

# DDialogue: A Collaborative Framework for Cross-Sectoral Dialogue through Data

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## Abstract

In tackling complex societal issues, cross-sector collaboration within interdisciplinary teams can leverage the diverse expertise of individuals from various organizations. Concurrently, data-driven methods are increasingly central to effective decision-making. However, there is a notable gap in research at the intersection of cross-boundary collaboration and participatory data analysis. To address this, we propose *DDialogue*, a conceptual framework designed to facilitate collaborative data analysis within cross-sector partnerships, while simultaneously enhancing data literacy skills among stakeholders. The *DDialogue* framework is instantiated as a workshop composed of nine sessions, each with a specific purpose, leading to the co-creation of outputs aimed at tackling complex issues. The framework was tested through a pilot workshop and a fully implemented workshop addressing the problem of juvenile delinquency in Turin, Italy. These activities yielded formative evidence suggesting that *DDialogue* can be a useful tool for researchers or practitioners who seek to engage diverse stakeholders from different sectors and with varying levels of data literacy in data-driven projects. Participant feedback highlighted the framework's adaptability and its potential to support data-informed collaboration.

## CCS Concepts

• **Human-centered computing** → **Computer supported cooperative work**; **Empirical studies in collaborative and social computing**; **Participatory design**; Visualization systems and tools; • **Social and professional topics** → **Computing literacy**; Cultural characteristics.

## Keywords

Collaborative Data Analysis, Cross-Sector Collaboration, Data Literacy, Workshop

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## 1 Introduction

Since the end of the 20th century, there has been a rise in cross-sector collaboration, where professionals from different organizations and backgrounds work together to tackle complex issues, often in the context of public-private partnerships or living labs [11]. Such collaborations have become essential in fields like urban planning, public health, and social services, where combining expertise is critical to delivering impactful joint solutions [19]. At the same time, decision-making processes across the world have become increasingly data-driven [7, 17]. Given that organizations in different sectors (including public sector agencies and offices, private sector enterprises, non-governmental organizations, and academic institutions) often hold complementary knowledge and data resources that can help address complex issues, it becomes critical to coordinate efforts to analyze shared data and support coordinated action jointly. Nonetheless, these stakeholders frequently operate in silos, which reduces the potential power of shared data for collective problem-solving [80]. Another challenge in data-informed collaboration among stakeholders from diverse backgrounds lies in varying levels of data literacy. Accordingly, these stakeholders may have limited experience working with complex datasets, which could hinder their ability to engage effectively in analysis and discussion.

Despite the progress seen in cross-sector collaboration, data literacy, and participatory data analysis, there is a lack of research that integrates these topics. Existing studies on data literacy do not comprehensively explore cross-sector approaches or focus on methodologies for collaborative data analysis. The same is true for studies centered on participatory and collaborative data analysis, which tend to overlook cross-sector collaborations. This motivates the development of a framework that addresses these gaps, enabling diverse groups of stakeholders to make evidence-informed decisions by combining their perspectives. Such a framework should not only facilitate cross-sector collaboration but also provide methods for stakeholders to collectively analyze and interpret data, ensuring that all voices are heard regardless of technical expertise. This would facilitate greater inclusion of data and stakeholders, so that diverse perspectives inform data-driven insights. Therefore, the purpose of this work is to develop an approach that can simultaneously address the following goals:

- Goal 1:** Generate actionable insights from collaborative data analysis.
- Goal 2:** Facilitate data-driven decision-making in cross-sector collaborations.
- Goal 3:** Promote collaboration and partnerships across diverse organizations through data.
- Goal 4:** Support cross-sector understanding and knowledge exchange.
- Goal 5:** Strengthen participants' data analysis skills and knowledge.

In this context, we address the question of how to design structured collaborative approaches that integrate the five goals mentioned above, and we answer this question through the *DDialogue* framework<sup>1</sup> to facilitate cross-sector collaboration in tackling complex issues using data visualizations as a medium. *DDialogue* is instantiated as a workshop comprising nine sessions, designed with the overarching objective of enhancing participants' data analysis skills and knowledge while concurrently fostering the exchange of cross-sectoral insights. *DDialogue* aims to address the need for a standardized framework to guide the design and implementation of participatory data analysis workshops across sectors. It facilitates the co-creation of actionable outputs grounded in data and a shared understanding of the issues at hand. We have tested and implemented this framework through a pilot and a full implementation workshop in the Italian city of Turin, focusing on understanding the complex issue of juvenile delinquency.

## 2 Background

### 2.1 Cross-sector collaboration

Cross-sector collaboration occurs when multiple organizations across different sectors work together to achieve specific goals [3, 74]. This practice has become increasingly essential in addressing complex social challenges, in which the knowledge and resources of multiple stakeholders (e.g., government, non-profits, academia, and businesses) must converge to develop holistic solutions [60]. This becomes crucial when tackling intricate, multifaceted issues (so-called wicked problems [84]) and crises [2, 8].

Previous work [53, 59] has offered recommendations to initiate cross-sector teams and conduct successful collaboration. These encompass the establishment of team objectives that garner sufficient support from their members, the formulation of manageable problem statements that prevent undue delays or early setbacks, the identification of achievable actions at each stage to enable incremental progress, and the strategic planning of activities that balance taking action with continuous learning. Bryson et al. [11] proposed a comprehensive framework to understand cross-sector collaboration. Through 22 propositions, the framework categorizes key elements affecting collaboration, including initial conditions, processes, structural and governance components, constraints, contingencies, outcomes, and accountability issues. It recognizes the involvement of multiple sectors, including business, nonprofits, media, community organizations, and government. These propositions focus on the design and implementation of cross-sector collaborations to effectively address public challenges [11, 12] that we consider in our work.

Recent work in participatory design highlights the critical role of interdisciplinary collaboration in enabling effective knowledge transfer across professional boundaries, even though it presents several challenges [9, 50]. In fact, collaboration between public and private actors is not only a matter of aligning goals but is also continuously shaped by institutional contexts as well as everyday technologies, documents, and protocols, which can both enable and constrain cooperation across sectors [72]. An example is given by Gryada et al. [35], who highlight that successful knowledge transfer between architects and service designers depends on close collaboration, mutual understanding, and actors' capabilities. At the same time, Pilemalm [68] analyzed applications of participatory design for civic engagement within Sweden's emergency response system, emphasizing the relevance of citizen involvement and multidisciplinary participation in e-government initiatives.

### 2.2 Collaborative Methods for Data Analysis

There is increasing interest in methods that enable collaborative, participatory data analysis, enabling both researchers and organizations to leverage collective intelligence to derive deeper insights from datasets [77]. However, for such collaboration to be substantive, participatory data practices should be grounded in the lived experiences and values of local communities, making data literacy key to meaningful participation [66]. Approaches range from participatory action research involving stakeholders to interdisciplinary frameworks aimed at collaboration in diverse research groups. These methods have been shown to improve the quality and robustness of analytical outcomes.

Williams [86] introduced the idea of *data action* to describe processes that use data to drive social change for good and address real-world problems. This idea highlights the importance of translating data insights into actionable strategies that can improve communities and inform decision-making, encouraging collaboration among researchers, data scientists, and communities to ensure that data-driven solutions are effective for affected publics. McCosker et al. [54] developed this concept further into *collaborative data action*, proposing a more situated approach that takes into account the specific needs and contexts of different organizations. They argued that traditional approaches to data literacy training, which focus on individual skills and knowledge, have not been effective in addressing the complex data challenges [27, 54].

Several other approaches have emerged to support collaborative engagement with data in policy and decision-making contexts. For example, van Veenstra and Kotterink [82] propose a Policy Lab approach to data-driven policymaking, tackling wicked problems in society. This consists of an experimental setting for collaboration among stakeholders to develop and test policies [81, 82]. Franz [31] proposed the Data Party approach, a participatory event designed to create an enjoyable environment for collaborative data interpretation that incorporates aspects of a party in data analysis to improve stakeholders' engagement [31, 49].

Finally, in this work, we define *data-driven decision-making* as a deliberative practice in which proposed actions are based on shared data and the situated expertise of stakeholders. In this sense, data analysis is linked to institutional and organizational decision-making processes [71]. This relates to the socio-technical character of data and the need to clarify where participation occurs throughout the process [28].

<sup>1</sup>The name derives from the abbreviation of the expression "Data Dialogue".

**Table 1: Goals of the *DDialogue* Framework**

No.	Goal	Description
1	<b>Generate actionable insights from collaborative data analysis</b>	Enable groups to interpret quantitative data and synthesize situated insights for action.
2	<b>Facilitate data-driven decision-making in cross-sector collaborations</b>	Link collective interpretation to deliberation and co-creation of recommendations.
3	<b>Promote collaboration and partnerships across diverse organizations through data</b>	Build trust and coordination across organizational boundaries.
4	<b>Support cross-sector understanding and knowledge exchange</b>	Support shared understanding through exchange of expertise and perspectives.
5	<b>Strengthen participants’ data analysis skills and knowledge</b>	Lower barriers to participation and build confidence and competence in data analysis.

### 2.3 Data Literacy and Data Visualizations

Data literacy can be defined as the “ability to ask and answer real-world questions from large and small datasets through an inquiry process, with consideration of ethical use of data. It is based on core practical and creative skills, with the ability to extend knowledge of specialist data handling skills according to goals” [87]. Improving data literacy is essential to include and involve stakeholders in the cross-sector collaboration process, as they can make data-driven decisions [38]. Jonas and Hanrahan [44] stress the importance of critical digital literacy to incorporate participants’ values in participatory design, with a case in rural communities.

Research highlights the effectiveness of interactive sessions in developing data literacy [16]. Some studies have used workshops to teach data and information literacy [10, 36], while others have focused on alternative new literacies, including social media literacy [34] and AI literacy [48]. However, gaps remain in adapting these methods to contexts where participants vary significantly in their familiarity with data [15], and existing studies fail to address challenges posed by cross-sector collaborative settings.

Data visualizations are powerful tools that can be used to gather insights from datasets. It is also necessary to consider the process by which people gain insights from visualizations. Yi et al. [88] identify four distinct processes: providing an overview, adjusting, detecting patterns, and matching mental models. Moreover, researchers have proposed a variety of evaluation methods to gauge the appropriateness of visualization given specific contexts [25, 43, 75]. A variety of approaches grounded in participatory design literature exist to design and implement effective data visualizations in collaborative and participatory environments. Examples are *Joint Action Storyboards* proposed by Homaeian et al. [41], and *Narrative Maps* by Keith Norambuena and Mitra [45].

### 2.4 Dialogic and Deliberative Processes

Another relevant stream of research concerns dialogic processes and deliberative democracy. In deliberative democracy, legitimacy stems from reason-giving among free and equal participants [5]. In particular, deliberation aims to transform preferences through exchange and revision, even though this deliberative process is inconsistently defined in the literature [26]. Fischer [29] argues that in a deliberative democracy, public policy inquiry should be seen as a deliberative-analytic practice in which expert and lay knowledge interact in discursive arenas to enable social learning

and legitimacy beyond mere technocratic expertise. Young [89] explains that legitimate processes must include multiple forms of communication so that historically marginalized groups can effectively participate. At the same time, recent work on expertise and politics cautions that the authority of expert knowledge should be rendered accountable and revisable within democratic fora to avoid technocratic drift or “black-boxed” decision-making [61].

Dialogic psychology and related approaches, such as Open Dialogue, offer micro-level insights into interaction, including turn-taking, reflective listening, and tolerance of ambiguity [13, 32]. These insights align with facilitation methods commonly used in cross-sector settings, such as sequencing, prompts, rotation of roles, and explicit norms [47].

## 3 Objectives and Methods

### 3.1 Goals of the *DDialogue* Framework

*DDialogue* responds to the need for inclusive, dialogic approaches to collaborative data analysis in cross-sectoral settings. In contexts where complex societal issues involve fractured institutional landscapes, it offers a space of encounter where data can act not only as evidence but also as a shared language for dialogue and co-creation. Grounded in participatory design values and literature on collaborative data analysis (see Section 2), we developed the *DDialogue* framework to pursue five interrelated goals, shown in Table 1.

The first goal is to *generate actionable insights from collaborative data analysis*. This is based on the idea that collaborative analysis can produce rich insights because groups pool complementary expertise. Frameworks for collective intelligence in HCI synthesize how diverse groups surface patterns and converge on interpretations that individuals miss [77]. In civic and community settings, structured workshops further demonstrate that participants can collectively articulate locally grounded values and interpretations of data, turning raw measures into situated insights that matter for action [66]. This closely relates to Williams’s idea of *Data Action* [86], or McCosker et al.’s Collaborative Data Action [54].

Williams’s and McCosker et al.’s work also influenced the second goal, to *facilitate data-driven decision-making in cross-sector collaboration*, as they show how communities can co-create analytic infrastructures that integrate local knowledge and institutional data systems. The framework should support deliberation and co-design

**Table 2: Comparison of the existing frameworks**

Framework	Generate insights from collaborative data analysis	Facilitate data driven decision making	Promote cross sector collaboration	Support knowledge exchange	Strengthen data literacy skills
Bryson’s Cross-Sector Collaboration Framework [11, 12]			✓	✓	
Data Action [86]	✓	✓			
Collaborative Data Action [54]	✓	✓	✓		✓
Policy Lab approach [82]	✓	✓	✓		
Data party [31, 49]		✓			✓
<b>DDialogue (ours)</b>	✓	✓	✓	✓	✓

of data-informed actions in a way that links collective interpretation of data to the co-creation of recommendations.

The third goal, *promoting collaboration and partnership across diverse organizations through data*, is grounded in Bryson’s work on cross-sector collaboration [11, 12], arguing that collaboration is not a static arrangement but an emergent process of aligning institutional logics and accountability across boundaries. By working together, individuals can identify trends, patterns, and correlations that may not be apparent when working in isolation and without specific domain knowledge [14]. Bringing together stakeholders from fragmented systems (e.g., NGOs, law enforcement, schools), *DDialogue* aims to cultivate trust to improve inter-organizational relations.

With respect to the fourth goal (*fostering cross-sector understanding and knowledge exchange*), Fischer and Mandl [30] showed that shared visualization and synchronous communication tools shape collaborative learning processes, even though true convergence of understanding depends on learners’ interaction dynamics. Knowledge sharing is a key factor in innovation, yet it often proves challenging across different organizations due to trust and a low willingness to engage with different ways of working [64, 67, 85]. Effective communication is essential to enhancing teamwork quality, and diverse teams do not always share the same language and communication style [37, 52].

Finally, in its fifth goal, to *strengthen participants’ data literacy skills*, *DDialogue* is aligned with Franz’s work on data parties [31]. This goal also resonates with D’Ignazio’s work on data literacy [21], according to whom access to data skills and resources remains profoundly unequal. *DDialogue* should democratize data practices by reducing barriers to participation in data-driven processes, improving individuals’ data literacy, and encouraging them to use tools that may be outside their comfort zone.

In summary, the *DDialogue* framework aims to simultaneously address these five goals, providing a framework for practitioners to organize cross-sector teams that tackle complex issues in a data-driven way while taking diversity into account. Table 2 compares several existing frameworks described in Section 2 in terms of how well they satisfy the five aforementioned goals, highlighting the contribution of *DDialogue* in filling the existing gaps.

### 3.2 Design Principles

Building on the existing literature discussed in Section 2, we outline a set of design principles to inform the definition of the *DDialogue* framework. These principles provided a foundational structure for the design process and helped align the framework with the five goals shown in Table 1. The design principles are the following:

- **Flexibility and adaptability.** The framework should be adaptable to a large variety of applications and avoid imposing strict constraints so that it can be easily implemented in different circumstances. Different sectors have unique needs and contexts, so this flexibility would allow organizers (i.e., those responsible for instantiating the framework for a particular complex issue) to adapt it to their goals, collaborative settings, and data types. This largely aligns with existing toolboxes and frameworks in participatory design literature.
- **Modularity.** To increase its adaptability, the framework should be composed of short sessions. Each session would have specific purposes and address challenges. The organizer would then be able to redefine the content of each session based on participants’ needs and characteristics.
- **Collaboration and participation.** The framework should facilitate participatory design and cross-boundary collaboration.
- **Capacity building.** The implementation of the framework should enable its participants to improve their data literacy and feel more confident engaging in collaborative data analyses. This includes providing training, resources, and support adequate to their knowledge.
- **Transparency.** In order to maintain trust in the system and effectively engage stakeholders, participants should be able to easily access and understand all relevant information. To do so, clear communication is fundamental, as everyone involved in the process should fully understand the methodology, the data usage, and the decision-making processes.
- **Centrality of a facilitator.** The framework should place emphasis on the role of a skilled facilitator to guide sessions effectively, manage discussions, and facilitate engagement among all participants. The moderation carried out by the facilitator should ensure that the process remains focused and productive.
- **Inclusivity.** Given that the framework aims to bring together individuals with diverse backgrounds, activities

**Table 3: Participants in the Pilot Study of the *DDialogue* Framework**

No.	Age range	Sex	Educational level	Organization type	Position
A1	30–40	F	Bachelor’s degree	Local police	Police officer
A2	50–60	M	Master’s degree	Local police	Police officer
A3	20–30	F	Master’s degree	Local government	Project manager
A4	20–30	M	Master’s degree	Local government	Project manager
A5	20–30	F	Bachelor’s degree	Local government	Communication manager
A6	30–40	F	Master’s degree	International NGO	Project manager
A7	20–30	F	Postgraduate degree	University	Researcher
A8	20–30	M	Master’s degree	University	Researcher
A9	40–50	M	Master’s degree	Local NGO	Coordinator

should be organized and adapted in a way that satisfies everyone. This ensures that multiple perspectives are considered, enhancing the richness and applicability of the analysis.

### 3.3 Testing the Framework

After identifying the *DDialogue*’s goals and delineating the design principles, we designed all of its components and instantiated it as a workshop. Following this, we conducted a pilot study to assess the feasibility of the framework’s design and implementation strategy. Based on feedback from the pilot, we made minor refinements and then conducted a full implementation of the framework to test it in a realistic setting. By *full implementation*, we mean the complete delivery of the workshop from start to end, comprising all nine sessions that constitute *DDialogue*. In both studies, participants completed a pre-assessment questionnaire before the workshop, which included Likert-scale questions, open-ended questions, and two questions focused on analyzing a histogram. At the end of the workshop, participants completed a post-assessment questionnaire similar to the pre-assessment structure. Additional data collected during testing included observational notes, meeting minutes, and completed activity canvases from the nine sessions. Unfortunately, for logistical and organizational reasons, it was not possible to conduct one-on-one interviews with the participants to gather a more precise impression of the implementation. However, several open-ended questions in the post-questionnaire helped in getting feedback on the pain and gain points of the framework. The study received ethical approval from the Idiap Research Institute’s Data and Research Ethics Committee, and all participants provided informed consent to participate in the study through signed consent forms prior to the start of the workshops.

**3.3.1 Pilot Study.** The pilot was conducted in Turin on November 21st, 2023. It lasted one hour and followed the sessions of the *DDialogue* framework. The topic of the workshop centered around factors that could potentially affect the well-being of young people in the city. Nine participants (6 F and 3 M) attended the pilot workshop, each bringing a distinct background relevant to urban security. Table 3 provides demographic and institutional information on the participants, including three municipal employees, two police officers, two researchers, and two NGO representatives (one from an international NGO and one from a local NGO). It is important to note that all participants had a degree from a higher education institute.

The pre- and post-assessment questionnaires used in the pilot are available in Appendix C.1 and Appendix C.2, respectively. Based

on the insights gained from the pilot study, we refined the framework. Given the overall positive outcomes of the pilot, only minor adjustments were made to the workshop.

**3.3.2 Full Implementation.** The full implementation of *DDialogue*, with the purpose of assessing the feasibility of the complete framework, occurred in Turin on January 22nd, 2024, within the context of a larger European project addressing the problem of juvenile delinquency in the city [1]. The topic of juvenile delinquency was well-suited for this work, as it lies within a very interdisciplinary area [90], and requires experts from different backgrounds to deal with multiple aspects of the issue. Hence, the large European project provided an appropriate context to test the *DDialogue* framework in a realistic setting with several professionals from organizations working with youth, law enforcement and NGOs. The goal of this workshop was to enable all participants to collaborate using data visualizations toward a common goal and identify relevant pain points on the prevention of juvenile delinquency in the city that could later be addressed by policymakers or taken up in subsequent work. In total, 22 individuals (6 M and 16 F) took part in the workshop, representing 8 different organizations, as can be seen from Table 4. 13 participants represented different departments, offices, and neighbourhoods of the local police, while the others represented public sector organizations, municipal offices, and NGOs.

Similar to the pilot, participants completed pre- and post-assessment questionnaires on their data literacy and familiarity with concepts of collaborative data analysis. The questionnaires are available in Appendix E.

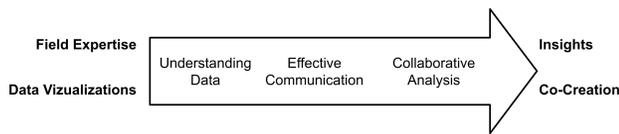
## 4 The *DDialogue* Framework

The *DDialogue* framework is designed to harness both individual and collective expertise from participants across diverse sectors and backgrounds, using data visualizations to develop actionable insights and co-create action plans or recommendations. To achieve this, *DDialogue* is instantiated as a collaborative workshop consisting of 9 sessions, each with a specific purpose aligned with the five goals described in Section 3.1.

The framework follows a progressive learning and collaboration trajectory, as shown in Figure 1. The first part aims to improve the participants’ data literacy skills, focusing on individual capacity

**Table 4: Participants in the Full Implementation of *DDialogue* Framework**

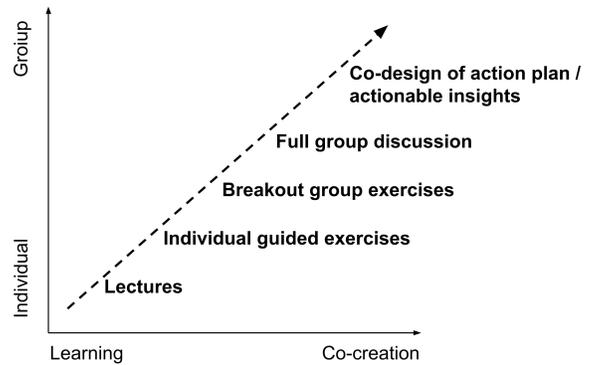
No.	Age range	Sex	Educational level	Organization type	Position
B1	30-40	F	Postgraduate degree	NGO	Psychotherapist
B2	20-30	F	High school diploma	NGO	Event organizer
B3	30-40	F	Bachelor’s degree	NGO	Event organizer
B4	30-40	F	Postgraduate degree	NGO	Social services officer
B5	40-50	F	Master’s degree	NGO	Youth services officer
B6	20-30	F	High school diploma	Public sector	Public services officer for prisoners’ advocacy
B7	40-50	F	Master’s degree	Public sector	Public services officer for prisoners’ advocacy
B8	50-60	F	Master’s degree	Public government	Social services officer
B9	50-60	F	Master’s degree	Public government	Education officer
B10	30-40	F	Bachelor’s degree	Local police	Police officer
B11	30-40	M	Bachelor’s degree	Local police	Police officer
B12	50-60	M	High school diploma	Local police	Police officer
B13	30-40	F	Bachelor’s degree	Local police	Police officer
B14	20-30	F	Bachelor’s degree	Local police	Police officer
B15	60-70	F	High school diploma	Local police	Police officer
B16	50-60	M	Master’s degree	Local police	Police officer
B17	30-40	F	High school diploma	Local police	Police officer
B18	40-50	F	High school diploma	Local police	Police officer
B19	50-60	M	High school diploma	Local police	Police officer
B20	50-60	F	High school diploma	Local police	Police officer
B21	30-40	M	High school diploma	Local police	Police officer
B22	20-30	M	Bachelor’s degree	Local police	Police officer



**Figure 1: Process map of the *DDialogue* framework**

building (goal 5). This is done through lectures and individual exercises targeted at the specific group attending the workshop. A breakout session in groups follows; this helps participants improve their communication and understanding of others’ data (goals 3 and 4). In this phase, participants begin to engage in collaborative data analysis, while also exchanging knowledge and personal experience. Then, all participants are reunited for group work, which helps them critically discuss and comment on insights from the data. In the final phases of the workshop, these insights can be developed into action plans or policy recommendations (goals 1 and 2). Table 5 outlines the structured flow of the nine-session *DDialogue* workshop. As shown in Figure 2, a *DDialogue* workshop starts by targeting the individual participants to foster their understanding of data concepts, focusing on their learning. Then, while it develops, it tends towards co-creation by the whole group of participants.

The core of the workshop is made up of Sessions 5 and 6, which focus on collaborative data analysis. Session 5 (breakout-group exercises) creates a low-stakes environment in which small, mixed teams begin to interpret visualizations alongside their own situated knowledge. While intentionally flexible to suit different problem



**Figure 2: Activities of the *DDialogue* framework, indicating how a workshop would develop from learning at the individual level to co-creation at the group level.**

domains and specific interdisciplinary groups, these activities need to be based on material provided by the facilitator. These include a compact set of data visualizations (using the media (printed or digital) most appropriate to the context), discussion prompts, and any other relevant tools. This combination ensures that participants can quickly anchor the discussion in a shared evidence base without being overwhelmed by raw data. Session 6 (full-group discussion) then synthesizes insights in plenary. The process remains guided by the organizers, both directly (through moderation) and indirectly

**Table 5: Structure of a *DDialogue* workshop**

No.	Session	Purpose
0	Pre-workshop preparation	Invite participants, collect datasets, prepare material
1	Welcome, introduction, and icebreaker	Informally welcome the participants and get to know each other
2	Workshop overview and scope	Formally introduce the topic to participants
3	Introductory lecture	Teach participants about relevant topics (e.g., concepts of data analysis) [Goal 5]
4	Individual guided exercises	Improve participants' data analysis skills [Goal 4; Goal 5]
5	Breakout-group exercises	Support participants' communication of data and collaboration [Goal 3; Goal 4]
6	Full-group discussion	Develop insights through collaborative data analysis [Goal 2; Goal 3]
±	<i>Iteration</i>	<i>Sessions 3-6 can be iterated multiple times, based on specific needs and purposes</i>
7	Individual action planning	Generate ideas of actionable outputs based on the insights [Goal 1; Goal 2]
8	Group discussion on action plan	Discuss and agree on a shared output [Goal 1]
9	Closing	Wrap up the workshop and discuss future developments

(through the curated prompts and visualizations). Participants are explicitly invited to reconcile apparent discrepancies and surface data limitations, explaining their reasoning to one another.

Because the quantitative evidence is often partial or uneven, the method emphasizes complementarity: experiential and institutional knowledge fills gaps that the numbers alone cannot resolve. In contrast, the numbers aim to anchor the discussion in empirical evidence. Therefore, the visualizations complement field expertise. Given the cross-sector composition of the groups, individuals learn how peers in other organizations see the same data, exchanging assumptions and tacit knowledge, as shown in Figure 1.

To provide a more concrete example, in both the pilot study (November 2023) and the full implementation (January 2024) in Turin, participants received printed *data placemats* [63], each devoted to a specific dataset related to juvenile delinquency (e.g., schools and calls to local police) and containing 3–5 visualizations (such as pie charts, histograms, maps, and line plots). Alongside the placemats, teams were provided with *conversation canvases* containing prompts to guide the dialogue and analysis. A photo of the data placemats and canvases in a breakout group is shown in Figure 3.

To support future adaptation and implementation of the *DDialogue* framework, a detailed facilitation guide has been included in Appendix A. This guide outlines the recommended preparation steps and provides a session-by-session breakdown of the full workshop structure, covering logistical considerations, data and visualization preparation, instructional content, and collaborative exercises. This detailed description of the *DDialogue* sessions is intended to assist facilitators, researchers, or practitioners in organizing and conducting *DDialogue* workshops.

## 5 Implementation and results

As mentioned in Section 3.3, we conducted a pilot and a full implementation of *DDialogue* with specifications detailed in Table 6. The first author acted as a facilitator for both workshops and conducted them in Italian. Each workshop employed the same datasets and visualizations, incorporating data from various sources related to juvenile delinquency. Data sources included open data from the municipality's public repository as well as data provided by stakeholders' organizations. The datasets covered a range of topics, such as data on school locations, police stations, calls to local police, as well as information on addiction rates and prolonged school



**Figure 3: Data placemats and conversation canvases used during the workshops.**

absences. These were visualized using common chart types such as pie charts, maps, histograms, and bar charts.

### 5.1 Pilot Study

The pilot study followed a preliminary version of the format proposed in Section 4. As participants were already acquainted with each other and had been introduced to the workshop's objectives, Session 1 (including a general introduction and icebreaker) was omitted, and the workshop lasted one hour. The detailed structure of this pilot workshop is presented in Appendix B.

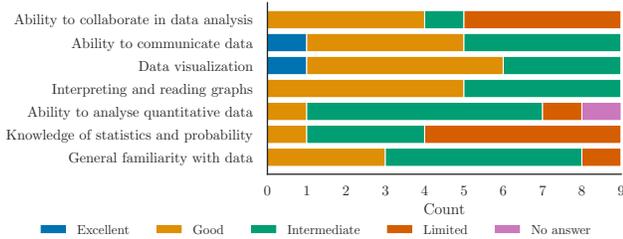
**Table 6: Specifications for the implementations of the *DDialogue* framework**

	Pilot Workshop	Full <i>DDialogue</i> Workshop
<b>Intended output</b>	Propose individual action plans to address issues of juvenile delinquency	Ideate possible solutions to relevant problem areas connected to the phenomenon of juvenile delinquency in the city
<b>Datasets</b>	Data related to juvenile delinquency in the city	Data related to juvenile delinquency in the city
<b>Support</b>	Data placemats	Data placemats and a digital dashboard
<b>Type of visualizations</b>	Pie charts, bar charts, histograms, and maps	Pie charts, bar charts, histograms, and maps
<b>Topics for the lecture</b>	Correlation (very short lecture)	Collaborative data analysis techniques, description of the types of visualizations
<b>Other material</b>	Canvases for the guided activities	Canvases for the guided activities
<b>Duration</b>	1 hour	2 hours

**5.1.1 Results and Analysis of the Pilot Workshop.** Throughout the workshop, participants remained attentive, engaged, and collaborated proactively, allowing individuals to express their opinions. This positive dynamic enabled breakout groups to work effectively, producing insightful observations on the datasets and identifying gaps in the data visualizations.

The pre-assessment questionnaire results showed that, although all participants held higher education degrees, their self-reported data literacy skills varied significantly, as illustrated in Figure 4. When participants were presented with two questions on histogram analysis, all of them correctly identified the purpose of the chart, and 8 out of 9 correctly recognized the statistical mode.

Self-assessment of participants' data analysis skills (Pilot study, N=9)

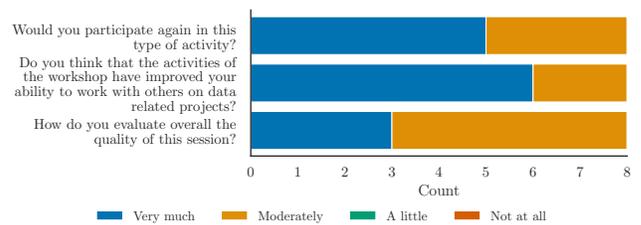


**Figure 4: Results from the data literacy questionnaire of the pilot workshop**

The post-assessment questionnaire indicated a favorable reception of the framework, with all participants answering that they found the activities of the workshop useful, and that they would participate in similar activities again, as shown in Figure 5<sup>2</sup>. When asked which activities they found most (allowing multiple selections), 6 participants chose the breakout group exercise, 6 selected the full-group discussion, 1 indicated the action planning, and none selected the initial explanation or individual exercises. These results suggest that the group sessions were well executed, while the initial phase may benefit from further refinement.

<sup>2</sup>Only 8 out of the 9 total participants in the workshops answered the feedback form. As a consequence, N=8.

Workshop Feedback (Pilot study, N=8)



**Figure 5: Results from the feedback questionnaire of the pilot workshop**

Overall, the pilot workshop's outcomes and feedback were encouraging. Participant A1 (Table 3) remarked, "It was interesting to involve different people from different organizations." The hands-on activities and breakout groups were particularly valued, as they facilitated interdisciplinary collaboration; participant A5 (Table 3) noted, "Analyzing the data as a group made it easier to understand and set up a straightforward approach to reading the data." The data-driven focus was also appreciated, with participant A4 (Table 3) stating, "It was very interesting to see how collecting and comparing different quantitative data provides a clear view of phenomena such as juvenile delinquency."

**5.1.2 Adaptation of the Framework Following the Pilot Study.** The feedback received during the pilot study suggested that only minor adjustments were necessary to the conceptual design of *DDialogue*. The primary issue identified was the limited time allocation: one hour proved insufficient for a thorough execution of all activities, and certain sessions, such as the full-group discussion, felt rushed. Consequently, a minimum duration of two hours is recommended for a more comprehensive experience.

Additionally, participants did not find the lecture and guided exercise session particularly useful, indicating a need for substantial revision. In response, the final version of the *DDialogue* framework separates this content into two distinct sessions: Session 3, dedicated to theoretical lectures and presentations, and Session 4, focusing on individual guided exercises. Emphasizing these sessions can help

participants improve their data literacy level and increase their confidence.

## 5.2 Full Implementation

As mentioned in Section 3.3.2, the full implementation of *DDialogue* took place in Turin with 22 participants, focusing on juvenile delinquency. The full implementation followed the structure presented in Table 5 and described in Appendix A. The main difference from the pilot was an extended duration of two hours, plus additional time for participants to complete two questionnaires. The detailed unfolding of activities can be seen in Appendix D.

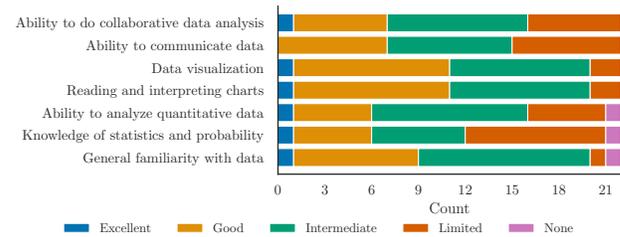
**5.2.1 Observations during the Full Implementation.** Participants in the workshop (Table 4) were divided into four breakout groups for the activities in Session 5; of these groups, three were cross-sectoral, and one was entirely composed of police officers. Consequently, the dynamics of the collaboration in the breakout group sessions were quite different. As expected, the police officers' group worked cohesively and quickly, as they shared the same working language and tended to agree more both in identifying problem areas and in proposing solutions. The other three groups engaged in longer discussions, highlighting the greater challenge of performing data analysis with teammates from diverse backgrounds. In particular, one participant was dominant throughout the session, raising skepticism about the purposes of the workshop. They questioned the whole purpose of the methodology for tackling the issue of juvenile delinquency during the initial phases of the workshop, and kept an adversarial attitude throughout the workshop. This negatively impacted the work of their breakout group, which was vaguer and less focused than that of other groups, without a clear definition of problem areas and possible solutions.

Nonetheless, the presence of the facilitator in the full-group discussion led to a positive collaborative environment, and participants were able to propose some suggestions for potential solutions to juvenile delinquency problems. The workshop was therefore generally considered fruitful and proceeded according to plan and expectations, confirming the real-world applicability of the conceptual framework offered by *DDialogue*.

During the workshop, the conversations primarily revolved around the interpretation of statistics related to schools and crime patterns in specific neighborhoods. Several exchanges focused on identifying sources of bias and missing information in the datasets; for instance, inconsistencies in how offenses were categorized, over-estimation of certain incidents because of data aggregation, or the absence of up-to-date data from particular institutions. These reflections highlighted several data gaps and underscored the importance of contextual understanding in interpreting data collaboratively.

**5.2.2 Results and Analysis of the Full Implementation.** Firstly, the answers to the pre-assessment questionnaire revealed a wide range of educational backgrounds and familiarity with concepts related to data literacy skills. As shown in Figure 6, self-assessment of seven data literacy competencies varied significantly, with most participants rating themselves as either "good" or "intermediate." This is also indicated by the fact that only 4 out of the 22 participants had previously taken part in a collaborative project that

Self-assessment of participants' data analysis skills (Full implementation, N=22)



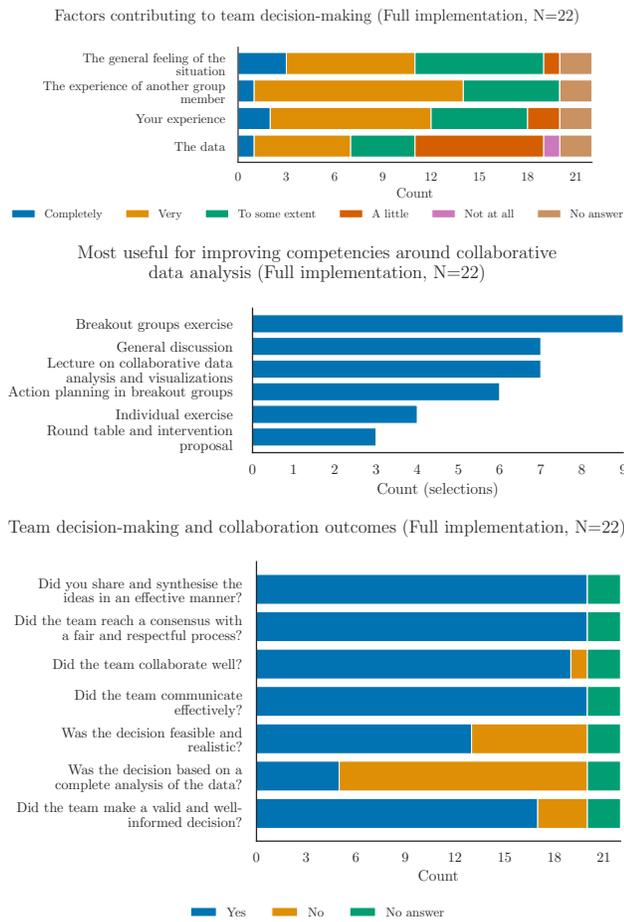
**Figure 6: Results from the data literacy questionnaire of the full *But* workshop**

involved the use of data. This suggests that the sample of participants provides a good testing environment for the framework, as this implementation of *DDialogue* was carried out with participants who not only came from a very diverse range of organizations, but also had different data literacy levels.

Overall, the feedback on the workshop was favorable. When asked if the decision-making process was improved by the framework, 68% of participants ( $N = 15$ ) answered that it was improved, 18% ( $N = 4$ ) answered that it was unchanged, and only one participant stated that it worsened (2 participants did not respond). Moreover, as shown in Figure 7, participants stated that the main drivers of their decision-making process were a combination of their own experience, the experience of other members, as well as the data, albeit to a lesser extent. When asked to select the sessions that they found particularly useful, the answers varied greatly. 3 participants indicated that all sessions of the framework were useful to them. This is a positive evaluation for the framework, as it indicates that all sessions have some value to participants.

Open-ended responses corroborated these results. Participant B6 noted that "this collaboration between sectors and organizations can improve the decision-making process, since it creates an opportunity to receive different ideas and viewpoints that can provide a more comprehensive scope of action." Participant B13 commented on the value of data-sharing, stating, "Greater diffusion of data and collaboration among agencies can help make more thoughtful choices," while participant B4 recognized the framework's adaptability: "The model has potential to be effective and applicable to other social phenomena." The potential use of the framework in the context of policymaking was also a recurring theme, with participant B1 arguing that "Data analysis is important to account for the work that has been done and to show what is happening on the territory, so that it can be taken in higher consideration by policy makers," and participant B20 argued that the framework can be truly effective for policymaking "only when actual policymakers are present during the analysis."

Participants also gave valuable recommendations for future implementations of *DDialogue*. With respect to data selection, participant B20 suggests using "A more effective method of collecting data so that they do not overlap and give as real a view of various situations, within the realm of possibilities," and participant B4 recommends "to view data interactively on devices, so as to avoid the confusion and fragmentation," thereby suggesting more interactive



**Figure 7: Results from the feedback questionnaire of the full DDialogue workshop**

visualization types. On the other hand, participant B18 proposes to include a preliminary session where “Small groups with members from the same sector or organization can discuss the issue, so that they can later report and share information with the other participants, during the workshop.” This suggestion proposes a further initial step, happening within the organization, to make use of both the efficiency of the fast intra-organizational collaboration and the insights of cross-sector approaches.

## 6 Discussion

### 6.1 Lessons Learnt from DDialogue

The implementation of *DDialogue* in Turin, where the main issue centered around the prevention of juvenile delinquency, showed the adaptability of the framework to a very specific challenge. The positive outcomes, as well as the feedback, obtained in both the pilot and the full implementation, seem to suggest the potential usefulness of *DDialogue* for applications where cross-sector collaboration is required, and quantitative data can be used as a tool to both foster discussion and improve the decision-making process.

A limitation observed during the second pilot workshop consisted of the tendency for certain participants to dominate discussions, which especially hampered the collaboration at the level of the breakout group. While the facilitator took action to encourage balanced participation, certain voices dominated the overall workshop, with a partly adversarial tone. Moving forward, the framework could benefit from incorporating facilitation strategies that can help reduce this type of imbalance, including the use of post-its in the individual exercises and breakout sessions, reducing the size of the breakout groups, and setting a clear code of conduct. The use of consensus-reaching techniques such as the nominal group method [20] can help mitigate this issue.

### 6.2 The Role of Data

In *DDialogue*, the experience and expertise of participants are treated as indispensable interpretive resources. From the outset, facilitators explicitly clarify that data are not objective mirrors of reality but constructed artifacts that reflect the choices, constraints, and assumptions embedded in their production [33, 46]. This framing establishes an epistemic grounding for the participants: datasets help the conversation, but they are only supposed to be read alongside situated experiences and professional judgment. Stakeholders from different sectors are thus encouraged to interpret data in light of their contextual knowledge and to articulate how institutional perspectives shape their readings. The facilitator makes it clear that divergent or even contradictory interpretations are not only legitimate but expected, since they reveal how data acquire meaning through practice rather than abstraction.

Therefore, the data visualizations in *DDialogue* serve as the basis for cross-disciplinary discussion and guide collective reasoning. Their function is to render data accessible, but also to provide a ground for confrontation and knowledge-sharing. This dialogic interplay between charts and lived experience helps participants examine where data are missing and the shortcomings of institutional data.

Because trust in data production is uneven across sectors and often lower among communities most affected by decisions, the flexibility of our framework allows for adaptations to low-trust or polarized contexts [55]. For example, before the meeting, the organizers can co-select with the participants minimally acceptable data sources and document caveats for contested topics.

### 6.3 Asymmetry and Diversity

It is also important to consider the “paradox of diversity” to which participants are susceptible: cooperation among very different stakeholders can foster innovation through shared ideas and new points of view, but it can also create divisions that hinder trust and communication [73]. These differences can be exacerbated by varying levels of data literacy, motivation, and attitudes towards the attainment of a shared goal. While *DDialogue* aims to simultaneously address these complex issues, outlined in the five goals of Section 3.1, the underlying challenges remain present and can never be completely annulled by the application of the framework.

Diversity can deliver epistemic benefits, but it also introduces frictions that complicate collaborative data analysis. These frictions are increased by asymmetries in authority and institutional power [91]. In such settings, the same visualization may be treated as true evidence by one actor, as contingent on questionable classifications by another, and as incomplete or misleading by a third [24]. In

polarized or historically marginalized contexts, these dynamics may risk eroding trust not only in particular datasets but also in the process itself [42].

It is crucial to take this into consideration while engaging with a multi-stakeholder collaborative data analysis process such as *DDialogue*. While the framework aims to partly address these challenges by making asymmetries explicit and assigning a facilitator, there is always the concrete risk that some voices and perspectives are not heard, or that conflicting viewpoints cannot be reconciled. This is in line with existing literature in participatory design, not necessarily linked to collaborative data analysis.

#### 6.4 Implications for Participatory Design

*DDialogue* extends literature on data-centric deliberation through the complementarity of quantitative data and lived experiences. This builds upon McCosker et al.'s work [54] by transposing the collaborative data action approach into a cross-sectoral context, where collaboration involves not just organizations of similar types but heterogeneous coalitions of public institutions, researchers, and civil-society actors. Moreover, *DDialogue* extends the methodological dimension of McCosker et al.'s framework by introducing a modular and adaptable structure for conducting collaborative data analysis.

*DDialogue* is therefore a suitable framework for cases in which problems are cross-sectoral, data are plural but partial, and decisions benefit from transparent, participatory sense-making. For example, *DDialogue* could be extremely beneficial in the context of living labs, which are platforms combining innovation ecosystems made of cross-sector stakeholders from the quadruple helix of innovation (private sector, public government, research institutions, and citizens), with real-world experimentation to tackle complex challenges [4, 76]. By contrast, *DDialogue* may be less suitable where time-critical, high-stakes decisions preclude deliberative cycles, where crucial information is classified or highly asymmetric, or where stakeholders are inherently adversarial, and would likely undermine the collaborative process.

#### 6.5 Challenges and Limitations

The implementation of the *DDialogue* framework can be very resource-intensive and expensive, as it needs to be carefully tailored to the specific characteristics of the participants and their goals. From the engagement of participants to the collection, preparation, and visualization of the datasets, the compilation of digital and printed material, the need for human labor is considerable. Some techniques can help reduce this: for example, it would be possible to prepare some standardized templates for canvases and dashboards or data placemats, or curate pre-built datasets and visualizations that can be used for a variety of circumstances, in order to reduce the burden of each workshop. Moreover, the use of large language models and generative AI can facilitate the preparation and customization of the material. Nonetheless, each workshop has to be customized to its participants and specifications, and the complex structure of *DDialogue* will always result in time-consuming preparatory work.

Another potential issue of the framework is that of data friction, i.e., “the complex socio-material factors that coalesce to slow

down and restrict data generation, movement and use” [6]. Data flows are often time-consuming, complicated, and inefficient in inter-organizational and interdisciplinary settings [62]. This can provide a considerable impediment to the implementation of the framework, as organizers may need to stipulate data-sharing agreements with the different partners, and process data according to specific principles [22].

### 7 Conclusion

This paper introduces *DDialogue*, a participatory framework designed to enable inclusive, cross-sector collaboration around data to address complex societal issues. Through its nine-session structure, *DDialogue* aims to foster mutual understanding across institutional boundaries and empower participants with varying levels of data expertise for a deliberation grounded in evidence and lived experience. The contribution of this work lies in its integration of participatory design, collaborative data analysis, and cross-boundary collaboration, addressing a clear gap at the intersection of these areas. Unlike existing approaches that prioritize either data literacy or participatory decision-making in isolation, *DDialogue* synthesizes these domains to offer a comprehensive framework for data-driven dialogue.

The framework was tested through two real-world implementations in Turin, where it supported professionals from municipalities, NGOs, law enforcement, and educational institutions in jointly addressing youth deviance. The formative findings from these workshops suggest *DDialogue*'s potential to address its five intended goals of generating actionable insights (**Goal 1**), facilitating data-driven decision-making in cross-sector collaborations (**Goal 2**), promoting cross-institutional dialogue (**Goal 3**), supporting knowledge exchange (**Goal 4**), and strengthening participants' data literacy (**Goal 5**).

These contributions position *DDialogue* not only as a tool for facilitating data collaboration but as a civic infrastructure for participatory and deliberative processes, which can offer concrete design knowledge for those seeking to organize evidence-informed participatory engagements. Future research can explore the application of *DDialogue* in different policy domains and geographic contexts, as well as in the context of living labs. In-depth qualitative studies, such as interviews and ethnographic follow-ups, could better explain the effects of the framework.

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## A Guide to the Implementation of a DDialogue Workshop

This appendix provides a detailed description of the *DDialogue* workshop, designed to support its replication or adaptation in diverse settings. It includes practical guidance on pre-workshop preparation as well as structured documentation of each of the nine sessions that make up a standard *DDialogue* implementation. The instructions are flexible by design, intended to be adapted based on the specific goals, participants, and data literacy levels relevant to the context.

### A.1 Pre-Workshop Preparation

The first step is selecting and appointing a facilitator to moderate the session, ensuring smooth operation. Ideally, this facilitator, or at least one among multiple facilitators, should have a solid background in quantitative methods, data analysis, and visualization to effectively support participants during the session.

Participant selection is a crucial aspect of preparation, involving the invitation of stakeholders or practitioners from diverse backgrounds relevant to the workshop’s objectives. After selecting participants, organizers should assess their data literacy levels to tailor lectures and exercises accordingly. Various assessment methods are available, as highlighted by systematic reviews from Cui et al. [18] and Pinto et al. [69]. This assessment might involve practical questions or self-reporting tools, chosen to fit the specific workshop context. Then, the organizers need to determine the

key specifications of the workshops, which include the following elements:

- **Intended output** of the workshop. This is a key component, and it is related to the scope and objective of the implementation of the *DDialogue* framework.
- **Datasets** that need to be collaboratively analyzed during the *DDialogue* session. Relevant datasets should be chosen thoughtfully, considering participants’ backgrounds, data literacy levels, and the workshop’s objectives. It is important not to overload participants with excessive data, as it can lead to information fatigue and reduce engagement [70].
- **Support** of the visualizations. *DDialogue* allows for flexibility in visualization tools, accommodating both analog and digital supports based on preference and context. These can range from traditional printed visuals to multi-modal digital displays, such as tablets or tabletop displays, to enhance interaction [40].
- **Type of visualizations**. The chosen datasets must be accompanied by visualizations, as appropriate data visualizations are paramount to help participants make sense of data [56]. When working with diverse stakeholders, it is important to consider the specific needs of each group, and choose adequate accessible data visualizations that can cater to every attendee [23].
- **Topics and material for the lecture**. As the workshop begins with a lecture session, the presentation should be prepared to address gaps in participants’ knowledge and reinforce their understanding of key data concepts. This content should be customized based on participants’ backgrounds, data literacy assessment, and the workshop’s goals.
- **Other material**. Organizers may opt to use a variety of other supporting materials in the different phases of the workshops. This may range from structured templates and canvases, which can provide participants with clear models for organizing their thoughts and ideas, to more interactive elements, such as serious games or interactive exercises, which can foster engagement and creativity.
- **Location and Layout**. An appropriate location is needed to facilitate all workshop activities, including lectures, breakout sessions, and group discussions. The room should be arranged to accommodate these activities comfortably, with necessary technological equipment and accessibility considerations in place for all participants.
- **Duration**. The recommended duration of a workshop is two to four hours, to allow for a proper unfolding of all sections, but without overwhelming the participants. However, depending on the participants’ prior knowledge and the number of iterations, the duration can be shorter or longer.

The planning and customization of all these elements are key to the effectiveness of the *DDialogue* framework and should be adapted to the specific context and aspirations of the participants and organizers. Although not necessary, incorporating participants in the planning through a participatory approach can enhance relevance and engagement.

Following these steps, organizers should complete the preparation, including lectures, handouts, discussion prompts, data collection, cleaning, processing, and visualization.

## A.2 Welcome, introduction and icebreaker (Session 1)

The first session of the *DDialogue* workshop sets the stage for collaboration with icebreaker activities. It consists of an informal welcome and introduction of all the participants, especially among those unfamiliar with each other, and it helps to set the tone for the rest of the sessions. Participants can be asked to wear name tags with their organization and introduce themselves.

Icebreaking activities are valuable in creating a positive collaborative environment [51, 83] and trust among participants [79]. A wide range of activities exists to enhance trust, interpersonal connections, and teamwork [51], from casual activities to more academically-oriented ones [57]. Organizers should select an icebreaker that aligns with the participants' characteristics and the session's objectives.

## A.3 Workshop overview and scope (Session 2)

In the second session, facilitators provide a formal introduction to the workshop, outlining its goals, theme, methods, and scope. This includes an overview of the data to be discussed, using initial examples of the visualizations participants will encounter. Facilitators may also explain the intentions behind the data collection and its contextual relevance.

By the end of Session 2, participants should have a clear understanding of the workshop's purpose, scope, and methodology, along with their roles and the expected outcomes.

## A.4 Introductory lecture (Session 3)

The third session aims to instill a basic understanding of the data analysis process among the participants and to help them improve their data literacy competencies, addressing goal 5. This phase is geared more towards individual learning and introduces participants to a theoretical grounding that can provide them with a common foundation for the subsequent phases.

The lecture can be delivered by facilitators or guest experts in the form of a presentation. Its content is highly adaptable, and organizers should also consider the possibility of incorporating multiple sections on different topics. Potential topics may include a crash course on data analysis and statistics, AI tools, ethics, and collaboration methods. To ensure that participants receive instruction tailored to their needs and expertise, the session should be adapted to the level of data literacy of the participants, which ideally should be assessed prior to the session. The session's duration can range from 10 minutes to an hour, depending on the depth of information organizers wish to convey.

For example, some themes that can often be useful to feature in this phase include data ethics, the presence of bias in data, and effective collaboration methods. The lecturer may present real-world examples of ethical dilemmas related to data collection and analysis. For instance, discussing a case where data privacy was compromised or a study that had unintended consequences due to biased

data collection can illuminate the importance of ethical considerations in data analysis. Similarly, they can define the need and importance of collaboration and explain collaboration techniques, discussing how building trust and relationships is necessary for success.

## A.5 Individual guided exercises (Session 4)

The fourth session is designed to enhance participants' data literacy (goal 5) and prepare them for collaborative data analysis. Participants are introduced to sample visualizations of the datasets they will analyze in the subsequent session. If participants have volunteered data from their own organizations, these familiar datasets can be used to increase engagement and help contextualize the analysis process.

In this session, participants are guided through a step-by-step data analysis exercise. These exercises may present scenarios with counterintuitive findings, subtly misleading visualizations, or challenges in distinguishing correlation from causation. This hands-on experience allows participants to apply their data analysis skills to practical situations and makes them more comfortable in engaging with others in collaborative data analysis.

## A.6 Breakout-group exercises (Session 5)

The fifth session aims to improve collaboration within small groups of participants, encourage diverse perspectives, and improve data communication skills, contributing towards goals 3 and 4. Each group should ideally consist of participants from various professional backgrounds and organizations who do not typically work together.

Within these groups, participants work collaboratively to derive initial insights and interpret the visualizations. Facilitators can provide discussion prompts, canvases, templates, or spreadsheets to facilitate discussion and analysis. This session encourages participants to learn from each other's expertise and understand how data from different organizations can intersect to support informed decision-making across boundaries.

As a sample activity, participants within each group can be tasked with presenting their organization's data, highlighting key trends and insights, drawing from the results of the individual exercise of Session 4. Then, they can be asked to respond to specific prompts given through canvases, whose answers can provide some preliminary insights that can be used for later activities.

## A.7 Full-group discussion (Session 6)

The sixth session aims to develop insights from the data visualizations through the collective intelligence of all the stakeholders (goal 1). This session involves the convergence of all breakout groups into a full assembly of participants to discuss the insights gathered in the previous session. By sharing the mini-group discussions, the participants gain a collective understanding of the issues at hand. This allows them to identify root causes and address concerns supported by data while drawing on individual domain expertise. The facilitators should ensure that all participants are given a say in this phase and are available to clarify any doubts that may arise regarding the visualizations, the data, or the statistical analysis. In this phase,

participants should focus solely on defining the main insights and problems, refraining from discussing potential solutions.

### A.8 Iteration (Optional)

If time allows and multiple datasets need analysis, organizers may opt to repeat Sessions 4 to 6 (individual exercises, breakout group exercises, and full-group discussion). This iterative approach enables participants to examine issues from various perspectives, consolidating insights across thematic areas with supporting visualizations. The discussions can be repeated for different thematic areas, where visualizations are provided to support their discussions. In cases of multiple iterations, participants should be encouraged to work with different group members to promote collaboration with a broader range of perspectives and approaches. Alternating between small-group and full-group discussions enhances exposure to diverse viewpoints.

However, given the high level of flexibility of the framework, it is also possible to only iterate on some specific sessions, such as the full-group discussion of the visualizations. The iterative process can help stakeholders explore multiple angles of the data and continue to refine their collective understanding. Once the participants reach a consensus on the problem definition and identify the areas of improvement, the moderators can move to the next session.

### A.9 Individual or small-group action planning (Session 7)

The seventh session builds on the common ground established in the previous sessions and allows individual participants to come up with new ideas and solutions to address the main issues, helping in data-driven decision-making and policy proposal (goal 2). Specifically, each participant is encouraged to sketch a potential action plan or solution, suggesting how the issue at stake can be tackled both within their organization and outside of it.

Alternatively, instead of an individual exercise, participants can be divided again into small groups to come up with potential solutions. Several brainstorming activities can be adopted during this phase, both for individual and group action planning and ideation. Organizers may facilitate this process with tools ranging from serious games to brainstorming support systems based on LLMs [58].

### A.10 Group discussion on action plan (Session 8)

The eighth session is the last collaborative phase of the workshop, addressing goals 1 and 2. Here, the full group convenes to discuss individual proposals and converge on final guidelines, policies, or action plans, thereby formalizing the workshop’s output. Participants select representatives, alongside the facilitators, to draft a document that may serve as an action plan, policy advisory, or resource for participatory action research. The emphasis in this session is on translating data analysis into practical, actionable steps.

### A.11 Closing (Session 9)

The final session serves as a conclusion and debriefing. Participants gather to reflect on the workshop process, reviewing highlights

and outcomes achieved through the data analysis. This session involves summarizing the main findings, recommendations, and proposed solutions. It also provides an opportunity for participants to offer feedback on the workshop’s structure and effectiveness, informing improvements for future iterations. The session ends with the concluding remarks from the facilitators.

### A.12 Suggestions for an effective implementation

When conducting a workshop following the *DDialogue* framework, it is paramount to take into account some aspects that can heavily impact its outcomes, both positively and negatively. Hence, here we provide some considerations to help better implement an effective workshop. First of all, we recommend that the duration of a *DDialogue* workshop should last at least 2 hours. While the first pilot workshop described in Section 5.1 only lasted one hour, one of its major drawbacks consisted of its short duration.

It is also necessary to tailor the content of each workshop to address specific needs. In this sense, the flexibility of the *DDialogue* framework allows for a relatively easy adaptation. Different sectors require different approaches and materials, depending on the participants. For example, a workshop attended by public government officials may focus more on foundational skills, while advanced techniques may be better suited for academic participants.

As discussed in section A.1, both the datasets and the visualizations need to be carefully selected and curated for a good execution of the workshop. The use of data volunteered by the participants’ organization can be highly beneficial in increasing engagement and improving the quality of the data analysis, as the different stakeholders would already have a certain level of familiarity with some datasets. However, it can often prove a difficult task to persuade organizations to share their data with external partners [65]. As described by Susha et al. [78], there are several drivers that can motivate organizations to volunteer their data in cross-sector partnerships, including reciprocity, self-interest, and pressure from public institutions [78]. Nonetheless, while this work focuses on the use of real-world datasets, it is also possible to use speculative data work and speculative dashboards [39], which can mitigate the problems related to data scarcity.

In case of multiple reiterations of the workshop, there should be a focus on continuous improvement and adaptation based on participant feedback. Both the participants and the researchers or practitioners who implement the workshop should perceive it as a learning experience. In this respect, every participant should be well aware of both the scope and goals of the workshop, and should be proactively engaged in the activities. It is key that everyone is motivated in the workshop to obtain optimal results.

## B Specific Structure of the Pilot Study

- (1) **Data literacy survey.** A data literacy survey was administered immediately before the workshop to assess participants’ knowledge and capabilities. The survey questions are included in Appendix C.1.
- (2) **Short introduction and workshop overview (Session 2).** This part, which lasted 8 minutes, included a short description of the scope and outline of the workshop. Then,

a brief overview of the data and the visualization methods was presented.

- (3) **Introduction to the analysis and sample exercise (Sessions 3 and 4).** In approximately 8 minutes, participants were shown two visualizations of demographic data of the city, which may intuitively lead to some misleading interpretations. A short explanation of statistical analysis principles, specifically on the difference between correlation and causation, was provided to the participants.
- (4) **Small-group exercise (Session 5).** Lasting 10 minutes, participants were divided into three groups of three, each composed of individuals from different organizations. Each group received data placemats [63] with 3-5 visualizations related to juvenile delinquency. Using a provided canvas template with prompt questions, each group noted their insights from the data.
- (5) **Full-group discussion (Session 6).** After the first group exercise, everyone reunited in the full group around a central, large table. Participants were then encouraged to discuss the insights together.
- (6) **Individual action plan (Session 7).** Participants spent 3 to 5 minutes individually outlining potential policies or action plans that could be implemented by their institutions to address the problems that they had identified earlier.
- (7) **Group round table on action plans (Session 8).** Following the individual planning, participants briefly described their action plans, potentially leading to policy proposals. This part lasted 5 minutes.
- (8) **Concluding remarks (Session 9).** The last few minutes of the workshop were dedicated to a short conclusion, summarizing the contents and results of the workshop, and summing up the next steps.
- (9) **Feedback and final assessment questionnaire.** At the end of the workshop, participants completed a questionnaire to reassess their data skills and provide feedback on the session. The questionnaire is included in Appendix C.2.

## C Questionnaires used during the Pilot Study of the DDialogue Framework

### C.1 Pre-workshop Data Literacy Survey

- (1) How would you evaluate the following aspects? [*None (1) / Limited (2) / Intermediate (3) / Good (4) / Excellent (5)*]
  - (a) General familiarity with data
  - (b) Knowledge of statistics and probability
  - (c) Ability to analyze quantitative data
  - (d) Reading and interpreting charts
  - (e) Data visualization
  - (f) Ability to communicate data
  - (g) Ability to do collaborative data analysis
- (2) Have you ever participated in collaborative projects based on data? [*Yes / No*]
- (3) Can you briefly explain your experience with data analysis?
- (4) In your professional activity, with what frequency do you do the following activities? [*Never (1) / Rarely (2) / Sometimes (3) / Often (4) / Very often (5)*]
  - (a) Collect quantitative data
  - (b) Analyze quantitative data
  - (c) Clean and manipulate data
  - (d) Execute database queries
  - (e) Visualize data and charts
  - (f) Communicate information with data and charts
  - (g) Present data to other professionals
- (5) The following questions are based on a sample histogram included showing the age distribution of some individuals.
  - (a) Based on this histogram, what is the mode of the age of students? [*17 / 18 / 20 / 24*]
  - (b) In this histogram, what does the height of each bar represent? [*The number of students in each age group / The percentage of students to the total population / The average age of students / The age of each student*]

### C.2 Post-workshop Self Assessment and Feedback

- (1) Following this workshop, how would you evaluate the following aspects? [*None (1) / Limited (2) / Intermediate (3) / Good (4) / Excellent (5)*]
  - (a) General familiarity with data
  - (b) Knowledge of statistics and probability
  - (c) Ability to analyze quantitative data
  - (d) Reading and interpreting charts
  - (e) Data visualization
  - (f) Ability to communicate data
  - (g) Ability to do collaborative data analysis
- (2) Which are the contents or activities of the workshop that you found the most useful to improve your competencies in collaborative data analysis? [*Initial examples / Data analysis in small groups / General group discussion / Action planning and intervention proposal*]
- (3) On a scale from 1 to 4, answer the following questions. [*Not at all (1) / A little (2) / Moderately (3) / Very much (4)*]
  - (a) How do you evaluate the overall quality of this workshop?
  - (b) Do you feel that the activities of the workshop helped your ability to work with others on data-related projects?
  - (c) To what extent would you participate again in this type of activity?
- (4) Which datasets and graphs were particularly interesting to you today?
- (5) How do you think that this collaborative data analysis model could improve the decision-making process to prevent youth deviance?
- (6) What are the main observations you have made about your organization's dataset and those of other organizations?
- (7) What is your overall opinion about this workshop?
- (8) What suggestions would you give to improve this framework?

## D Structure of the Full Implementation

- (1) **Data literacy survey.** Upon their arrival, participants completed a pre-assessment questionnaire, which can be seen in Appendix E.1. This served to gauge the data literacy of the participants.

- (2) **Welcome and introduction (Session 1).** The facilitator welcomed participants and introduced the workshop agenda.
- (3) **Explanation of the methods and purpose of the workshop.** Over approximately 20 minutes, the facilitator explained the workshop's objectives, emphasizing the importance of collaborative data analysis in creating interventions for juvenile delinquency prevention, and outlined the components and principles of collaborative data analysis.
- (4) **Explanation of the visualizations (Session 3).** Participants were introduced to the data visualizations and the datasets used, including familiar datasets volunteered by their organizations. This 15-minute session included a 5-minute Q&A.
- (5) **Individual exercise (Session 4).** Each participant received a data placemat [63] with visualizations from their organization's datasets and was asked to identify interesting aspects and suggest additional data that could complement the current visualizations.
- (6) **Breakout groups exercise (Session 5).** Participants were divided into 4 groups, of 5–7 people each. As described in Section 3.3, three breakout groups consisted of participants from different backgrounds and organizations, while one group was entirely composed of 7 police officers. This decision was made to assess the different dynamics in the collaborative data analysis process. This 15-minute session aimed to observe different dynamics in collaborative analysis. Each participant shared insights from their organization's data, and groups identified one primary problem area related to juvenile delinquency, along with two contributing factors.
- (7) **Full-group discussion (Session 6).** A representative from each breakout group presented their findings to the full group. Participants then collaborated to identify two overarching issues related to juvenile delinquency in the city and two influencing factors based on the data visualizations.
- (8) **Breakout group action planning (Session 7).** Following the group discussion, participants returned to their original breakout groups for 10 minutes to propose a solution addressing one of the identified issues and explain its potential impact.
- (9) **Round table on action plans (Session 8).** While the primary goal of the *DDialogue* workshop was to train participants in collaborative data analysis rather than develop concrete action items, a brief roundtable allowed each group's representative to present their action plan and motivation behind it.
- (10) **Feedback and final assessment questionnaire.** As in the pilot, for evaluation purposes and for the scope of this research, participants completed a questionnaire about their experience during the workshop and provided feedback. The questionnaire can be found in Appendix E.2.
- (11) **Closing remarks (Session 9).** Participants were then thanked for their participation and informed of the next steps.

## E Questionnaires used during the Full Implementation of the *DDialogue* Framework

### E.1 Pre-workshop Data Literacy Survey

- (1) How would you evaluate the following aspects? [*None (1) / Limited (2) / Intermediate (3) / Good (4) / Excellent (5)*]
  - (a) General familiarity with data
  - (b) Knowledge of statistics and probability
  - (c) Ability to analyze quantitative data
  - (d) Reading and interpreting charts
  - (e) Data visualization
  - (f) Ability to communicate data
  - (g) Ability to do collaborative data analysis
- (2) Have you ever participated in collaborative projects based on data? [*Yes / No*]
- (3) Can you briefly explain your experience with data analysis?
- (4) In your professional activity, with what frequency do you do the following activities? [*Never (1) / Rarely (2) / Sometimes (3) / Often (4) / Very often (5)*]
  - (a) Collect quantitative data
  - (b) Analyze quantitative data
  - (c) Clean and manipulate data
  - (d) Execute database queries
  - (e) Visualize data and charts
  - (f) Communicate information with data and charts
  - (g) Present data to other professionals
  - (h) Draft/develop new policies
  - (i) Make important decisions
  - (j) Collaborate with other organizations
  - (k) Make decisions based on data
- (5) What are the main problems that you currently have to face with respect to decision-making based on data?
- (6) How would you assess your confidence in your decision-making skills? [*I almost always feel that I make wrong decisions. (1) / Very often, I feel undecided about the choices to make. (2) / I often have second thoughts or feel uncertain about my decisions. (3) / I normally feel confident in my ability to make sound decisions. (4) / I think I am almost always able to make the best possible decisions. (5)*]
- (7) How would you define the decision-making speed in your team? [*Slow / Moderate / Fast*]
- (8) How important do you think that collaborative data analysis is in decision-making? [*Not important / Moderately important / Important / Very important*]
- (9) Do you think that collaborative data analysis can improve the decision-making process? [*Yes / No / I am not sure*]
- (10) Do you think that cross-boundary collaboration can improve the decision-making process? [*Yes / No / I am not sure*]
- (11) What are your expectations about this collaborative data analysis model?

### E.2 Post-workshop Self Assessment and Feedback

- (1) Following this workshop, how would you evaluate the following aspects? [*None (1) / Limited (2) / Intermediate (3) / Good (4) / Excellent (5)*]

- (a) General familiarity with data
  - (b) Knowledge of statistics and probability
  - (c) Ability to analyze quantitative data
  - (d) Reading and interpreting charts
  - (e) Data visualization
  - (f) Ability to communicate data
  - (g) Ability to do collaborative data analysis
- (2) Which are the contents or activities of the workshop that you found the most useful to improve your competencies around the subject of collaborative data analysis? [*Initial examples on the dashboard / Individual exercise / Data analysis in small groups / General discussion / Action planning in small groups / Round table and intervention proposal*]
- (3) How would you evaluate the accuracy of the decision made using the proposed collaborative data analysis framework, compared to previous methods? [*Improved / Same / Worse*]
- (4) On a scale from 1 to 5, answer the following questions. [*Not at all (1) / A little (2) / To some extent (3) / Very (4) / Completely (5)*]
- (a) Are you satisfied with the quality of this activity?
  - (b) Do you feel that the activities of the workshop helped your ability to work with others on data-related projects?
  - (c) Would you participate again in this type of activity?
- (5) How would you assess your confidence in your decision-making skills? [*I almost always feel that I make wrong decisions. (1) / Very often, I feel undecided about the choices to make. (2) / I often have second thoughts or feel uncertain about my decisions. (3) / I normally feel confident in my ability to make sound decisions. (4) / I think I am almost always able to make the best possible decisions. (5)*]
- (6) How do you think that this collaborative data analysis model could improve the decision-making process to prevent youth deviance?
- (7) How do you think that this collaborative data analysis model could help decision-making processes in general?
- (8) Please answer the following questions about the activities carried out today. [*Yes / No*]
- (a) Did the team make a valid and well-informed decision?
  - (b) Was the decision based on a complete analysis of the data?
  - (c) Was the decision feasible and realistic?
  - (d) Did the team communicate effectively?
  - (e) Did the team collaborate well?
  - (f) Did the team reach a consensus with a fair and respectful process?
  - (g) Did you share and synthesize the ideas in an effective manner?
- (9) On a scale from 1 to 5, what are the factors that contributed the most to your team's decision-making? [*Not at all (1) / A little (2) / To some extent (3) / Very (4) / Completely (5)*]
- (a) The data
  - (b) Your experience
  - (c) The experience of another group member
  - (d) The general feeling of the situation
- (10) Do you believe that this collaborative data analysis framework can influence the involvement of the main stakeholders in the decision-making process? Please explain.
- (11) What suggestions would you give to improve this framework?