# Informal skill-sharing in collaborative immersive analytics

Pierre Vaslin and Yannick Prié

**Abstract**—Newcomers to immersive analytics systems would benefit from informally learning data analysis skills (e.g. reading a vis, using a system) when collaborating with more expert participants. We want to design tools that facilitate this informal learning by encouraging the informal sharing of data literacy skills during collaborative immersive analysis. A first step toward this goal is to understand how informal skill sharing takes place in order to identify how it could be improved. We experimentally studied informal skill-sharing in pairs of participants analyzing scatterplots in a shared virtual reality environment. We used an original mixed-method to analyze video and log recordings as well as subjective experiential data, based on common ground theory and the grounding process. We uncovered 101 episodes of skill-sharing, organized in 14 recurring types, and identified associated problems from which we could propose six implications for designing systems that favor informal skill-sharing, hence skill learning. The method can be used to study informal skill sharing in other systems enabling embodied face-to-face collaboration, but would need to be simplified for large-scale use.

**Index Terms**—Collaborative Immersive Analytics, Common ground, Data Literacy, Informal skill-sharing, Virtual Reality.

## 1 Introduction

Immersive analytics (IA) benefit both from 3D representations and embodied interaction means, thereby changing the manner in which individuals interact with data. Novel forms of visualizations such as space-time cubes or 3D scatterplots, as well as data manipulation with natural gestures, including touching, grabbing, throwing or moving closer to objects, can enhance the overall immersive experience. Collaborative immersive analytics adds a social dimension to data analysis, allowing people to work together remotely in new ways [1], [2]. The spatialization of data and interfaces, together with the embodiment of avatars in shared spaces, allow close-to-reality face-to-face collaboration mechanisms [3]. For example, users can move freely around the data and explore at their own pace, they can participate in the analysis using gestures as simple as pointing [4], they can whisper to each other, etc. Compared to traditional user interfaces on conventional computers, which are limited by 2D screens and keyboard and mouse interactions, collaborative immersive analytics both simplify handling 3D data visualization and may facilitate collaborating around data [2], [5].

This simplification may attract new actors to visual analytics, contributing to its democratization. However, newcomers must learn the skills associated with data analysis, a complex task that requires expertise and practice, e.g. in visualization reading, data, understanding or mapping manipulation, regardless of the quality of the system [6].

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This can be done with formal conventional methods such as tutorials, training programs, or workshops, but some of those actors, such as decision makers who aim to conduct data-driven decision-making, or beginners who want to understand quickly, lack the time or will to participate in learning sessions. In such cases where formal and explicit learning does not seem the most appropriate approach, a solution may be to leverage naturally occurring learning within collaboration, where those involved learn from each other as they analyze data, a phenomenon often referred to as informal learning [7]. In our research, we want to facilitate *informal skill learning* during collaborative immersive data analysis. Our idea is that beginners may enhance their skills informally during analysis sessions, where skills would be shared and learned in the course of task organization and execution. Leveraging informal skill learning among collaborators in complex collaborative tasks may also be beneficial to more experienced participants, who also have different levels of expertise in the tool or in the tasks, as well as apply to other domains than immersive analytics, such as collaborative editing or games.

Fostering informal learning can be challenging due to difficulties in identifying what skills are to be acquired, which may not even be named, and evaluating their successful acquisition. To address this issue, our approach rather focuses on designing immersive analytics tools that encourage informal skill *learning* by facilitating informal data literacy skill *sharing* among participants during analysis. Our idea is that by studying how and when skill-sharing spontaneously occurs [8], [9], we may be able to evaluate IA systems with respect to skill-sharing and improve them so as to promote these occurrences, and by doing so, improve informal learning of data analytics skills.

Skill-sharing is a phenomenon that occurs spontaneously between participants in a collaborative task to facilitate its execution. It can be essential to success when participants possess differing skills [10], [11]. Theoretically, the sharing of knowledge and expertise during a collaborative task can be considered as part of building and maintaining a *common ground* between participants [12], and a successful joint activity is directly related to the success of this grounding process [13].

We conducted an empirical evaluation of how informal skill-sharing occurs between pairs of participants collaborating on a data analysis task within a shared VR environment. We collected a diverse range of data, encompassing both behavioral and experiential aspects, which we analyzed looking for episodes of skill-sharing as part of the grounding process. Our contributions in this paper are 1/ a definition of informal skill-sharing and its different types; 2/ a method for assessing informal skill-sharing in social VR from participants' exchanges and their lived experiences; 3/ the application of this method in the case of immersive collaborative analytics of 3D scatterplots gave us 14 skill-sharing episodes types and their characteristics (initial context of sharing, reason for success or failure, etc.); and 4/ the problems identified from failed episodes, and the related implications for designing shared virtual analytics environments that facilitate spontaneous skill-sharing, therefore skill learning and common ground building, contributing to the improvement of collaborative immersive analytics systems.

## 2 Related work

Here, we review several topics related to our research.

### 2.1 Collaborative immersive analytics

Immersive analytics (IA) has been explored in various application domains since the 1990s [14]. It has been increasingly recognized as a valuable approach to data understanding and decision making, based on embodied, engaging analysis tools [15]. IA systems allow us to analyze data through interaction with visualizations such as space-time cubes, 3D parallel coordinates plots, or 3D scatterplots [16]. A key feature of IA is the ability to interact with visualizations in intuitive ways involving the whole body, *e.g.*, circulate around a visualization, or grab data points. Another is to facilitate collaboration between users. Collaborative immersive analytics is defined as "the shared use of immersive interaction and display technologies by more than one person for supporting collaborative analytical reasoning and decision making" [17]. Collaboration can take several forms, depending on space and time [17], [18], but co-located or distributed synchronous collaboration has been the most studied [14]. In collaborative IA, participants can freely move around and interact with visualizations, adjusting positions relative to each other. They can also use deictic gestures to highlight data points or environmental elements and leverage spatialization of sound to aid distant and group collaborations, *e.g.*, whispering to a neighbor [19], [20]. Compared to classical computer-based data analysis, this simplifies collaborative activity, which can be close to what it would be like in standard face-to-face interaction [1].

Some studies focus on describing collaboration in immersive analytics. Lee et al. [19] investigated the individual and collaborative behaviors of ten groups of three users using an immersive environment for multidimensional data analysis, using third-person point of view videos and logs that they annotated to identify various stages of collaboration. Resky et al. [9] analyzed data analysis communication patterns in VR and web hybrid asymmetric collaboration. They used thinking aloud, interaction log, and interview data, demonstrating the successful use of pointers to share spatial references through deictic references and positive acknowledgments. Benk et al. [8] employed the "pair analytic method" to analyze collaboration between nine asymmetric pairs of participants playing the role of risk officer and machine learning engineer to solve an industry-relevant machine learning task, using third-person PoV video annotations to identify phenomena related to group dynamics, work division, common ground building, referencing, engagement, consensus, and decision making.

In our work, we explored how collaborative immersive environments could facilitate informal learning of data analysis skills, as would happen in reality. We used pair analytics and collected a variety of data (first- and third-person POV videos, logs, experiential interviews) to describe skill learning-related moments of the collaboration, rather than focusing on the completion of the task or its dynamics.

### 2.2 Informal learning

Informal learning is defined as "any activity involving the pursuit of understanding, knowledge, or skill which occurs outside the curricula of educational institutions, or the courses or workshops offered by educational or social agencies" [21]. It is predominantly studied to identify methods to improve the acquisition of knowledge and skills in professional activities.

It can be characterized by intentionality (the desire to learn something) and consciousness (the awareness of ongoing learning) of the learning [22], leading to four main forms. *Self-directed learning* is intentional and conscious. It is "a process in which individuals take the initiative, with or without the help of others, in diagnosing their learning needs, formulating learning goals, identifying human and material resources for learning, choosing and implementing appropriate learning strategies, and evaluating learning outcomes" [23]. *Tacit learning* is unintentional and non-conscious. It is "the internalization of values, attitudes, behaviors, skills, etc. that occur during everyday life. Not only do we have no *a priori* intention of acquiring them, but we are not aware that we learned something" [22]. *Incidental learning* is unintentional but conscious. It is defined as "a byproduct of some other activity, such as task accomplishment, interpersonal interaction, sensing the organizational culture, trial-and-error experimentation, or even formal learning" [24]. Finally, *integrative learning* is intentional and non-conscious. It was introduced in [22] as a probable form of learning, although complex. Bennett suggests that this type of learning may be responsible for creative insights, intuitive leaps, and moments of sudden understanding. He adds that learning something integratively allows non-conscious problem solving, resulting in a conscious solution representation and a feeling of insight, manifested as memory fragments, images, and sensory data [7].

Observing informal learning can be difficult, as it can occur in various contexts, sometimes with learners not noticing it. Controlled situations, such as workshops or collaborative tasks, can be used to assess acquired knowledge or skills. Those can be evaluated with tests (see [25], [26] for self-directed learning or [27] for incidental learning), or interviews (e.g. [28] for tacit learning). Integrative learning is difficult to observe, as it lacks a common definition.

All four types of informal learning can occur in collaborative analytics, but the skills to be learned are difficult to define in advance and to test afterward, making the design of tools that encourage this type of learning difficult. That is why we rather focused on designing tools that foster informal skill *sharing*. As a first step towards this goal, we empirically assessed episodes of skill-sharing, and the methods employed by participants to try and make informal learning occur. Describing successful or failed informal skill-sharing episodes also gave us design opportunities.

### 2.3 Skill-sharing

Surprisingly, there are only a few studies related to skill-sharing in the literature, spanning a few domains. Several healthcare studies focused on training programs for music therapists to share their skills with health professionals [29], family caregivers [30] or social workers [31]. Learners acquire those skills and become ”indirect music therapists”, based on the observation of music therapists, practical engagement alongside them, and leading music therapy sessions independently.

In education science, Yu et al. [32] tried to promote skill-sharing between students of different disciplines by having them work together through a series of workshops. Skill-sharing is not defined, it is considered as an informal pedagogical mechanism or an objective to attain, and only the overarching effectiveness of the proposal is evaluated.

In HCI, Maddali and Lazar studied the sharing of gardening skills between experienced and novice gardeners of a shared garden [33], mostly identifying the various means of communication they used, such as forums, online videos, messages or face-to-face meetings. They also studied whether skill-sharing could be done remotely using AR or VR [34]. They carried out a thematic analysis of the transcriptions of the audio and their notes, identifying interesting topics. Skill-sharing occurred primarily through verbal interactions and the utilization of tools that allowed placing plants, capture photos, and draw. When tools were not enough, the experts tried to transmit sensory descriptions of skills (”a gentle pull, and if it comes off easily, then it's ripe”). Some technological limitations could hamper skill-sharing such as the lack of details or the quality of VR models and images, the absence of olfactory and tactile stimuli, and the difficulty in perceiving 'embodied emotional cues' coming from novices.

Skill-sharing has mostly been thought of as an objective to attain. Informal skill-sharing was only addressed in [29] to describe an informal way to share music-therapy skills to fellow health workers during work day. When it is assessed, skill-sharing is treated in the same way as informal learning, by evaluating the result, *i.e.*, the acquired skills. Only in [34] is skill-sharing described as a process but with no systematic approach. In our study, we specifically focused on identifying and describing occurrences of informal skill-sharing episodes during the course of the collaboration, which could be interrupted, and succeed or fail.

### 2.4 Common ground theory

Participants in any collaborative task do not have the same knowledge and skills at the beginning and need to actively promote mutual understanding throughout the collaboration, contributing to the establishment of a common ground, established through a grounding process [35]. Leplat defined common ground as ”the functional representation shared by operators, which guides and controls the activities they perform collectively” [36]. The common ground is in construction during the entire collaborative task, through all the verbal and nonverbal exchanges that contribute to collaborative action [12]. These exchanges contribute to expanding or updating the common ground as is necessary for the smooth running of joint activity [11]. The structure of the common ground depends on the activity considered and its duration, which can range from a few minutes to several years [35], [37]. The common ground constituted in a joint activity is a shared creation, but participants only access it through their own internal representation, which they need to update and maintain. This can lead to potential divergences due to differences in the assumed initial common ground and/or poor grounding.

The grounding was described by Clark as the set of processes that contribute to building a common ground [12]. It ”implies anticipating, preventing, detecting and repairing misunderstanding” [38], and depends on the medium of collaboration (face-to-face, telephone, videoconferencing, email). A grounding process is composed of episodes, which have two phases: the presentation phase (communication of an utterance) and the acceptance phase (communication of one's understanding). These communications use various modalities depending on the collaborative task and the environment in which they take place [12], [39]. In teaching driving trajectory, the instructor, for example, communicates utterances such as verbal directions (advising to look ahead and stay aligned with a lane), pointing gestures (showing direction), and gazes (explicit monitoring). Learners show understanding (acceptance) by following instructions and giving positive or negative feedback. Misunderstanding can be indicated by questions or by stating confusion. For a grounding process to be efficient, it is crucial that the exchanges result in a well-constructed common ground with minimal divergences between participants' internal representations. The most commonly used method to analyze grounding consists in identifying positive or negative acknowledgments during the acceptance phase, usually in transcriptions of exchanges that occurred during the collaborative task [8], [12], [38]. Let us note that acknowledgments do not necessarily correlate with the success of the intended sharing (a participant could answer ”yes” to a partner only to move on and progress in the task without real understanding), so it is difficult to rely solely on them to evaluate effective grounding [38].

Common ground theory provided us with a framework to identify and evaluate episodes of skill-sharing. We consider skill-sharing episodes taking place during the realization of a collaborative task as participating in the construction of a common ground and delineated them through their presentation and acceptance phases. We also assessed grounding observational indicators with experiential data.

### 2.5 Collecting lived experience of collaboration

Lived experience is defined as "that which a singular subject is subjected to at any given time and place, that to which s/he has access 'in the first person' " [40]. It can be composed of perceptions, sensations, thoughts, emotions, etc. Moments of lived experience are often *pre-reflective*: they are not sufficiently conscious to have been reflected upon at the time of experience, making them challenging to capture.

For collaborative tasks such as immersive data analysis, think-aloud [41] can be used to capture thought processes [16], [42]. However, it has been criticized for not being adapted to collaboration, as it hinders exchanges between participants. Moreover, it alters the completion of the task, as participants have to verbally express their mental and physical actions in addition to performing them, which is cognitively demanding [40]. This is why the pair analytics method, which aims at "generating verbal data about thought processes in a naturalistic human-to-human interaction with visual analytic tools" [13], can be of use. However, it may not be sufficient to understand the mental actions of the participant that were not verbalized [13]. Methods have been proposed to effectively collect descriptions of lived experiences after the task has been completed [43]. Among these are microphenomenological [40] and self-confrontation interviews and their derivatives [44], [45].

Micro-phenomenological interviews help interviewees verbalize what they have lived, mostly prereflectively. The first step is to help the interviewee get into an "evocation" state, where they are "in contact" with the experience of a moment in the past. The next step is to ask non-inductive questions to obtain descriptions of the experience in question: context (*e.g.*, settings), actions (*e.g.*, gestures, thoughts), perceptions (*e.g.*, of an object), etc. before proceeding to the next moment. Precise descriptions of the method can be found in [40], [46]. These interviews have been used in numerous projects, including in VR [47] to identify skilled expertise, causes of errors or dysfunctions, etc. [48].

Crossed self-confrontation interviews involve two participants in an activity that has been recorded on video. One is asked to "verbalize about the recording of their colleague" [44], [49], and what they say is then validated by said colleagues, before turning roles, the experimenter helping the participants come to an agreement. Mollo and Falzon explain that such confrontation to the activity of the other "brings the participants to better justify their knowledge and to make explicit some aspects of action that they would not have explained otherwise" [44]. Initially developed by Clot this method is used to study professional collaborative activity so as to foster common understanding [49].

We used third person observations to identify and describe episodes of skill-sharing between participants that we complemented with first person descriptions of their lived experiences. Micro-phenomenological and crossed self-confrontation interviews allowed us to collect information on the unfolding of perceptions, thoughts, and actions during these specific episodes of grounding.

TABLE 1: Four types of informal skill-sharing

| Name | Type | Example |
|---|---|---|
| Didactic | intentional conscious | An expert provides a didactic step-by-step verbal explanation and/or physical demonstration of how to implement a skill, with guidance. |
| Emphatic | intentional unconscious | An expert spontaneously verbalizes physical and mental actions related to their task. |
| Tacit | unintentional conscious | An expert knows a novice is watching the implementation of a skill, but does not change anything. |
| Incidental | unintentional unconscious | An expert implements a skill while being unwittingly watched by a novice. |

## 3 Studying skill-sharing in collaborative immersive analytics

Our objective is to understand informal learning of data literacy skills during collaborative immersive analytics. Informal skill learning being difficult to assess, we focus instead on a mandatory and preliminary aspect of any informal learning process, namely informal skill-sharing. This leads us to two research questions. RQ1: What skills are informally shared during data analysis, when and how does informal skill-sharing occur, and is it successful? RQ2: What are the problems related to informal skill-sharing?

### 3.1 A definition of informal skill-sharing

We define informal skill-sharing as *implicit or explicit information sharing that could result in informal skill learning*. As we have seen, the "informality" of learning can be described using both the degree of intentionality and the level of awareness of the learning process. Accordingly, we propose to classify informal skill-sharing based on this established categorization of "informality". We define *intentional* informal skill-sharing as the deliberate act of adapting the implementation of a skill to make it understandable to others. This could involve a person sharing step-by-step instructions on how to send an email. We define *unintentional* informal skill-sharing in a social context as the implementation of a skill similar to what it is when alone. This might occur when someone demonstrates how to execute an action without interrupting their work or when someone is simply observed applying a skill. We define informal skill-sharing as *conscious* (resp. *unconscious*) when the individual sharing the skill is aware (resp. unaware) of doing so. This might occur when a person is unknowingly observed by another who lacks the skill while implementing said skill.

Based on the intentionality and consciousness of sharing, four possibilities of informal skill-sharing emerge. We propose to name these *didactic*, *emphatic*[1], *tacit*, and *incidental* skill-sharing, as illustrated in Table 1. Let us note that it is easy to switch from one type of informal skill-sharing to the other and that it may be difficult to assess incidental informal skill-sharing. Importantly, informal skill-sharing can be successful while associated skill learning fails. This can happen when sharing is incomplete; for example, when someone shows how to perform a task that involves a

1. Emphatic skill-sharing occurs in a situation when a participant verbalizes what they are doing in a pre-reflective way. This is unconscious in the sense that the utterance is spontaneous and may not be noticed at all by the participant, while being still intentional because the utterance has the clear goal of doing something to the other (here help them understand what is going on).

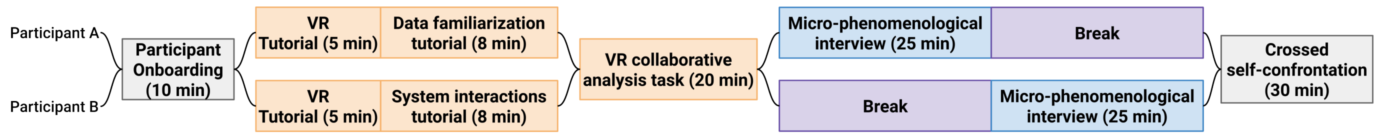


Fig. 1: Protocol of the experimentation (123 min in total for each participant)

complex series of actions, the learner may not catch some of them and only partially learn the skill. In such cases, it is necessary to identify what is lacking in skill-sharing for successful skill learning. Let us note that these types of informal skill-sharing do not have one-to-one relationships with types of informal learning. For example, didactic skill-sharing can occur spontaneously or in response to a question, thereby influencing the way the learner perceives the sharing process. In that case, informal learning can manifest in various forms: self-directed if the learner actively inquires about how to accomplish something; incidental if they passively listen without a deliberate intention to learn; or even tacit if they observe but do not actively engage, likely because they are preoccupied with another activity.

## 3.2 Rationale of the study

As a method to identify and assess various types of informal skill-sharing episodes during collaborative immersive analytics, we propose to leverage the common ground theory to analyze the data collected during pair analytics.

This theory provides us with a framework generic enough to describe the information exchanged between participants and each participant's internal representation of the common ground. From the perspective of informal skill-sharing, this gives us: a way to describe internal knowledge and skills necessary to achieve a collaborative task (common ground); a way to describe informal skill-sharing as part of the grounding process (grounding process); and the possibility of assessing the actual skill-sharing based on acknowledgment signals (both). The analysis can then be conducted by studying the multimodal exchanges between collaborators, paying specific attention to the positive or negative acknowledgments that signals whether a piece of information (skill or knowledge, here related to data analysis or business knowledge) has been successfully grounded.

However, this method does not prevent misinterpreting acknowledgments, in particular, signals that do not correspond to the actual grounding process (*e.g.*, issued to move interaction on or out of distraction). We then propose to interview participants about specific moments of informal skill-sharing they were involved in. Micro-phenomenological interviews can help gain a deeper understanding of the grounding process and identify and validate the successful sharing of skills. Moreover, crossed self-confrontation interviews on videos of skill-sharing moments can allow us to compare common ground internal representations, identify differences resulting from a dysfunctional grounding process (leading to unsuccessful skill-sharing), get information on the participant's action during these moments, and assess success or failure. Both types of interviews can also give us insight into skill-sharing user experience, which may be important to designing facilitation tools.

## 3.3 Experimental setup

We created a VR experimental environment in which two participants could collaborate to analyze data. We taught them different skills/expertise, so as to encourage them to informally share these with one another[2]. To this end, we implemented two different tutorials, one participant had a tutorial focused on explanations of the data, and the other on the specifics of the tools available in the environment.

### *3.3.1 Procedure*

Figure 1 describes our protocol. After being presented with the experiment, the participants sign the consent form, go to separate rooms, and are equipped with an HMD. A first common tutorial explains them with the basics of VR interaction, while a second one familiarizes them either with the dataset that will be used during the main task, or with the analysis tools on a generic dataset. The participants are unaware of the differing content of the second tutorial. They are then teleported to the main environment, where they are challenged to find as many insights as possible with their partner in 20 minutes. They primarily engage in data exploration, which involves selecting variables, discussing insights with their partners, and recording the agreed-upon findings (*e.g.*, that a certain category of population goes to work mainly by car). For each insight, they must record a video of their discovery with a specific tool.

The dataset describes statistics on geographical subdivisions of the urban area of Nantes Métropole (10 features / 235 data points). It has qualitative (*e.g.*, *Main means of transportation*) and quantitative variables (*e.g.*, *Population* or *Unemployment percentage*). Participants can analyze patterns such as aggregations, isolated points, trends, and minimum or maximum values on the axes. The dataset has been selected because the participants live in the city, making their interpretation easier. The expected insights include understanding trends and patterns within the areas, such as "Monselet is the area with the highest median income" or "This area activity dwellers mainly walk to work."

The participants are observed (third-person video stream) by the experimenter, who takes notes on potential moments of skill-sharing. This non-exhaustive list of episodes identified during the task provides moments on which to focus during the interviews, which will also uncover new interesting episodes (only the final analysis on

2. We observed such situations where informal learning occurs between two experts of our local administration: *e.g.*, when a data scientist and a public agent expert try to get insights to constitute arguments on an ongoing problem, or when a public agent shares their analytical process and analysis results to help a decision-maker (department director or elected official) make a decision. Let us note that this also applies in educational or instructional contexts, the differences being that: the respective skills of the participant would be more clearly identified; there would be more willingness to share them before or during the task; the task itself would be perceived as an exercise.

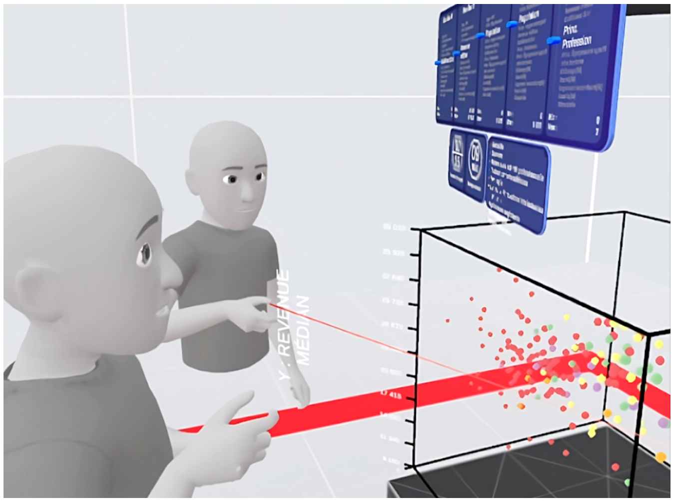


Fig. 2: Third person point of view of the data analysis environment during the main task

all the data allows to settle on the definitive list of episodes; see Section 4). Once the activity is over, each participant either has a break or undergoes a 25 min individual microphenomenological interview, during which they describe their lived experiences of skill-sharing moments, either those previously identified by the experimenter or those that emerged during the interview process and the recollection of the experience of the collaborative task [40]. Finally, both participants have a 30 min crossed self-confrontation interview, where they are asked in turn to describe the actions of their partner for moments selected by the experimenter. Their partner then validates or invalidates their descriptions, initiating discussions on the expertise of the participants and any understanding problems they had [44].

#### 3.3.2 System

Our application, built with Unity, is specifically designed to leverage both the eye and face tracking capabilities of Meta Quest Pro HMDs, and Meta avatar features. Participants use avatars that mimic head, hand, and facial movements, improving immersion and interpretation of body language. Participants can communicate verbally, and activate a red designation pointer (see Fig. 2), they also see their controllers and their commands. The participants can interact with the UI either by touching it or remotely with an interaction pointer. However, this pointer is not visible to the other user of the system, and they need to use the designation pointer to communicate something to their partner. We chose to represent data with 3D scatterplots because of their simplicity (each point in the scatterplot represents a data point) and because of the richness of the associated manipulations. This was also to destabilize participants who were more accustomed to 2D visualizations. We wanted to push them to fully exploit 3D representations and explore complex relationships between variables rather than mere geographical connections based on a single metric. Participants could zoom in and out, select data points to get details, highlight data points (for communication purposes), highlight data points similar to another one according to a variable, change the mapping and record their insights. We used an internal XR toolkit to streamline participant monitoring, control, and trace recording in the collaborative VR environment.

#### 3.3.3 Data collection

We recorded the interactions of each participant (*e.g.*, pointing, zooming in/out, pressing a button, recording an insight, etc.), the areas looked at (*e.g.*, scatterplot area, menu area, right controller area, etc.), and the positions and rotations of their heads and hands. We also recorded a first person point-of-view video for each participant, and a third person point-of-view video for the pair so as to add context to the events and capture gestures and facial expressions, which are important when identifying acknowledgment signals. Microphenomenological and self-confrontation interviews were recorded and subsequently transcribed.

#### 3.3.4 Participants

We recruited 12 public officials (P01-12) from the digital resources department of Nantes Metropole (4 females, mean age=42, SD=9.5). Their median educational level was Master's degree, and 2/3 of them had received training in data analysis during their studies and/or as part of their work. All except one had prior experience using data analysis software at least as sophisticated as Excel. They were not offered monetary compensation; however, the study was conveniently scheduled during their regular work hours. We ensured that each pair included at least one individual engaged in data analysis activities on a weekly basis. Due to their job, some participants were familiar with the dataset. This prior knowledge did not alter the balance of the collaboration dynamic, as these participants simply explored more complex relationships between the variables than the others. The study protocol received approval 11072023-3 from our IRB (IORG0011023).

## 4 Data analysis

The analysis mainly aimed to describe and evaluate episodes of informal skill-sharing from the collected data.

### 4.1 Data analysis as video annotation

We carried out our analysis using the Advene video annotation tool [50]. As shown in Fig. 3, Advene allows us to load and play multiple synchronized videos, in our case first-person videos of the two participants and the third-person video. Annotations are organized in a timeline composed of superposed annotation layers, that we used to present and manage collected data and analysis constructs.

**Collected data** (see 4 in Fig. 3). These annotations were imported from the data recorded by the headset during the collaborative task, temporally synchronized with the videos. To enhance readability, we separated the annotations corresponding to the interaction events A and looked at areas B for both participants, resulting in 4 layers that are further analyzed in phase 2 of the analysis (see 4.2).

**Analysis data** (see 5 in Fig. 3). During the various phases of our analytical process, we added new annotation layers that correspond to our analysis constructs. Each action layer C contains descriptions of the actions of one

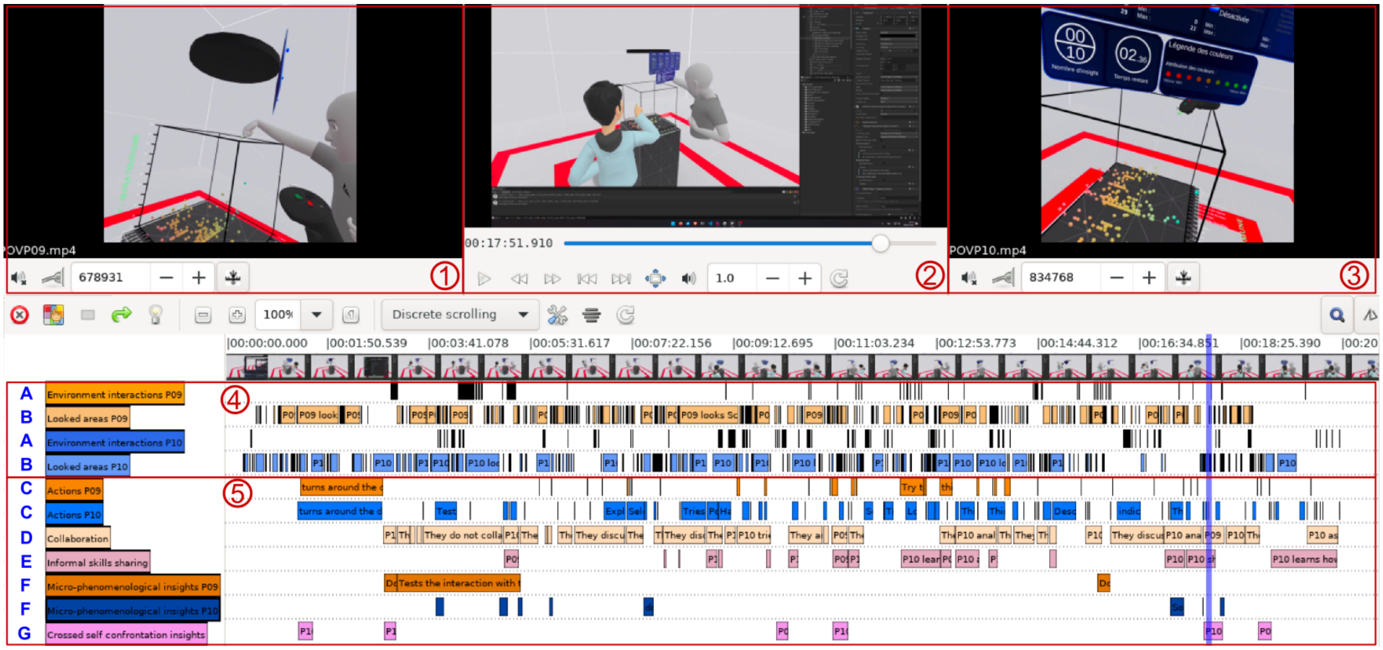


Fig. 3: Analyzing one pair of participants: (1) (3) first-person points of view of the participants, (2) third-person perspective on the task and participants, (4) annotation layers for collected data, (5) annotation layers resulting of the analysis.

TABLE 2: Detecting skill-sharing episodes of different types.

| Type of skill-sharing | Analysis phase | Basis for identification | Basis for episode qualification | Cases for success qualification | Cases for failure qualification |
|---|---|---|---|---|---|
| **Didactic** | 2 | All forms of communications between the participants. | Acknowledgement | Positive ack. | Negative/No ack. — Receiver's lived experience of incomplete sharing. |
| **Emphatic** | 2 and 3 | Verbal communications | Ack. — Receiver's lived experience of being shared something. | Positive ack. — Receiver's lived experience of sharing being completed. | Negative ack. — Receiver's lived experience of incomplete sharing. |
| **Tacit** | 2 | Verbal comms — Emitter/ receiver lived experience of sharing episodes. | Ack. — Emitter/receiver lived experience of sharing episodes. | Positive ack. | Negative/No ack. — Emitter/receiver's lived experience of incomplete sharing. |
| **Incidental** | 2 and 3 | Verbal communications — Receiver's lived experience of being shared. | Ack. — Receiver's lived experience of being shared something. | Positive ack. — Receiver's lived experience of sharing being completed. | Negative ack. — Receiver's lived experience of incomplete sharing. |

participant, as we interpreted it during phase 1 from the areas looked at and the interactions, together with first-person and global videos. For example: "P11 reads the value on the axis", and "P04 moves closer to P03 to share her point of view". The collaboration layer (D) (phase 1) is used to delimit collaborative episodes and their topics *e.g.*, "P11 and P12 discuss the understanding of the data visualization". The informal skill-sharing episode layer (E) describes these together with interpretations of whether informal skill-sharing interpreted as grounding was grounded or not. ("P04 explains how to select a point / grounded / P03 acknowledges and immediately selects a point"). The micro-phenomenological interviews layers (F) (phase 3 of the analysis) contain insights from the lived experiences of each participant for different moments of the activity that were described during the interview (*e.g.*, "P07 said that she understood the procedure after seeing P08's doing it." or "P04 said that he struggled to grasp P03's explanation of the color's meaning"). The crossed self-confrontation layer (G) (phase 3) contains insights derived from the lived experiences of participants as recounted during crossed self-confrontation interviews (*e.g.*, "P03 was unaware that the recorder does video capture, therefore he did not frame the insight during his verbal explanation").

### 4.2 Analysis procedure

Our overall analysis took place in several phases, which we performed for all pairs of participants before moving on to the next one. As there was no established method to assess informal skill-sharing episodes, we had to go through an iterative process to define ours. After the first author completed a round of all phases, both authors thoroughly reviewed the constructs (annotations (C) to (G)) and the results (descriptions of episodes of skill-sharing). This allowed us to stabilize and fine-tune both the process and the interpretation of what counted as an informal skill-sharing episode. After a second round of analysis, updating the episodes, finding new ones, and getting rid of unnecessary constructs, the second collective review allowed to reach a consensus, before a third and last round of analysis.

**Phase 1: identify individual actions and collaboration episodes**. A preliminary screening of the 3 videos is carried out to document individual actions, as well as active collaboration episodes (see (C) and (D) Figure 3).

**Phase 2: identify informal skills sharing episodes**. Collaboration episodes are specifically reviewed using videos, individual actions and collected data (looked at areas and interactions with the system) to further identify informal skill-sharing episodes. This identification is informed by

TABLE 3: Two example descriptions of episodes

| | Episode #31 | Episode #48 |
|---|---|---|
| **Pair / Time** | P11-P12/ 06:31 | P9-P10 / 12:57 |
| **Initial context** | P11 tries to zoom on points | P09 takes his turn to analyze the data visualization after P10 has shared his analysis. |
| **How** | P12 observes P11 trying to zoom | P09 describes the X, Y and Z axis |
| **Skill-sharing** | Incidental | Didactic |
| **Skill** | Zoom | Understand a visual representation of data |
| **Learner** | P12 | P10 |
| **Informal learning** | Self-directed learning | Incidental learning |
| **Status** | Failure | Success |
| **Status justification** | P12 asserts that it is possible to select a point ($\neq$ zoom) | Acknowledgement ("Yeah Yeah, it is true") |
| **Skill learned** | No | Already had the skill |
| **Justification** | Misunderstood P11 action (interview). P12 did not use zoom. | Has already applied this skill before. |
| **Problems** | P12 cannot assess from observation what actions P11 is doing | |
| **Comment** | P12 comments P11's actions, but misinterprets them, assuming it is point selection. P11 corrects P12 by explaining that he is actually zooming in. | P10 was not fully focused on P09 utterance at the beginning. |

the spotting stages of the grounding process, which are characterized by specific verbal and non-verbal cues (layer E). For example, one participant may demonstrate a skill ("shows how to zoom in on the data", "selects a data point", "looks at what the partner is talking about"), followed by either a confirmation ("says, 'Got it!' ", "shakes the head", "looks at the same area"), request for clarification from another participant ("says, 'I don't understand' "), or a direct application of the skill by the observing participant ("immediately applies the zoom technique"). Each type of informal skill-sharing has its own method of identification and qualification, which is detailed in Table 2. Skill-sharing episodes are described and their success or failure is assessed.

**Phase 3: confirm and complete the descriptions of episodes with lived experience**. The transcriptions of the micro-phenomenological interviews are analyzed, focusing on the moments that describe the lived experience of collaborative exchanges and informal skill-sharing. The insights obtained are mostly related to 1- the divergences in the common ground based on the comments made by the participants on their partner, 2- the difficulties encountered during data analysis and exchanges, notably on tools usage and task understanding, and 3- the feelings/evaluations on the visualization and the partner. These insights are used to annotate the moments of the collaboration the participants refer to. Next, the transcriptions of the crossed self-confrontation interviews are searched for insights about the differences between participants' internal representations of the common ground; the success and failure of informal skill-sharing (*e.g.*, "I did not hear you"); or how participants evaluate their partners. These insights are also added as annotations on the corresponding moments (layers F and G of Figure 3). Notice that the identification of didactic, emphatic, tacit, and incidental sharing from the sole experience can originate in this phase (Table 2).

**Phase 4: identify problems**. The results are collected in a table that describes each informal skill-sharing episode (see examples in Table 3). For consciously shared skills (didactic or tacit), we look for positive or negative explicit acknowledgments or the emitter or receiver's experience of incomplete sharing. For unconsciously shared ones (emphatic or incidental), we look for positive or negative explicit acknowledgments or justifications in the interviews of the receivers. For each episode, we first assess whether the skill was effectively learned[3], and add supporting evidence. Then, for each episode that either failed or did not lead to effective skill learning, we check the reasons inside the grounding process (such as negative/lack of acknowledgment, too many utterances and acceptance phases, or partial sharing), and describe the associated problems.

Table 3 presents two episodes of informal skill-sharing. The first episode takes place between participants P11 and P12, where P12 comments on P11's actions, misinterpreting them as point selection instead of zoom-in. P12 provides a positive acknowledgment ("this is point selection") to P11 that indicates the success of the grounding process; however, P12's micro-phenomenological interview reveals that she did not understand what P11 was sharing. As a result, we consider this episode of skill-sharing as a failure and detect an observation problem. The second episode is successful, due to P10's positive acknowledgment of P09 utterances. However, we estimate that P10 did not learn the skill here because he already had it, as evidenced by his previous reading of the data visualization.

## 5 Results

We obtained a total of 101 informal skill-sharing episodes[4], related to 14 types of skills, within 12 types of initial contexts. We identified 58 problems from the 25 failed episodes.

Table 4 summarizes all episodes, grouped by shared skills, indicating: the number of episodes we found; the number of concerned pairs of participants; the initial context types in which the episodes occurred; the types of informal skill-sharing; the different ways in which the skill was shared; the number of successful episodes/learning; and the types of problems. During the 20 minutes of collaborative activity, all groups effectively shared skills within the environment (mean number of episodes: 16.8, SD: 3.76).

There is no discernible temporal pattern for (P01, P02), (P05, P06), and (P07, P08). We can notice an increase during the final minutes for (P03, P04); that (P09, P10) concentrates a majority of episodes in the middle of the task, and that most episodes for (P03, P04) occurred during the second half. No definitive conclusion can be drawn, except that the collaboration could have taken time to really start.

3. Our protocol only allowed us to identify self-directed and incidental learning: we would have had to space interviews over time to identify integrative learning, without certainty of a result, and to space the activity with another one to identify tacit learning.

4. The full table is at https://espace.science/phd/isse-annexe.html

TABLE 4: Informally shared skills and related information *(#P: number of pairs; S/L: successfully Shared/Learned skill)*, tool related skills in blue, data analysis skills in red.

| Skill | # | # P | Initial contexts | Types of skill-sharing | The way its shared | S/L | Problems |
|---|---|---|---|---|---|---|---|
| **Select points** | 9 | 4 | B asks A how perform an observed action (4) — B seeks A's confirmation (2) — B observes A perform one or more actions (1) — B asks A how to perform an action (1) | Didactic (7) Incidental (1) Tacit (1) | Verbal explanation (7) — Observation (2) | 8/5 | Partial learning (2) — Poor establishment or loss of attention (1) — Communication breakdown (1) — Communication problems (1) |
| **Change mapping on dimensions** | 5 | 5 | B observes A perform one or more actions (3) — A teaches B a tool (1) — A and B discuss data interpretation (1) | Didactic (2) Incidental (2) Tacit (1) | Observation (3) — Verbal explanation (2) | 4/3 | |
| **Make a record** | 5 | 2 | B asks A how perform an observed action (2) — A identifies B's mistake or skill gap (2) — B asks A how to perform an action (1) | Didactic (5) | Verbal explanation (5) — Verbal explanation with pointing the controller record button (1) | 3/2 | Poor establishment or loss of attention (3) |
| **Point with designation pointer** | 4 | 3 | B seeks A's confirmation (3) — A teaches B a tool (1) | Didactic (4) | Verbal explanation (4) | 4/4 | Lack of efficient communication tools (1) |
| **Zoom** | 3 | 3 | B observes A perform one or more actions (2) — A identifies B's mistake or skill gap (1) | Incidental (2) Didactic (1) | Observation (2) — Verbal explanation with tool movement demonstration (1) | 2/2 | Partial learning (1) |
| **Manipulate menu position** | 2 | 2 | A teaches B a tool (1) — B asks A how perform an observed action (1) | Didactic (2) | Verbal explanation (2) — Interactive explanation with menu manipulation (2) | 2/2 | |
| **See points details** | 2 | 2 | B observes A perform one or more actions (1) — A discovers something worth sharing (1) | Didactic (1) Incidental (1) | Verbal explanation (1) — Observation (1) | 2/0 | Partial learning (2) — Communication problems (1) |
| **Zoom out** | 1 | 1 | B asks A how to perform an action (1) | Didactic (1) | Verbal explanation (1) | 1/1 | |
| **Point with interaction pointer** | 1 | 1 | B seeks A's advice on visualization interpretation (1) | Didactic (1) | | 0/0 | Poor establishment or loss of attention (1) |
| **Reset view** | 1 | 1 | B asks A how to perform an action (1) | Didactic (1) | Verbal explanation (1) | 0/0 | Communication problem (2) |
| **Share insights** | 1 | 1 | B seeks A's advice on how to share visualization interpretation (1) | Didactic (1) | Verbal explanation (1) | 1/1 | |
| **Plan and execute data analysis** | 29 | 6 | A and B analyse a new visualization (15) — A and B discuss data interpretation (7) — A performs confirmatory analysis. B observes (4) — A records a data insight. B listens (3) | Didactic (27) Incidental (1) Emphatic (1) | Verbal explanation (29) — Guided explanation with designation pointer (7) — Guided explanation with interaction pointer (4) — Highlighting by selecting a point (3) — Gesture explanation (1) — Zooming in on a point to isolate it (1) | 19/29 | Poor establishment or loss of attention (10) — Misalignment of points of view (6) — Lack of validation (3) — Lack of efficient communication tools (3) — Communication breakdown (2) — Communication problems (1) |
| **Understand a visual representation of data** | 24 | 6 | B seeks A's advice on visualization interpretation (10) — A and B analyze a new visualization (9) — A identifies B's mistake or skill gap (3) — A discovers something worth sharing (1) — B asks A how to perform an action (1) | Didactic (24) | Verbal description of axis or point details (24) — Potential interpretation of point (7) — Guided explanation with designation pointer (4) — Guided explanation with interaction pointer (4) — Gesture explanation (1) | 18/14 | Poor establishment or loss of attention (8) — Lack of efficient communication tools (2) |
| **Identify patterns / outliers** | 14 | 5 | A and B analyse a new visualization (7) — A discovers something worth sharing (7) | Didactic (14) | Verbal explanation (14) — Gesture explanation (5) — Highlighting by selecting a point (2) — Guided explanation with designation pointer (2) — Guided explanation with interaction pointer (1) | 11/14 | Poor establishment or loss of attention (4) — Misalignment of points of view (3) — Lack of efficient communication tools (3) |

### 5.1 RQ1: Shared skills

As seen in Table 4, 11 shared skills are about *tool use* (34 episodes out of 101), 3 about *visual data analysis* (67/101).

**Initial contexts of sharing.** Regarding tool use, skills were primarily shared in two ways: when a participant asked their partner how to perform an action they noticed, or when they observed their partner performing an action. Nearly half of visual data analysis skills sharing happened after one participant changed the mapping of the data visualization (31/67). The other initial contexts were skill-specific, for example, the *identify patterns* skill was shared after something worth sharing had been discovered by one participant. In addition, the sharing of how to *understand a visual representation of data* was initiated by learners trying to make sure that they understood the visualization correctly, or at least in the same way as their partner. Another scenario involved participants identifying an incorrect interpretation made by their partner. Consequently, they felt compelled to share their perspective, which they believed was the accurate way to understand the data visualization.

**Types of skill-sharing.** We could identify the four types of informal skill-sharing. *Didactic* skill-sharing episodes account for 90% of the episodes, *Incidental* for 7%, *Tacit* for 2% and *Emphatic* for 1%.

**Ways of sharing.** Tool-related skills were shared mainly through verbal explanations. Observation by learners only led to partial learning, due to a limitation of the environment that did not allow one to see the controllers of the other participant and understand which buttons were pressed. In one case, the participant with expertise in the tool did a tutorial to his partner so as to later collaborate and progress in the task in an easier way (as explained during the interview). Participants initially shared data visualization skills verbally, describing any patterns or outliers they identified, later they used the designation pointer or gestures (*e.g.*, encircling a group of points with the arm).

**Success of sharing and learning.** Skill-sharing succeeded for 76% of the episodes. Although there is no baseline to compare to, this, together with the feedback of the participants, suggests that our environment was effective and allowed successful communication between the participants. The skill learning rate is more difficult to interpret due to the uncertain assessment of effective learning (cf. 2.2). Interestingly, successful tool-related skill learning was often associated with successful sharing of the same skill in the other way around to seek confirmation of the right use of the tool. Self-directed learning was observed primarily when participants learned about data manipulation tools and understanding of visual representation. Incidental learning occurred mainly for data manipulation tools, specifically when a participant was told how to use it. The *identifying patterns/outliers* and *planning and executing data analysis* skills were exclusively learned incidentally.

### 5.2 RQ2: Problems

We identified 58 problems in the 101 episodes that we grouped into 6 categories[5].

**Lack of attention of the partner.** During visual analysis skill-sharing episodes, when they were *identifying patterns or outliers* within the data, participants often failed to ensure that their partners were focused and ready to listen before sharing their analysis. They tended to spontaneously share their conclusions or interpretations of visualizations, without checking whether their partner was engaged in the discussion or trying to get their attention. This often happened when confronted with a new visualization, prompting them to immediately formulate their observations aloud.

**Lack of shared point of view.** One of the main issues that contributes to the failure of episodes related to *identifying patterns or outliers* and *planning and executing data analysis* is the lack of a shared point of view during the sharing process. Misalignment in perspectives occurred in 9 of 14 failed episodes. This problem is compounded by the attention issue mentioned above: when participants spontaneously share their insights they also often fail to confirm if their partner can see what they are discussing.

**Lack of tools to show 3D shapes.** When attempting to exchange insights about patterns or outliers, or to guide others through the interpretation of the data visualization, participants struggled significantly to effectively communicate about 3D shapes using the tools provided. It took them a long time, often multiple grounding cycles, to ground their explanations, and at times their attempts to share their insights even failed. They often improvised means of delineating the shapes they observed in the 3D scatterplot by adapting the tools at hand, *e.g.*, circling around shapes with the cursor or designation pointer, making gestures with the controllers, or even their arms.

**Lack of full access to the partner's actions.** Incidental skill-sharing of data manipulation tool related skills often resulted in partial learning: while learners could observe their partner's actions and understand their intent, they were unable to perform the actions themselves. Indeed, the partner's controllers were replaced by virtual hands, and learners could not see the physical actions needed to operate the tools effectively, *i.e.*, the buttons that were pressed. We also noticed difficulties during didactic sharing episodes, largely due to such lack of access: the grounding process was challenging for participants who had trouble communicating the required input to their partners.

**Misunderstanding of the use of the interaction pointer.** We always displayed interaction pointers to simplify distant interaction with the UI. However, participants often used it to show something in the visualization instead of the designation pointer. They mistakenly believed that their partner could see it (5 / 22 pointer uses), leading to failed skill-sharing or trial on other channels (*e.g.*, gestures, use of the designation pointer, more precise verbal description).

**Lack of practice with tools.** Some participants reported that they deliberately avoided trying new data manipulation tools or commands during collaborative data analysis sessions, as they did not wish to disrupt their partner who was performing data analysis, which in some cases led to incomplete or unsuccessful learning outcomes.

## 6 Discussion

### 6.1 Shared skills and skill-sharing

All pairs shared skills on all tasks they could carry in the environment: *i.e.*, manipulating, reading, and interpreting the visualizations. Individually, and depending on the tutorial they had, participants shared skills based on their respective expertise. Unsurprisingly, we observed the efficient sharing of erroneous skills about both tool usage or visualization reading and interpretation.

For each type of skill except "Share insights", we obtained a sufficient number of episodes to allow us to assess them in detail and extract problems. Those skills were predominantly related to tool use and data analysis, which is aligned with data literacy skills [6], [51]. Sharing problems were mainly related to 3D skills or communication between the participants. These findings are consistent with other investigations into collaborative behaviors in immersive analytics environments: we observed the same types of acknowledgment in the grounding process as Benk et al. [8]

5. Let us notice that the number of problems in table 4 is not related to the number of failures. For instance, not all problems identified during phase 4 inevitably lead to unsuccessful sharing or learning, they can simply slow down the sharing process (cf. 4.2) as is the case for the "point with designation pointer" skill: both sharing and learning were successful, yet there were "lack of efficient communication tools" issues.

did, and identified problems with sharing elements of a 3D data visualization similar to those described in [9], [19]. In addition, our method allowed us to successfully identify all four types of informal skill-sharing (Table 1). However, didactic skill-sharing episodes constitute the vast majority. This observation aligns with the common ground theory, which suggests that collaboration works well due to information sharing between partners, ensuring smooth execution and ultimate success of the task. We were nevertheless able to identify unconscious skill-sharing instances (tacit and incidental) that might otherwise have been disregarded.

We chose to have participants follow different tutorials, which worked well, leading them to identify their partner's expertise and try and establish a stronger common ground to facilitate collaboration. In particular, as we learned from the interviews, they tended to monitor their partner more closely to correct them if necessary, and their explanations were more detailed. Interestingly, P03 and P04 did not realize the differences in tutorials, and we observed increased monitoring and spontaneous sharing, often triggered by some action by the partner. In contrast, P05 and P06 became rapidly aware of the differences, and P05 decided to switch to a more instructional setting, sharing many skills at the outset of the task and providing guidance later. This shows the fluidity of any collaboration, which is filled with more or less instructional modes of collaboration, and hence the benefits of facilitating informal skill-sharing in any context.

There are two other remarks we can make. First, with regard to spontaneous verbalization, we noticed that when in difficulty interpreting data, participants often shared out loud their understanding to obtain confirmation from their partners. We also noted a change in the tone of the voice of some participants when they spontaneously shared insights: it tended to slow down and become lower. Though only one such episode was clearly distinguishable in our corpus, we interpret this change as related to *emphatic skill-sharing*: one is unaware of the act, but intentionally shares, being encouraged to verbalize one's thought by the situation. Second, changes in the visualization appeared to reestablish the collaboration of participants, who may have been engaged in different analyses, by providing an opportunity to reboot a common analysis. However, they had to devote most of their attention to understanding the new visualization, which led them to lack attention to their partner until they were ready to discuss.

### 6.2 Implications for design

The problems we identified are not original as such, yet our analysis offers additional insight into their specifics, *e.g.*, their origin with regard to grounding or what strategies were used to handle them. This is why, even if some of our proposals have been previously studied (*e.g.*, grab attention [3] or share one's point of view [2], [52]), such understanding allows us to propose solutions that leverage spontaneous gestures and unconscious sharing to facilitate informal skill-sharing.

**Direct collaborators' attention on the sharing of elements of data visualization**. Sharing something may fail if the partner is not focused on the shared element or does not notice the intention of sharing, as we observed when participants had difficulty grabbing the attention of the other while identifying insights. A solution could be to enhance the natural gesture of showing, without modifying it. For example, including a visual guide within the field of view of the participants, activated when sharing is detected (*e.g.*, when finger or pointer pointing and talking are associated), that would direct them towards the shared elements (*e.g.* by highlighting them), could improve the effectiveness of data analysis informal skill-sharing (Table 4), particularly didactic ones, by promoting tighter collaboration.

**Encourage accessing the point of view of collaborators**. We observed participants share insights without verifying whether their partner followed, assuming they had the same point of view. Effectively communicating one's perspective could be addressed by enabling users to freely access one's point of view (*e.g.*, PoV on a screen), even from a distance. We also observed that participants often moved closer when discussing elements of the visualization, either spontaneously or when invited. Encouraging such behavior could be done by showing a path, or a landmark, that incitates one to get closer to another participant when sharing is detected, potentially enhancing unintentional skill-sharing (tacit and incidental) of data analysis skills.

**Enable to delineate complex 3D shapes**. We observed that simple ray pointers are not sufficient to point at complex 3D shapes, such as groups of points or trends in a 3D scatterplot: our participants used their arms and their hands, or moved the pointer rapidly to create a trail that forms a shape around a group of elements or a trend. Besides tools allowing multiple selection, we would advocate allowing bimanual interaction for delineating the contours of encompassing shapes with both hands, maybe with some use of go-go techniques for more distant points. This could improve didactic skill-sharing of the "Identify patterns/outliers" skill, and empathetic skill-sharing in general if the sharer unconsciously draws what solicits them.

**Fully share the environment and the actions performed.** Users in VR tend to assume that part of their common ground consists of all the elements that make up the shared environment, namely what they see and interact with, as in reality. When there is a mismatch between this natural assumption and the reality of what is shared, there may be a problem. For instance, we identified that tool manipulation skill-sharing could be impeded by limited access to the actions of one's partner on their controllers (there was no problem for interfaces because we made sure those were shared, including button pressed). Addressing such a problem could be done by ensuring that *all* the elements constituting the environment are fully shared, *i.e.* visible by everybody, improving unconscious skill-sharing (emphatic and incidental) of tool related skills.

**Synchronize users around changes in the main visualization.** We identified that an unexpected alteration of the data visualization by a participant can surprise and interrupt their collaborator's analysis, notably prompting them to search for the variables used in the new mapping. Synchronizing them during these changes could happen before the change (*e.g.*, by requiring participants to use voice commands for any data visualization change), during (*e.g.*, by requiring collaborators' approval before changes are applied), or immediately after it (*e.g.*, by highlighting the newly implicated variables), improving the informal sharing of data analysis skills.

**Allow to experiment with tools without disturbing the ongoing visual analysis.** The lack of practice with tools resulted in failures in skill-sharing and learning. The learning rate could be improved by allowing users to experiment without disturbing the ongoing collaboration. For example, learners could duplicate the visualization nearby the main one, and practice on it, improving tool-related skill learning. This could be done by allowing participants to duplicate any data visualization and place it at the location where they want to practice, which could be close or far from the others depending on their will to be helped or not.

### 6.3 Limitations

This work has some limitations that we can underline. First, if our approach of using common ground and grounding to detect skill-sharing episodes seems effective because we could catch a lot of them, it is insufficient to guarantee that we caught all of them. Notably we may have missed episodes that are fully unconscious on both sides, *i.e.*, incidental skill-sharing for which we did not have explicit acknowledgments, or hints in the interviews that a skill was received, hence shared. We also could not guarantee the evaluation (success/failure) of an episode when we did not have explicit positive or negative acknowledgment or the receiver's experience of sharing being (in-)complete[6].

Second, our study was about pairs of participants collaborating on a single data visualization, so collaboration was mainly coupled, and only a few times loosely coupled, *e.g.*, when participants independently analyzed the 3D scatterplot. Other forms of collaboration could have happened with other conditions, such as more participants and/or several data visualizations or workspaces, which would likely significantly have altered the distribution of types of skill-sharing. For example, more data visualizations might have led to more emphatic and incidental skill-sharing episodes.

Finally, we had difficulty identifying tacit and incidental skill-sharing from micro-phenomenological and cross-self-confrontations interviews. We suggest conducting them after completing the first two phases of the analysis, because having already identified skill-sharing episodes and the skills used by the participants, would help to know which moment to focus on and what to ask from participants with regards to grounding problems or actual learning.

## 7 Conclusion

We proposed a definition of informal skill-sharing and a method to assess related episodes from mixed data. We could detect and describe various episodes and types of skill-sharing in our pair collaborative immersive analysis experimental scenario, outline several skill-sharing problems, and propose several design implications for collaborative immersive analytics systems. In our future work, we will use these ideas to design several tools that foster informal skill-sharing and learning and evaluate them.

We are confident that our method can be used in other immersive analytics contexts, *e.g.*, with multiple visualizations or different modes of collaboration. It could also allow the study of other immersive collaborative situations where skill-sharing occurs, provided that the collaboration under scrutiny is embodied in shared spaces and close to face-to-face collaboration, as body movement data are necessary. Non-HMD-based collaborative analytics on tabletop computers or wall display could clearly qualify, but, as videos and logs are crucial, data collection would be trickier. In that case, some of the uncovered episodes would probably be similar, while others would differ: when people are co-located, all of the environment is accessible to everybody. The proposed method could also be used to evaluate and compare collaborative systems in their potential to sustain informal skill-sharing and learning. However, it would probably need to be simplified, *i.e.*, more accessible and less time consuming. This could be done by focusing on easily identifiable failed episodes of skill-sharing, because of clear negative acknowledgment from the receiver or explicit assessment of the failure during crossed-self-confrontation interviews. Some important associated future research would be to further assess the relationship between skill-sharing and skill learning, by using a tailored protocol which primary focus would be to ensure that the origins of a demonstrably acquired skill can be directly linked to one or more specific skill sharing episodes.

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