided in the supplement (S.02).

The study received institutional ethical approval (approval number: ERB2024ID575). All participants provided informed consent, and data were anonymized and securely stored in accordance with institutional guidelines.

3.3 Data collection

We collected multiple forms of data as shown in Figure 2: (1) Screen recordings of tool use and visual modeling activities collected via Microsoft Teams; (2) audio recordings of participants' dialogue and interactions collected via Microsoft Teams recording, which were transcribed using Buzz[2] on the facilitators' local computers; (3) responses to pre- and post-task questionnaires; (4) output diagrams collected as screenshots from the online diagramming tool that

[2]See: https://buzzcaptions.com

the respective participant team chose to use in their study session (Miro or draw.io). The data was stored and processed locally, and apart from the audio transcriptions, no AI-based tools were used to process the data and generate the results reported in this paper.

3.3.1 Participants description. Our study involved 12 female, 10 male participants aged between 19 and 37 years (as can be seen in Table 1). Participants represented a range of educational backgrounds, from high school to PhD, and held roles including PhD candidates, Engineering Doctorate trainees, Assistant Professors, and industry practitioners. Approximately half of the sample reported expert-level data experience (mainly academics and professionals), while the others indicated basic to intermediate levels, mostly among Bachelor's and Master's students. Apart from the level of education and experience, there were also differences in the education type or background, from Computer Science, Data Science, and Biomedical Engineering to HCI and Interaction Design (not included in Table 1). This distribution provided a heterogeneous mix of expertise and perspectives, balancing highly experienced data professionals with participants at earlier stages of their education or careers. A detailed account of narrative participant profiles based on our observations during the studies is provided in the supplement (S.01).

3.4 Positionality statement

We are four researchers at different career stages in academia. Three of us are from Western Europe, and one is from Taiwan and has lived in Europe since 2017. Three identify as women and one as a man. Our diverse backgrounds shape how we approach and interpret data. Collectively, our expertise spans Computer Science, Human Factors, HCI, and visualization: one author has an in-depth background in databases, and the other three work in Human–Data Interaction, interactive systems, and data visualization. All authors contributed to analyzing the data, and interpreting and summarizing the study's findings.

Our disciplinary orientations, personal values, and lived experiences influence how we interpret participants' practices and what we consider meaningful in collaborative sensemaking. We reflected on these influences during our consensus discussions as part of the coding process. As researchers working primarily within Global North institutions, we acknowledge that the tools and methodological conventions we use reflect assumptions about technological availability and norms that may not hold in other contexts.

3.4.1 Participant team dynamics. We also recognize that dynamics within participant teams—such as differences in experience, seniority, gender, race, personality, or other factors—may have shaped their interactions and the data generated. We view these dynamics not as biases to be eliminated but as part of the contextual richness of real-world collaborative sensemaking.

3.4.2 Participants data experience. We acknowledge that participants may have brought prior commitments to particular modeling formalisms (e.g., ER, UML, or domain-specific notations), which can shape how they structure and label their sketches. While we did not prescribe a specific formalism, we considered these pre-existing tendencies a background factor potentially influencing modeling choices. To contextualize our findings, we therefore asked participants detailed questions about their experience with data and data modeling.

3.5 Analysis

Because the task was inherently collaborative, we analyzed the transcribed recordings at the dyad level. Transcripts ranged from 700–1200 utterances per pair, depending on the length and intensity of the collaborative task and participant conversations.

3.5.1 Coding procedure. In a multi-stage coding workflow, four coders first independently annotated the dataset from the study to develop an initial coding scheme that reflects the full range of researcher perspectives and experiences. Through an iterative review process, the team met in online discussions to resolve discrepancies and refine the scheme until consensus was reached; this process was conducted twice. Coders then continued coding their study data, followed by a second consensus meeting to address remaining issues and agree on a stabilized codebook. Next, we implemented a pairwise sharing procedure in which coders exchanged their study data and reviewed each other's coded data. A final consensus meeting was conducted to align coding strategies. After that, each coder recoded the full dataset using the finalized agreed-upon codebook.

3.5.2 Analytical approach. We follow Braun and Clarke's framework for reflexive thematic analysis [7], using a combination of inductive and deductive coding [40]. The research team iteratively refined the code book through collaborative discussions until patterns stabilized and saturation was reached [25]. Coding reliability was ensured through negotiated agreement rather than statistical measures, consistent with this approach.

The analysis was structured around three high-level areas of interest: (1) the conceptual data models produced, (2) participants' tool use, and (3) their collaboration practices. These areas were first examined separately and then connected through axial coding, supported by an analysis of patterns in code co-occurrences (S.05). Within these areas, we initially did a round of inductive coding. The formalization of the final codebook then included deductive elements informed by literature on data-centric sensemaking [22] and (code) comprehension [8, 29, 53], to align our inductive themes with established concepts and ensure theoretical grounding.

3.5.3 Tool usage analysis. The facilitators' institutional setup shaped tool usage, but participants could also introduce their own (e.g., paper, digital canvases). Facilitators documented tool use, and transcripts marked accordingly were examined to distinguish spreadsheet analysis from model diagramming. Spreadsheet interactions were categorized following von Landesberger et al.'s visual analytics taxonomy [52], with most actions relating to data exploration (filter, sort, hide) and visual exploration (zoom, pan). Model diagram interactions were coded according to Yi et al.'s taxonomy [57], capturing actions such as create, connect, and reconfigure. Demographic data and interaction labels were then analyzed for potential correlations.

3.5.4 Situational observations and narrative participant profiles. Due to the diversity of participants in terms of background, experience, age, nationalities, and other factors, we could expect a variety

Table 1: Study Participants

Participant ID	Dyad ID	Age	Gender	Education	Job title	Data experience
P1	D1	29	Female	MSc	PhD candidate	Intermediate
P2		32	Male	PhD	Start-up founder	Intermediate
P3	D2	34	Female	PhD	Assistant professor	Advanced
P4		25	Male	MSc	PhD candidate / Data engineer	Advanced
P5	D3	28	Male	MSc	PhD candidate	Advanced
P6		37	Female	PhD	Assistant professor	Advanced
P7	D4	31	Male	Master	EngD trainee	Basic–Intermediate
P8		23	Male	Master	EngD trainee	Basic–Intermediate
P9	D5	31	Female	Master	EngD trainee	Intermediate
P10		21	Male	High school	Bachelor student	Basic–Intermediate
P11	D6	26	Female	Master	EngD trainee	Intermediate–Advanced
P12		27	Male	Master	PhD candidate	Basic–Intermediate
P13	D7	30	Male	Master	PhD candidate	Intermediate–Advanced
P14		29	Female	Master	PhD candidate	Intermediate
P15	D8	28	Male	MA	PhD candidate	Basic–Intermediate
P16		28	Female	MA	PhD candidate	Basic
P17	D9	24	Female	High school	Bachelor student	Basic
P18		24	Male	High school	Bachelor student	Basic
P19	D10	24	Female	High school	Bachelor student	Basic
P20		30	Female	B.Eng.	Bachelor student	Basic
P21	D11	19	Male	High school	Bachelor student	Basic
P22		19	Female	High school	Bachelor student	Basic

of role dynamics in the study. Some pairs could be very polite, some might have more friction, some more fun. Those meeting for the first time might have to negotiate not only the task and applicable tools but also how to communicate and collaborate effectively. Others would be very familiar with each other and even tease each other during the task (which is perfectly fine given the collaborative nature).

We draw these observations from the main study, as well as from the debrief with participants and the facilitator. This debrief can take various forms; it can be an emotional debrief, a reflection between participants, a collection of thoughts on the overall experiences, fine-grained observations and suggestions for improvement, or speculations taking the study dataset further in time. We survey participants' age, experiences and expertise, background, and gender before the study begins, and we look at differences in these categories and how they influence the collaboration. Further, we observe how well participants seem to know each other, how they work with affirmation and alignment vs. friction and negotiation, and personality-related aspects such as confidence, extrovert or introvert personality.

As facilitators, we tried to pick up on nuanced or tacit aspects of participant interaction and collaboration, as well as their individual experiences during the study. For instance, regarding role in the hierarchy or power distance, we would then reflect on whether the collaboration seemed relatively equal or whether there was distance. We look for friction and conflicts not only in the coding but also from situational awareness, using nonverbal cues, tone, conversation pace, and, to some extent, body position and physical distance. Finally, we condensed our observation into short participant profiles for each study session, that is, for each dyad, which are available in excerpts in the results sections and in full in the supplemental material (S.01).

4 Results

Our results first contextualize participants' experience and the quality of their models, then describe how they approached the task, including evolving activities over time, emerging modeling patterns, tool use, and the communication practices that shaped collaboration.

4.1 Participants' experience and model outcomes

Participants reported limited experience with conceptual data modeling (average 2.1/5), which can be seen in Table 2. Familiarity was strongest with the relational model, while knowledge of star schemas was lowest. ER and UML modeling were known by about half of the respondents, whereas object-relational and graph data models were less consistently understood. Some participants did not recognize the terminology, but were familiar with the underlying concepts.

One of the primary outcomes of this study is the drawings or visualizations of conceptual data models produced by pairs of participants. A small sample of these results is represented in Figure 1, an overview of all models is in the supplement (S.03).

4.2 Activities over time

To better understand how the coded activities distribute over each study duration per dyad, we visualized the coded activities by normalized time (start to finish) in a scatterplot with colored codes on the y-axis. This allows us to see both conceptual data modeling

Table 2: Participants' reported familiarity with different data modeling approaches.

Response	Relational	Entity-Relational	Object-Relational	Graph Data	UML	Star Schema
Yes	12	12	9	10	11	5
No	8	9	12	12	11	17
Some	2	0	1	0	0	0

and collaborative activities as the conceptual models begin to take shape in the model visualizations. While some instances show little progress (see Figure 3 top), there are also instances that clearly show a progression from assumptions, ideation, and clarification to mental model, validation, and visualization-coded activities (see Figure 3 bottom). Similar for the collaboration codes: some instances show a progression from study questions and planning to explaining and compounding, all with a lot of affirmation and alignment that indicates a strong need for this particular team to synchronize and *be on the same page* (cf. Figure 4 bottom), whereas others do not need as much communication but instead are fully focused on the model (Figure 4 top).

For all of these figures, our narrative profiles (see S.01) show that participants' level of experience is reflected in their progression through the task. Dyad 7 (Figure 3 bottom) had some experience with data work. They were actively working towards a good model, using a lot of ideation and known semantics, as well as deeply conversing about the nature of the data. Dyad 9 (Figure 3 top) had a really hard time interpreting the data, and thus struggled to get to any productive conceptual model pulled together. Their graph shows their modeling is centered around assumptions and ideation, and not many instances of the more advanced processes. Dyad 3 (Figure 4 top) did not need much communication as they were the most experienced pair of all and were highly familiar with the task. Dyad 10 (Figure 4 bottom) had little experience with data work, and were not familiar with the domain of the dataset either. However, they managed to balance this out with heavy communication about the data in the first half of the study, and planning and discussion in the second half.

As part of our analysis, we also checked which codes for Conceptual Modeling co-occurred with codes for Collaboration. To this end, we processed the transcripts through a sliding window perspective, only looking at the codes that were used close together in time. The resulting heatmap is displayed in Figure 5. We decided not to include exact quantities for each code in the figure, as it is not meant for quantitative analysis, but rather as a starting point to support further analyses. We identify a solid block of co-occurrences for the collaborative codes of affirmation, questions and explaining, and reasoning and negotiation, with the modeling codes of ideation and mental models, and data references and connections. Further away, this also includes the modeling code of friction, opacity, and corrections. We also see a co-occurrence of uncertainty with friction and opacity. Another common modeling code is visuals and actions, which aligns with affirmation, communication, and planning.

4.3 Conceptual data modeling patterns

To investigate which conceptual modeling patterns emerge in a collaborative data exploration task, we analyzed the transcripts, specifically those utterances that were coded for pertaining to conceptual modeling elements. We distinguish the following elements of the models:

- **Entities:** a broad term that describes something that exists. In the domain we are discussing, some examples are countries, routes, and accommodations.
- **Attributes:** a characteristic or property of an entity, such as its name or location.
- **Relations:** a connection between two entities.

Our analysis surfaced the following model-building actions and states: i. Hypothesizing or assuming, ii. Connecting to prior knowledge, iii. Unfinished thoughts, iv. Milestones, v. Validating, vi. Metacognition, vii. Checking against the real-world knowledge. A summary of these findings can be found in Tables 3 and 4.

4.3.1 Hypothesizing or assuming. Forming hypotheses is an important part of sensemaking, especially for an unknown or unfamiliar task. Our participants started the task by looking through the data. Not only did they pose hypotheses to themselves and their partner, but many of them also made assumptions. Although hypotheses are more constructive than assumptions as they are more open to disproving, assumptions can also be useful, especially in this collaborative context where the participant's partner may have complementary insights. This section connects to the thematic analysis theme of *Assumption*, and the hypotheses and assumptions about both the context of the data and the data itself. One noteworthy finding for this theme is that, across all dyads, most posed hypotheses and assumptions were incorrect, but were not (fully) disproved by the participants.

4.3.2 Connecting to prior knowledge. Metaphors, analogies, and other connections to prior knowledge have been shown to be useful tools in education, as we learn and interpret new concepts by connecting them to things we already know [4]. A specific way our participants connected prior knowledge to the task was to draw on their individual geographical knowledge or common sense, e.g., typically only one currency is used in a country: *"[...] then we have the currency that will probably stay the same in one country"* (P11).

There were also other, more implicit ways in which our participants referred back to things they already knew and how this helped them understand the data. Two methods we identified are constructing stories and demonstrating experience. The former is related to the data itself, while the latter is connected to the task and the familiar actions or concepts that might be involved. We specifically saw the construction of stories for participants who were less experienced in the task of conceptual modeling (Dyads 8, 9, 10, 11), whereas demonstrating experience is connected to participants who are able to use correct terminology such as normalization and composite keys (Dyads 1, 2, 3, 5, and 7). Overall, the

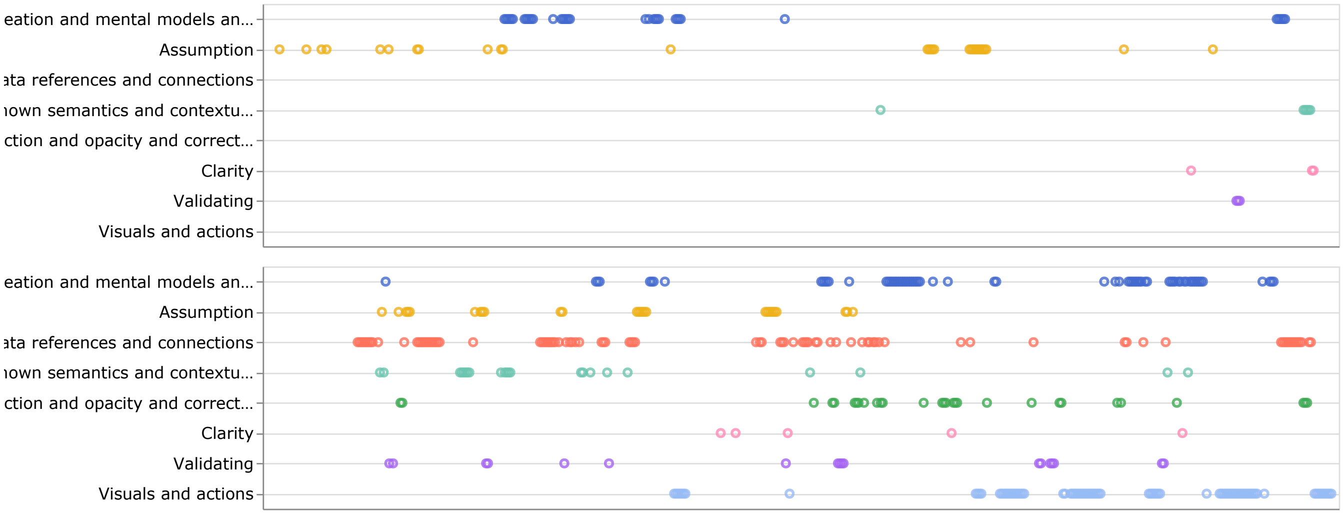


Figure 3: Scatterplot of conceptual modeling codes over normalized study time. The top figure is dyad 9, and the bottom figure is dyad 7.

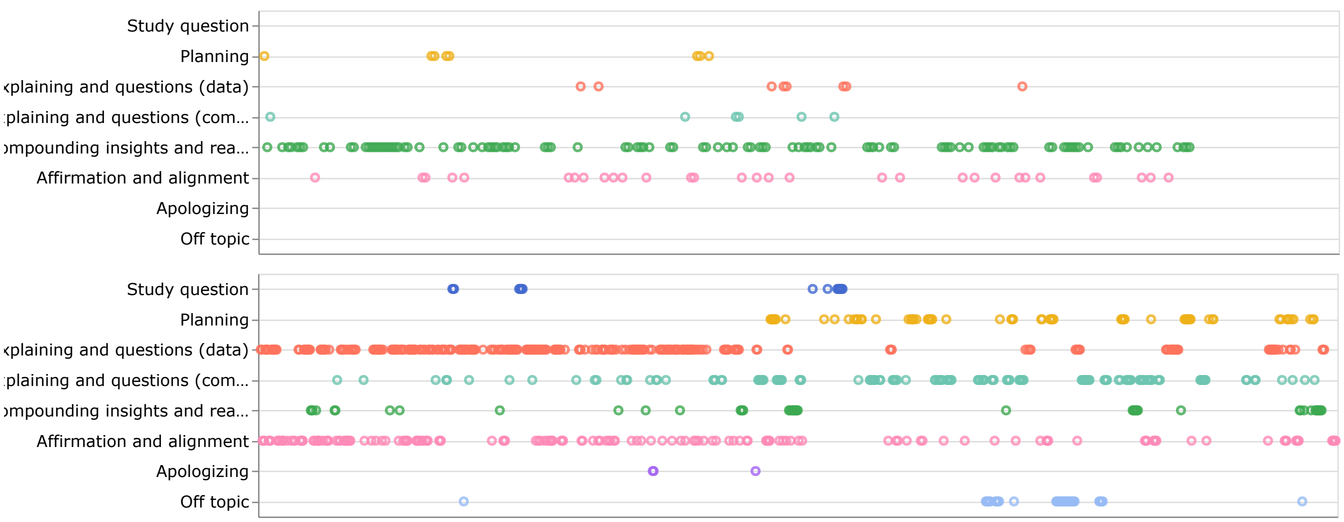


Figure 4: Scatterplot of collaboration codes over normalized study time. Top figure is dyad 3, bottom figure dyad 10.

content of this theme is related to the code *known semantics and contextualizing*.

4.3.3 Unfinished thoughts. Sometimes, thinking out loud and discussing were superseded by the participants' internal processing. When this happened, they were still producing words, but without communicating effectively. In other cases, they would share half a thought, but then did not finish it because they were preoccupied with trying to figure it out in their head, so much so that they were not able to share anymore: *"Like, I guess the logical association would be to…"* (P7). Although these processes do not illustrate the model building directly, they do highlight elements that our participants struggled with, such as integrating the contents of multiple columns into one entity and considering how the two markers in each row are related to the trail. Overall, these happened least for participants who focused on the task and mostly disregarded the context, such as Dyad 3.

4.3.4 Milestones. Through these previously mentioned actions, the participants are constructing a conceptual model. We can see clear progress when participants gain a deeper understanding of the underlying structure. We call these milestones, and they are mostly structural in nature. Some examples include identifying

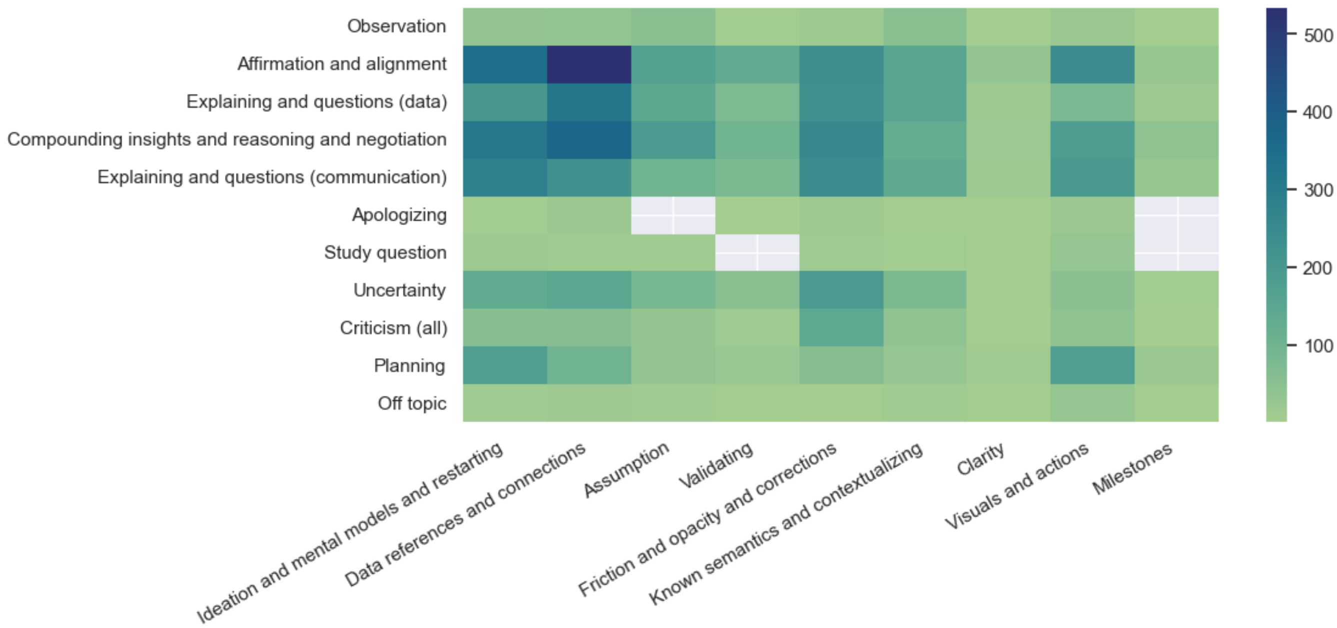


Figure 5: Heatmap of co-occurring codes for conceptual data modeling (x-axis) and collaboration (y-axis). Grey cells are those combinations of codes that were not present in our transcripts.

duplicates and the source of their repetition, identifying a relation between two attributes, and interpreting the meaning of an entity or relationship. These observations happened for all dyads, but more so for those who were effectively able to harness the tools, such as Dyads 2 and 6. Milestones are typically unrelated to the context of the data as our participants can identify specific details, but they could never conclude that their hypotheses about the context are true without clarifying with the moderator.

4.3.5 Validating. After making various observations, establishing whether these observations are compatible with other insights is an important next step. This is separate from (in)validating hypotheses by means of looking at the data, which participants did not do, but instead is about the process of integrating observations. Whether this was actively done by the participants seems unrelated to their expertise, but rather connected to wanting to perform the task as well as possible, as reflected by Dyads 1, 3, 6, and 8 and their goal-orientedness.

4.3.6 Metacognition. Finally, we were able to extract traces of the participants' mental models through metacognitive remarks (see [29]). Metacognitive remarks can include an extensive collection of actions, including reflections on what participants did (not) know, reflections on correctness, reflections on progress, and clarifications. These metacognitive contributions are some of the most powerful tools for understanding participants' processes of constructing conceptual data models. For example, awareness of model incompletion indicates a further understanding of the data structure, even when participants have not finished modeling to that extent. This section maps to many codes in our thematic analysis, such as *Friction*, *Opacity*, *Clarity*, and *Mental model*. Whether dyads showed Metacognition was dependent on how well they were able to gather their thoughts and think-aloud, which depends on the cognitive load of the participants. As such, we did not see many metacognitive remarks for Dyads 9, 10, and 11, who had a harder time constructing their conceptual model.

4.3.7 Checking against the real world. A final element we identified is to use a search engine to understand the data. This was done specifically by two dyads (9 and 11) with only basic knowledge of modeling. These participants were able to identify some entities based on concepts they already knew, but struggled with anything they did not know. Therefore, they decided to research external sources to identify additional context that could help build their model. In dyad 9, P17 took the lead in investigating and even tried to 'disprove' the data: *"This is somewhere in the mountain. Like, there's no trail there."* (P17). These searches imply that these participants did not know whether the data was 'real' in the sense of it representing existing entities. For them, this influenced their ability to understand and model the data, even though the schema normalization procedure is impartial to this.

4.4 Tool usage

Cognitive workload increases when using unfamiliar tools [51], and thus people tend to repeat known procedures. We observed similar tendencies in our study. Eight dyads used Google Sheets as a spreadsheet tool, three used Microsoft Excel online (owing to institutional tool use policies). There are similar differences for the drawing tools, which were split between Miro board and draw.io, with two teams using physical paper and one team using a digital canvas (iPad) as an intermediate step to their Miro board. Compared

Table 3: Tabular summary of uncovered themes on conceptual modeling

Theme	Description	Quote
Hypothesizing or assuming		
Hypotheses	Hypotheses were ubiquitous, expressed in terms of entities, connections, and the context of the dataset	"Maybe it doesn't have a relation like that. Maybe [accommodation and highlight] are related by being multi-determined by the trail segment." - P15
Assumptions	Maintaining momentum and aligning understanding	"Theoretically, you can't have a like 20 kilometers per day by just walking." - P18
Connecting to prior knowledge		
Knowledge and connotations	Connecting to familiar facts and feelings	"Marker just reminds me of, if there's a map and people are marking some points on the map. So there's x and y coordinates, and where is it on the map." - P12
Constructing stories	Collaborative sensemaking through story construction	"This is the rating based on each location, like it's an app, and this is the price per night, when US dollars and British pounds." - P18 "How can I have like, those and, like, recommendations? You have different parts of the same accommodation, as different names, like, based on the [room type]" - P17
Unfinished thoughts	Communication superseded by internal processing	"I mean… I wanted to check the… If you move… I wanted to… The name is… " - P11
Milestones		
Salient details	Observations that are central to building the conceptual model	"And the followed-up one, so the next marker in line. That's, I think, the marker 2. It's always, like, indicating… Oh… plus 1. So where this is 1, 2, 3, 4, that's 1, 2, 3, 5." - P8 "Yeah, so that's, like, maybe the starting point, end point?" - P7 "Yes, I think, like, how it links one point to the other." - P8
Reformulating	Incrementally realizing the conceptual model	"Right? Because it's all two. So countries, trails, difficulty, and [...] currency." - P9 "Yeah, so we have two trails. Each trail in one country has one currency because it's in one country." - P10

to the spreadsheet tool use, which was more varied, from view adjusting (i.e., *zooming* and *scrolling*) to view structuring (i.e., *filtering* and *sorting*), the use of drawing tools was largely homogeneous with the single exception of a hand-drawn visualization (i.e, D4). In Table 5, we summarize the tools and the corresponding main features used in the study. As an example action for each dyad, a representative one is added for better comparison.

Based on Table 1, pairs D1-D3, who have data experience above or at the intermediate level, tended to make decisions quickly and perform the tasks strategically. D1's participants aimed to arrange their screen space to switch between Google Sheets and draw.io effectively. This decision was probably made due to the limited size of the data we provided (20 columns and 22 rows). In contrast to having the data table overview, D2 and D3 incorporated *filtering* or *hiding* intentionally to validate their models. All D1-D3 pairs started using the drawing tools at the early stages of the study.

Dyads D9-D11 are participants who have basic knowledge of data experience. In comparison to D1-D3, these three dyads spent most of their study time on understanding the column headings and data cells, and thus frequently use search engines (i.e., Google) to understand the unfamiliar terminology, such as `marker_id` and `highlight_id`. The drawing tool is only used at the end of the study when they are convinced that most relationships embedded in the data have been discussed. Similar to D2 and D3, D11 also used *filtering* and *sorting* in the study, although their intention is less clear as they applied *sorting* on already sorted data, and performed *filtering* without concluding specific findings. This could be considered a trial-and-error approach for the tool features.

D4-D8 are dyads with more mixed data experience, from basic to intermediate or advanced, and tend to approach the tasks from different perspectives, such as ideas to accelerate the analysis process, strategies to avoid missing relationships, and design to present the final models. For example, D6 and D8 used paper (Figure 2), and D4 used a digital canvas as an intermediate step to clarify their thoughts and communicate with their partners. D5 created separate drawings to depict individual understanding, while the resulting diagrams were quite similar. D7 discussed the geometry and spatial arrangement of the diagram, which gives a clear overview of their model.

Table 4: Tabular summary of uncovered themes on conceptual modeling

Theme	Description	Quote
Validating	Establishing whether observations are compatible with other insights	"Let's see if those stops are as we've defined them now, [...] if they are indeed unique to... the route." - P2
Metacognition		
Reflecting on progress	Showing awareness of process (in)completion	"So I think for a fairly large part, we have visualized the table, but we still haven't made complete sense of it." - P10
Lack of understanding	Reflecting on what they do not know or understand	"Why? Because I can't see relationships between different tables. I don't understand that they're connected. [...] So, they are somehow related. I'm not sure how to show that. So, I mean, everything is related." - P16
Clarifying	Rewording and integrating previous observations	"So one thing we know for sure is at least that the coordinates and the markers we can separate from the route table that we identified, yes. Then the question mostly remains, what does it correspond to, to the route, to the county, but not to the hotel? Because it's all the same here, but they have different hotels. So probably county but it feels a bit weird." - P4
Checking against the real world	Using a search engine to understand the data	"I was thinking that maybe it would be something like a state or something. I'm not sure." - P21 "I think we just Google it." - P22 "No, I don't think it's real. No, it's not." - P21 "Yeah, but these are real names. And it's just this sounds real. So that's... Just Google Lochaber." - P22 "Are we allowed to Google?" - P21 [participants searching] "I think it's real, it's a real thing. It's like, a space." - P22 "The province [or] something." - P21

Table 5: Tool Features used in the study, including data exploration actions based on the visual analytics taxonomy [52] and model diagram creation based on the visualization interaction taxonomy [57].

	Spreadsheet		Drawing		Action
Dyad ID	**Tool**	**Used Features**	**Tool**	**Used Features**	**Representative Examples**
D1	Google Sheets	Zoom (to fit the display)	draw.io	Create/Edit/Lock	Add relationship one after another strategically
D2	Google Sheets	Filter/Hide	draw.io	Create/Edit	Add new entity whenever discovered
D3	Google Sheets	Filter	draw.io	Create/Edit	Geometry and color scheme of the entity is discussed before drawing
D4	MS Excel online	Pan	iPad/Miro	Handwriting	The model diagram is hand-drawn on the iPad
D5	MS Excel online	Pan	Miro	Create/Edit	The model was drawn once by each participant to allow for their own take, after which they realized that the drawing were quite similar.
D6	MS Excel online	Filter/Hide	Paper/Miro	Handwriting/Create/Edit	Repeated tool use to simplify the part of the dataset in view.
D7	Google Sheets	Filter (once)	Miro	Create/Reconfigure	Discuss the geometry and spatial arrangement
D8	Google Sheets	Filter	Paper/Miro	Handwriting/Create/Edit	Use a sketch map to build their model
D9	Google Sheets	Pan/Zoom	draw.io	Create/Edit/Copy/Paste	Use Google Maps to visualize the coordinates and search for trial names
D10	Google Sheets	Zoom (to fit the display)	draw.io	Create/Edit/Select	Adequate time is used to search unfamiliar names online
D11	Google Sheets	Filter/Sort	draw.io	Create/Edit	Discuss the geometry (i.e., rectangle) to be used in the diagram

Interestingly, many dyads discussed the object geometry they liked to incorporate in the drawings before starting the tasks. Unexpectedly, all dyads used rectangular boxes and polylines to construct their final models, regardless of their previous experience. Overall, the operation time spent on the tools is limited across all pairs.

4.5 Collaborative communication patterns

In this section, we illustrate the collaborative process between participants with a focus on the model negotiation and creation process. We highlight affirmation, compounding insights, friction, and role hierarchies as key dynamics that shape how participants jointly constructed meaning.

4.5.1 Affirmation. Affirmations, from subtle acknowledgments to explicit confirmations, occurred frequently and were central to how participants coordinated their joint sensemaking. They acted as small but meaningful interactional cues that helped them stay aligned, manage uncertainty, and sustain the flow of the collaborative task. We observed a range of affirmation forms, from minimal signals that maintained shared focus (grounding, coordination) to more substantive affirmations that helped shape and extend emerging interpretations (co-construction, validation, encouragement), which are presented in more detail in Table 6. These patterns show how seemingly minor utterances contributed systemically to the overall effectiveness of the collaborative modeling process.

4.5.2 Compounding insights. Compounding insights occurred when participants picked up one another's ideas and developed them further, step by step. In contrast to affirmation, which stabilized shared understanding, compounding expanded it by introducing additions, posing alternatives, or exploring tentative structures that moved the modeling forward. These exchanges often unfolded as iterative back-and-forths in which participants layered contributions, negotiated structural possibilities, or reasoned through small logical steps. Through the gradual accumulation and refinement of ideas, the collaborative model took shape. Table 7 summarizes three main ways in which participants compounded insights: layering, negotiating structure, and forming reasoning chains. Layering is the gradual co-construction of a model as participants add pieces of information without necessarily testing them. Negotiating structure is the joint adjustment of how elements are organized as participants discuss and refine the model's shape and relationships. Reasoning chains are sequences of connected steps in which participants walk through a line of thought to test or verify an interpretation.

4.5.3 Friction. Collaboration also introduced moments of friction. These occurred when participants struggled to align their interpretations, questioned each other's explanations, or disagreed about how the model should be structured. Some frictions took the form of misunderstandings, where confusion over terms or labels disrupted the modeling flow. Others involved interpretive conflict, with participants proposing and defending different explanations. Structural conflict emerged when modeling choices or representations were challenged. As shown in Table 8, these forms of friction varied in intensity but rarely escalated; instead, they usually prompted participants to pause, reconsider, and jointly resolve the issue.

4.5.4 Role hierarchy. Given the diversity of participant backgrounds, we observed a variety of role hierarchies within the dyads. Although most dyads knew each other, they had rarely worked together, so roles emerged through the interaction itself. In many dyads, one participant assumed a more leading role–often the one with greater experience or confidence in structured data–while the other adopted a more supportive or questioning position. In some dyads these roles shifted fluidly; in most, they remained stable or were negotiated through moments of friction or playful exchanges. Detailed accounts in the form of narrative participant profiles can be found in the supplement (S.01).

Educational and disciplinary training shaped these hierarchies to some extent. Participants familiar with structured data modeling guided the task more often, while those with less experience focused on clarifying details. Yet, this was not absolute: experienced participants also struggled at times, and less experienced ones occasionally took the lead. In general, the role hierarchies were formed dynamically rather than predetermined.

5 Discussion

In the discussion, we focus on the core interests of our study: conceptual data modeling and collaboration patterns. We start with a reflection on our distributed, multi-lab methodology and conclude with implications, limitations, and future work.

5.1 Conceptual modeling patterns

Our participants worked in a self-directed and self-negotiated process on the conceptual modeling task. While there is diversity in how they approached different steps, achieved milestones, and leaned on their expertise and knowledge, there were also patterns of reading and contextualizing data, finding and checking patterns, and generalizing intermediate insights towards an incrementally evolving conceptual model. We have visualized the most important links between artifacts, constructs, and activities in Figure 6, which shows a progression from data, via a more or less tacit data model, to the final conceptual model, while drawing from personal conceptual modeling expertise, storytelling, and real-world knowledge.

5.1.1 Sensemaking through hypotheses and assumptions. Our findings highlight how participants frequently relied on hypotheses and assumptions to navigate the conceptual modeling task. Hypotheses seemed to serve multiple functions for the participants: primarily externalizing the thinking process and decelerating the progress in case of doubts, but also for engagement and keeping the dyad on task. We know hypothesis generation as a central part of sensemaking, allowing people to explore uncertainties and test possible explanations or interpretations [38, 43]. In our study, we observed that participants' assumptions were often shaped by intuition or personal attitudes. While many of these assumptions were incorrect, they were often not disproved within the group discussion, persisted, and subtly shaped the direction of the collaborative modeling activities (see "Hypotheses" in Figure 6).

We also found that posing hypotheses differed per dyad. Participants who identified as having intermediate or advanced data modeling skills were more likely to be hypothesizing and validating. In contrast, participants with lower basic data modeling skills were more likely to reflect on the contents of the sheets and connect their

Table 6: Summary of subthemes on affirmation

AFFIRMATION as	Description	Quote
validation	Reinforcing tentative knowledge by confirming plausibility and reducing uncertainty, shaping confidence	"What does this mean then? These are the different counties that you cross or something or..." - P3 "It does sound like it, East Dumbarton does sound like a county." - P4
coordination	Maintaining momentum and aligning understanding, enables modelling steps.	*Lightweight cues such as "yeah," "OK"*
grounding	Signaling understanding, maintaining shared focus without introducing new content.	"So whenever I have it [marker_id], I have this value [coordinates] regardless of what it comes next [as marker 2]." - P6 "I understand, yeah. OK, mm-hmmm." - P5
co-construction	Elaboration and analogy-building. Agreement is used as a scaffold for collaborative reasoning.	"I think we're looking at two trails." - P7 "And these coordinates represent waypoints, and then for each waypoint, they've created, like, nearby locations of things to do." - P8 "Mm-hmm." - P7
encouragement	Supporting the process by motivating the collaborator to continue, refine, or explore further.	"We're making progress" - P15
Tentative affirmations	Affirmation paired with hedging, signaling incompleteness	"So it's just like, it's not country necessarily." - P19 "It's like, like, space." - P20 "They're, yes, the city. The province something." - P19 "Yeah, okay." - P20

observations to what they knew from their own experiences in the real world, also described as *placing* in the context of data-centric sensemaking [22]. Participants with more experience were more systematic in their tackling of the task, whereas inexperienced pairs sometimes circled back repeatedly to the same ideas.

5.1.2 Unfinished thoughts as markers of cognitive processing. We further observed what we term "unfinished thoughts", where participants verbalized fragments of ideas without reaching communicative clarity (see Fig 6, center). These episodes suggest that cognitive work continued internally also when outward articulation was not visible. Prior research on collaborative sensemaking notes similar pauses or incomplete utterances as indicators of transitions between individual and group cognition [48]. We found that unfinished thoughts functioned as subtle signals to indicate cognitive load, moments of uncertainty, or shifts from collaborative discussion back to individual processing.

5.1.3 Connecting to prior knowledge through stories and experience. Participants also drew on prior knowledge (see Fig 6, top) to make sense of the task, often through the use of metaphors, analogies, or other reference points. This aligns with literature on the role of prior knowledge in cognitive scaffolding and collaborative problem-solving [55, 59]. We identified two distinct modes of this connection: constructing stories and demonstrating task-related experience. Constructed stories were particularly visible among participants with less modeling expertise, who relied on narrative framing to reason about data entities and missing values (note the alternative "generalizing" path from Story to the Conceptual Model in Fig 6). These narratives served as shared conceptual models that guided exploration of the data but sometimes risked overfitting the data to an imagined context. By contrast, participants with more experience referred more to technical terms to anchor their reasoning and actions.

We found that dyads with lower self-identified experience were more likely to create full stories surrounding the meaning of entities or the context of the data. We hypothesize that this is due to their struggle with the task's abstract nature and the dataset's complexity, which requires a narrative to interpret the data and devise a plan to engage with the task. Dyads D9 and D11 even went as far as to assume the data must be someone's personal collection and tried to interpret the data in this light. Even though they struggled (as they found that accommodations had ratings that were not integers, and according to them, that should not be possible), they never moved away from this hypothesis. This might hint at a gradually locking-in conceptual modeling process where initial assumptions, if not immediately disproven, can be maintained throughout without appropriate reflection and revision. This mirrors dynamics described in information foraging [37] and the Data-Frame Theory [21], when early choices shape and constrain subsequent reasoning.

Table 7: Summary of subthemes on compounding insights

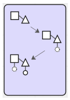
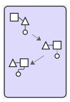
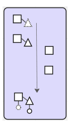
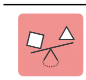
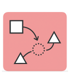
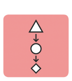
Compounding insights	Description	Quote
 Layering	Co-constructing through iterative additions. Emphasis on accumulation.	"We can maybe just separate the the accommodations." - P10 "Yeah, within one county, you have different accommodations. [...] we get one county, we have different accommodation types." - P9 "I think you'd you'd have different accommodations and each accommodation has a type." - P10 "Yeah, and then it has a name." - P9
 Negotiating structure	Incrementally negotiating and shaping the model's form.	"Not sure whether we should use the marker there or just one." - P14 "I'd almost take both. It looks like both are kind of a composite key, more or less, right?" - P13
 Reasoning chains	Steps to test hypotheses. Emphasis on logical progression.	"Difficulty. What's it even about? We have a marker..." - P1 "We have a marker..." - P2 "We have two markers, coordinates..." - P1 "Which are always different, right." - P2

Table 8: Summary of subthemes on friction

Friction	Description	Quote
 Misunderstanding	Confusion, misalignment	"And then column two with the country name." - P15 "There's a country name already." - P16 "There's county " - P15 "A county." - P16 "Country. Country. " - P15 " No, I'm confused again. And what was then county?" - P16 "County is a region." - P15
 Interpretive conflict	Competing explanations	"But it's it's with a zero and one." - P5 "So what's? It's not the exact value, right?" - P6 "So let's say here we have 3 [times] 1235 and here we have multiple. A three at the end and they're all in the same country." - P5 "Yeah, but it's not really like it's not really using this key or something." - P6
 Structural conflict	Differing opinions on modeling choices or representations	" So, yeah, and then, another one, the arrow is wrong, I think. And so, hard to draw it. Okay, and name, this one. So, this is regarding type and the name of… shall we write some here, they know something. [...] " - P20 " But we haven't written anything about the price and the comments. " - P19

5.1.4 Milestone moments in modeling. Observations across sessions revealed that the nature and depth of identified patterns varied considerably, with some groups producing richer, more comprehensive representations and others focusing on local, shallow connections without developing overarching structures.

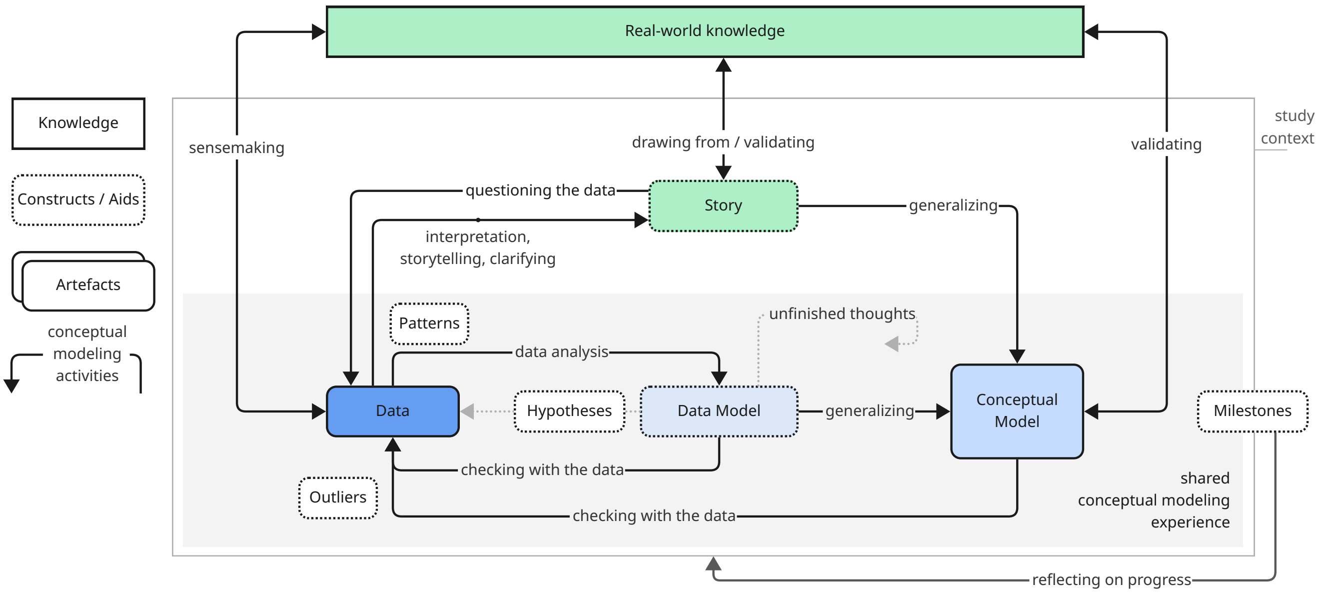


Figure 6: Schematic overview of identified CCM activities across dyads, emphasizing the roles of concrete artifacts like data and conceptual model, different constructs and aids like stories and data models, and the real-world knowledge being used to make sense of data and validate the final conceptual model.

Our analysis of 'milestone' moments revealed variation in how they manifested across sessions, highlighting that milestones were often subtle and not straightforward to identify. For some groups of participants, especially those for whom the task resembled familiar work practices, progress appeared continuous and procedural, with no distinct turning points; in these cases, milestones were rare or absent. Other groups approached the task more superficially, which also led to few clear moments of progress or achievement.

Participants experienced distinct milestones when they advanced their understanding of the dataset structure, for example, by recognizing duplicates, uncovering relations between attributes, or interpreting the meaning of entities. Such milestones can be seen as key sensemaking breakthroughs [43], moments where ambiguity gives way to more stable interpretations. Prior work on collaborative analysis has described similar incremental progress, where salient details accumulate to scaffold more complex representations. In our work, milestones surface not just as analytical outcomes but also as social signals: participants oriented to these moments as evidence that progress was being made, which in turn motivated further collaborative engagement.

These findings suggest that systems supporting collaborative modeling could benefit from scaffolding not only the articulation of hypotheses but also the surfacing and negotiation of assumptions, as both play a role in building shared understanding and navigating ambiguity.

Closely linked to the milestones that participants experienced in our task is the practice of validation. After generating observations, participants frequently checked whether these aligned with prior insights or with the broader model under construction. Validation functioned as a collaborative checkpoint, ensuring that progress was not only individual but collectively shared.

5.1.5 Contextualizing as a key activity in conceptual data modeling. Our findings show that participants often connected to prior knowledge to make sense of the data, using analogies (e.g., currencies in countries), recognizable names (e.g., well-known trails), or associative connotations (e.g., map markers). They also drew on stories and personal experiences to contextualize ambiguous attributes and relations. We have depicted these connections as "sensemaking", "drawing from" and "validating" in Figure 6. While such connections may be partial or imprecise, they provided useful entry points for collaborative interpretation and invited contributions. This aligns with prior work on how analogies and contextual knowledge shape sensemaking [15, 54] and with studies of how people use everyday associations to interpret datasets [22].

Participants who were familiar with the conceptual domain of hiking, trail running, or more generally geography had an easier time identifying the appropriate entities of the model, because they could utilize prior knowledge. On the other hand, knowledge of the domain also sometimes misled the participants, as the data was not modeled exactly as they expected. For example, in the originating data model, the highlights and accommodations were mapped to the county entity, yet some participants connected them to markers, segments, or other location entities.

The extent to which participants incorporated their own real-world knowledge as a form of authority in the sensemaking process varied. In some cases, participants explicitly invoked prior experience (e.g., about the size of the country) or made domain-specific assumptions (e.g., about the length of hiking routes, or the need for accommodations). In others, contributions took the form of examples or hypothetical scenarios, a form of storytelling, without asserting expertise. The prevalence and style of such real-world contextualization varied across groups and experience levels, influencing how participants framed the task and the data.

5.1.6 Temporal dynamics in conceptual model creation. Looking at the activities over time showed how the teams moved through cycles of collaboration. Some worked in a scattered way, while others followed clearer sequences, e.g., by starting with assumptions and ideas, then moving into validation and visualization. Across teams, a broader pattern emerged: they began by leaning on assumptions, encountered friction and negotiation in the middle, and ended with more convergence and produced the visual output. These temporal shifts mirror models of sensemaking that alternate between divergence and convergence, highlighting how affirmation and alignment help teams stay coordinated [38].

5.2 Collaboration patterns

The nature of negotiation and alignment processes played a central role in collaborative sensemaking. While some teams engaged in ongoing fluid negotiation—shifting between proposing interpretations, validating them through examples, and revising when inconsistencies emerged—others exhibited only occasional negotiation, instead forming alignments more directly.

As with the conceptual modeling patterns, the temporal perspective on collaboration reveals shifts in how pairs embarked on collaboration. For instance, D5 required study information and clarifications primarily at the outset. They predominantly used affirmation and alignment to maintain momentum during the study task, with occasional compounding that increased visibly towards the end of the study, similar to explaining the data and visualization (see Figure 4). The visualization also shows a clear progression from questioning and explaining data to higher-level communication. This shows how the team, not the individuals, changed "gears" as they built their mental models and confidence during the study, up to the point that they could generate the conceptual data model and validate it through questions and explanations.

5.2.1 Affirmation as a collaborative mechanism. Our analysis highlights affirmation as more than a conversational nicety. Instead, it emerges as a core mechanism for collaborative progress in conceptual data modeling. This can be traced in the over-time visualizations (see Figure 4) as well as in the situational observations and the narrative participant profiles. Across its forms, affirmation not only supported interpersonal rapport but also actively structured the joint reasoning process. Minimal cues such as "yeah" or "mm-hmm" grounded conversation [39], while stronger validations and coordinated affirmations reduced uncertainty and created momentum for modeling actions. Importantly, affirmations often worked recursively, sustaining confidence and reinforcing tentative knowledge until a shared understanding could be stabilized. This indicates that affirmation functions simultaneously on cognitive and relational levels: it scaffolds complex reasoning while also maintaining positive, encouraging engagement and trust between the participants [1, 48]. In collaborative conceptual modeling, where ambiguity and partial knowledge are inherent, affirmation becomes a subtle but crucial resource for aligning perspectives, negotiating meaning, and enabling co-construction of the data model.

What distinguishes conceptual modeling from other collaborative tasks is the inherently abstract, interpretive, and uncertain nature of the task: participants must forage relevant bits of information and negotiate meanings of entities, attributes, and relationships that often lack immediate real-world referents. In this context, affirmation plays a critical role in bridging ambiguity and stabilizing partial knowledge. In that sense, affirmation enables the modeling process to move forward despite incomplete or contested interpretations.

5.2.2 Compounding insights as collaborative sensemaking activity. Participants compounded insights by layering contributions, negotiating structure, and developing reasoning chains. As an alternative to simply affirming each other's statements, they extended and transformed ideas step by step, gradually building their shared model. This behavior differed by team; for some, there was a base level of affirmation with spikes of compounding insights, for others, both happened in equal proportions.

Through layering, participants added attributes and interpretations until a richer understanding emerged. This reflects work on collaborative sensemaking, where knowledge is built through incremental contributions (e.g., [48]).

Another form of compounding involved negotiating structure, where participants refined terminology, debated categories, and converged on schema elements such as keys or identifiers. These negotiations recall the role of boundary objects [26], which anchor different perspectives and provide common ground for collaboration. Participants also engaged in reasoning chains, verbalizing incremental steps to test and extend hypotheses, which often flowed directly into modeling action.

5.3 Methodological reflections

Our study was conducted in two countries and across four labs, with researchers acting as facilitators for a total of 11 study instances. While this structure enabled flexibility and inclusivity, it also resulted in a dataset that was heterogeneous and, in some cases, not directly comparable across contexts. Synthesizing and compressing such material into actionable insights proved challenging, underscoring the need to consider both the granular characteristics of the data and the broader analytical goals.

Collaborative interactions as a black box. In particular, coding and dialogue analysis were challenging due to the conversational format, characterized by short utterances and repeated talking over each other. Additionally, artifacts from the transcription process resulted in a dataset that was difficult to code and make sense of. However, it allowed us to have a less filtered look at the conversation style, where our participants often completed each other's sentences and joined thoughts. In short, we felt we opened a black box of truly collaborative experiences, and the data proved to be more than a proxy for surfacing people's conceptual models; we obtained insights into the "how" of the collaborative process and collaborative sensemaking.

Compartmentalizing data in distributed studies. Due to the different locations in Europe where the study took place, we had to pay attention to how personally identifiable information (PII) was handled as a study team and also within the team. This led to a design with separate processes to compartmentalize the audio and video material, the transcription and coding processes, and the writing and summative assessment of the participant profiles. This setup led to the first part of data processing and analysis that aligned the study instance with the respective facilitator, i.e., every facilitator processed and coded their dyads' data. For the following analysis steps, we used an orthogonal assignment of different analyses (see Figure 2) to facilitators who would then have a good overview of the data pertaining to "their" analysis, and who would prompt other facilitators for specifics as needed. This example of a study format that protects PII from leaking *within* the research team was effective in both steps, and provided for deep content discussions in the research team during regular touch points.

5.4 Conceptual modeling dynamics

In summary, conceptual modeling is a challenging task, both for the participants to execute as well as for the authors to study. We characterize the modeling process as an extension of prior knowledge in all its forms (hypotheses, assumptions, contextualization, stories, and expertise). These connections to prior knowledge also help build the mental model, which then guides the construction of the conceptual model.

Conceptual modeling can benefit from collaboration, as multiple perspectives enable affirmation and the compounding of insights. These two mechanisms were also the most common co-occurring codes with milestones in Figure 5. This sentiment was also echoed in participants' answers to the reflection questions at the end of the study, where none of our 21 participants indicated a preference for undertaking the task alone.

5.5 Implications

System design and tools development. Our results show that conceptual data modeling can indeed be a *social* data practice that also benefits from communicative acts during pair-wise collaboration [19]. Teams approach conceptual data models through iteration, which is necessary to align and integrate individual mental models, in line with existing literature (e.g.,[12]). Such iteration helps refine the model, and the richer mental model input might lead to better-formed and more appropriate conceptual data models, in particular in non-scripted settings where there is no right answer. Therefore, interfaces and tools for conceptual data modeling should support collaborative sensemaking processes as alternatives or additions to individual data practices. Tools could embed interaction cues such as inline reactions or uncertainty markers on entities or attributes. For example, collaborators could mark a class as "tentative/agreed/needs evidence", to show where alignment or uncertainty remains.

In addition, there is an explicit need to support visualizing and externalizing more generally. Our participants often drew, sketched, or switched back to data to exemplify their points. This suggests opportunities for exploration of the data and iteration of the model, for instance, through rough sketches and transitions from informal to formal. Systems could support a side-by-side display of model variants that allow to branch from the current diagram, sketch an alternative, and later compare or merge these versions. Lightweight forks or temporary sub-canvases would make provisional thinking visible without forcing early commitment, helping teams surface where they diverge.

Some participants and dyads demonstrated a good awareness of milestones during the study, knowing when to switch activities or review new data. This underscores the potential for system design to make milestones more visible, for example, through interfaces that highlight recognized patterns or validated relationships that can be "parked" to lower the cognitive load of the activity [28]. A plausible implication here is to equip conceptual modeling tools with storytelling support, such as a side panel where users can capture short notes, conversational context, or decisions linked to specific parts of the evolving model. This would help teams keep track of why and when transitions from informal to formal modeling steps occurred.

At the level of communication patterns, tool designs can benefit from support of turn-taking, and shared annotation and visualization of alternative modeling choices in order to surface different perspectives and mitigate the influence of role dynamics. In the same vein, it would be advisable to enable negotiation features, e.g., highlighting unresolved friction or trade-offs. This also relates to milestones and resolved issues that might need revisiting, as new misalignments might occur as the team makes further modeling choices. Systems might need to be equipped to better recognize and support lightweight affirmation practices, not merely as signals of agreement, but as key resources for coordination and collaborative sensemaking (resonating with findings by Convertino et al. [12]) in conceptual data modeling contexts.

Human-Data Interaction and HCI education. There is a need to better understand conceptual data modeling in HDI as part of HCI practices. In our study, the task was explicit and challenging, as one would expect it to be for a professional engagement with data. The collaborative aspects point to interesting research directions for data-centric interactions that require individuals to externalize part of their sensemaking. Apart from professional contexts, our results have implications for mundane data interactions and novice HDI, suggesting that collaboration should be encouraged and facilitated more by interfaces and *joint* data access opportunities. This allows laypeople to jointly make sense of data and develop skills in externalizing and negotiating concepts.

We found that participant teams either began their conceptual modeling by focusing on data and structural aspects of the dataset, or by using conceptual hints embedded in column headers and cells to construct the model from domain entities and relations. This underlines the flexibility required from systems that support collaborative modeling, as these two approaches can coexist within a single team working toward a shared conceptual model.

As a final implication, data literacy, specifically critical data literacy, is essential to broaden participation in computing [47]. Developing data literacy skills relies on and includes a certain level of modeling skills; teaching this early on is key to understanding and acting in our complex, data-driven Everyday. Despite the common stereotype of data being "dry" or "boring", our participants describe their experience of collaborating on accomplishing a task that could be characterized as dull and tedious as "fun" or "interesting puzzle".

They remain engaged and positive, even finding ways to scratch their creative itches (e.g., D4 extensively ideated on topics such as hiking routes, wheelchair accessibility, and hiking apps). Such creative engagement could support teaching aspects of data literacy in pairwise settings. Future work is needed to understand its effects on learning„ not least given the complex dynamics observed in studies of collaborative programming [49].

5.6 Limitations and future work

This study has several limitations. First, the generalizability of our findings is constrained. Some participants may have engaged with the task at a surface level, resulting in models that do not fully reflect their reasoning processes. Resonance with modeling concepts was also influenced by participants' domain knowledge and educational background. Aligning task complexity with varying expertise levels proved challenging when creating a study design for non-experts and varying expertise levels. As a reflective note, we acknowledge that our participant pool is skewed toward students and academic affiliates due to our recruitment methods and the requirement for basic digital tool skills. As a result, the sample does not reflect broader general populations.

Second, outcomes were also shaped by the short duration of the study. Participants had up to one hour to build and visualize their conceptual data model. In reality, this task typically takes much longer and is done in phases. Although we did see some evidence of multiple iterations in our transcripts and models, this study represents a simplified version of a real-world task.

Third, the authors sometimes had different interpretations of codes in the codebook. For example, the code *Negotiation* for some included only a repeated disagreement, whereas for others, limited discussion leading to agreement was classified under this code which resulted in the merging of some codes. These variations point to the complexity of interpreting collaborative discourse and underscore the need for transparency in how such processes are defined and analyzed.

Finally, the awareness of being audio- and screen-recorded may have altered participants' behavior, for instance by reducing openness during deliberation. Future studies could extend participation beyond pairs, for example, to small groups, perhaps through citizen science approaches, to broaden the range of perspectives and mitigate these constraints.

6 Conclusion

Conceptual data modeling is a challenging and highly relevant data practice. As much CDM work unfolds iteratively and through exchange with others, understanding how it works in collaborative settings is essential. This study examined how pairs of participants with different expertise collaboratively constructed conceptual data models. By analyzing their model sketches, screen interactions, and dialogue, we observed how communication strategies, negotiation, and moments of friction shaped both the process and the resulting models. Our findings highlight that conceptual data modeling is not only a technical activity, but also a social and communicative one.

Our results show that *collaborative* conceptual data modeling unfolded through tentative reasoning, prior knowledge, and shared insights, showing how participants balanced individual exploration with alignment. Apart from tangible benefits of collaboration, storytelling, and metacognition, our findings highlight diverse paths in modeling, ranging from more data-driven to more concept-driven starting points, each supporting effective outcomes. For design, this suggests opportunities for tools that make dialogue and negotiation more visible within the data modeling process. Taken together, these insights inspire future work toward modeling environments that treat communication and collaboration as central to working with data.

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