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► **To cite this version:**

Alexandre Battut, Kevin Ratovo, Michel Beaudouin-Lafon. OneTrace: Improving Event Recall and Coordination With Cross-Application Interaction Histories. *International Journal of Human-Computer Interaction*, 2024, pp.1-18. 10.1080/10447318.2024.2332848 . hal-04923157

HAL Id: hal-04923157

<https://hal.science/hal-04923157v1>

Submitted on 31 Jan 2025

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***OneTrace*: Improving Event Recall and Coordination with Cross-Application Interaction Histories**

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ABSTRACT

To coordinate and understand past actions in a collaborative activity, co-workers typically access shared artifacts and the interaction histories provided by their tools. We interviewed 12 knowledge workers who collaborate on shared text documents. We found that the scattering of historical data across collaborative and personal environments and the lack of compatibility between histories hinder coordination and event recall. To explore the design of cross-application history tools, we created *OneTrace*, a proof-of-concept system for sharing histories amongst applications and users based on a unified structure for representing interaction traces. We then introduce *TracePicker*, a tool that lets users cluster traces to contextualize past actions recorded by *OneTrace*. We evaluated *TracePicker* using a questionnaire- and scenario-based observation study. Results show that participants found the system helpful for communicating, understanding and contextualizing historical data. We conclude that designing cross-application histories such as *OneTrace* supports coordination and event recall.

KEYWORDS

interaction history; instrumental interaction; collaboration; coordination; sense making; event recall

1. Introduction

As we interact with digital objects such as files and documents in a digital environment, our interactions leave behind traces of this interaction history (Rosner, Ikemiya, Kim, & Koch, 2013; Schwanda Sosik, Zhao, & Cosley, 2012). These traces, also called “wear” (Alexander, Cockburn, Fitchett, Gutwin, & Greenberg, 2009; Hill, Hollan, Wroblewski, & McCandless, 1992), inform the different stakeholders about the evolution of these digital objects over time. They help end users better understand the steps that led to the current state of their artifacts (Grossman, Matejka, & Fitzmaurice, 2010) and document their own history (Yahiaoui, Prié, & Boufaïda, 2009). Researchers can also use and analyze such historical data to understand better users’ activities and behavior and improve our interactions with digital content (Belin & Prié, 2012; Carrillo, Lavoué, & Prié, 2016).

In current interactive systems, historical data are often tied to their source application and are only accessible from within that application. For example, a document modification history is displayed in the word processor’s history (Hill et al., 1992) while a web browsing history is displayed in the browser’s history (Hailpern et al., 2011). During an activity, users may interact with several tools and digital content in parallel, fragmenting their history and leaving traces in different places. While such

application-specific historical data can describe precisely the actions performed on the content and their date, their distributed nature makes it difficult to understand their context (Rule, Tabard, & Hollan, 2017; Schmidt, Doeweling, & Mühlhäuser, 2012). This hinders users’ ability to review and correlate events from different applications as they cannot link the different histories together.

Interaction histories also play an important role in collaborative environments (Malone & Crowston, 1994). Participants typically need to synchronize their activity with the rest of the group and thus need to keep track of their team members’ progress to position themselves within the overall project timeline (Avdic, Bødker, & Larsen-Ledet, 2021). In theory, the work practices that push team members to use a common set of tools and devices should facilitate history sharing. In practice, users often prefer to use their own tools and devices rather than such an “aligned artifact ecology” due to their work habits, activity or environment (Larsen-Ledet, Korsgaard, & Bødker, 2020). The resulting fragmentation and heterogeneity of historical data then hinder coordination.

To address both the need for *making sense* of past actions and *improving coordination* in collaborative projects, we set out to re-think the concept of interaction histories. This article explores the possible benefits for users of a shareable, cross-application history.

After reviewing related work, we describe a preliminary study where we interviewed 12 knowledge workers about their use of history in collaborative document editing activities. We then conducted a workshop to understand how users want to shape and gather historical data into collections. Based on these observations, we introduce *OneTrace*, a proof-of-concept system that logs the actions performed by users and their context, and shares them across applications and users thanks to a unified historical data structure. We used *OneTrace* to create *TracePicker*, a tool that helps users re-document historical data from different sources by building custom historical data collections. Finally, we report on an 8-participant scenario-based observation study of *TracePicker* to investigate participants’ perception of this tool and the *OneTrace* system. We conclude with directions for future work.

2. Related Work

To make sense of historical data and recall context across activities, users need to focus on important traces and cross-reference histories from different applications. We first review related work on history systems for improving event recall. In collaborative settings, communicating and understanding traces left by team members is part of the coordination process. We then review related work on the role of histories for collaboration and coordination.

2.1. *Enriching Histories to Enhance Event Recall*

While users can retrieve information by filtering the interaction history by time or keywords, they also find past events through their relationships to other events. This is described by Rule et al. (2017) as a reconstruction of the mental context of a past situation. Previous work has enhanced interaction histories with visual aids to support and enhance event recall. *EditWear* and *ReadWear* (Hill et al., 1992) display history as “wear” on the scrollbar of a text document, with varying intensity according to the density of historical data. *ReadWear* was later revisited (Alexander et al., 2009) by

adding marks and thumbnails as well as an overview of the areas impacted by past events. Thumbnails were also used in *SenseMap*'s "history map" (Nguyen et al., 2016) to enrich a tree representation of the user's browsing history; in *ScreenTrack* (Hu & Lee, 2020) by playing back screenshots of previously visited websites; and in *Contextual Web History* (Won, Jin, & Hong, 2009) to enrich the web browsing history.

Other works help reconstruct context by clustering historical data to let users interpret it as ensembles rather than isolated actions (Weick, Sutcliffe, & Obstfeld, 2005). Systems such as *UEMA* (Kaptelinin, 2003), *Sphere Juggler* (Morteo, Gonzalez, Favela, & Mark, 2004) and *CAAD* (Rattenbury & Canny, 2007) build contextual structures representing the high-level tasks in which the documents were used. *Variolite* (Kery, Horvath, & Myers, 2017) and *Verdant* (Kery, John, O'Flaherty, Horvath, & Myers, 2019) connect together their historical data when the logged actions share the same goal. Grouping traces as ensembles has also been explored by Schmidt et al. (2012) who found that linear representations were unsuitable for finding context and instead introduced graph representations to link traces together. *Lifeflow* (Wongsuphasawat et al., 2011) provides users with scalable sequences of related events instead of a linear timeline to facilitate understanding of these events' history. Finally, *Chronicle* (Grossman et al., 2010) groups historical data into "chronicles", sequences of actions represented as a single higher-level transition between two important system states.

These works show that reconstructing context often requires referring to histories from other applications or tools and observing the history of interactions at a higher level (Nancel & Cockburn, 2014). For example, *FileBiography* (Lindley et al., 2018) uses a content-centered history that synthesizes actions performed on or with a file (modifying, sharing, annotating and commenting) to understand the file's life cycle. *YouPivot* (Hailpern et al., 2011) introduces the concept of "pivoting" between applications during an activity and helps contextual recall by associating the main activity's history with meaningful but unrelated events. *Switch!* (Maalej & Sahn, 2010) supports such pivoting by remembering the context of the transitions between applications. In a similar vein, *WindowTrails* (Waldner, Bruckner, & Viola, 2014) and *CAAD* (Rattenbury & Canny, 2007) combine the histories from individual applications with the navigation history to provide users with a higher-level view of their activity.

Several projects explored a more application-agnostic approach based on timelines. *Lifestreams* (Freeman & Gelernter, 1996) gathers files into a single interactive timeline to enhance personal information management. *TimeScape* (Rekimoto, 1999) is an alternative to the current desktop environment in the form of a timeline organizing every digital content created on the computer. *TimeCasting* (Rekimoto, 1999) builds on *TimeScape* and lets applications share temporal information so that users can recall events by associating them with the different activities they were involved in at a given time.

These works show that histories from different sources are entangled and must be combined to enhance recall. However, most previous work focuses on specific and closed environments (Hailpern et al., 2011; Waldner et al., 2014) and on enhancing the history of a single object or document. *TimeScape* (Rekimoto, 1999) explored a more flexible solution with *Time-machine Computing* but does not support the enrichment and customization explored by other systems such as *CAAD* (Rattenbury & Canny, 2007), the *Footprint Scrollbar* (Alexander et al., 2009) or *Chronicle* (Grossman et al., 2010).

Our work addresses these issues by designing a universal interaction history system that deals with historical data from any application across the user's environment. This allows for the design of application-agnostic history tools.

2.2. The Role of Histories in Coordination

Coordination is defined by Malone and Crowston (1994) as “*managing dependencies between activities*”. It can be understood as the means and strategies used to manage cooperation, collaboration and competition among participants so that joint activities can run smoothly. Coordination is critical for successful collaboration and typically requires team members to access each other’s histories to position themselves within the timelines generated by the various tools.

Avdic et al. (2021) studied the effect of coordinating through traces exchanged in collaborative environments. The authors underline the importance of timeline awareness for coordination in the context of smart homes: “*a configuration of a specific command such as how one changes the temperature in a room, can lead to confusion amongst the members who are unaware of the changes*”.

Hawkins, Sano, Goodman, and Fan (2019) used traces of past visual communications as a shared artifact to enhance coordination and found that sharing traces increases collaborators’ knowledge alignment. *DocuViz* (Wang, Olson, Zhang, Nguyen, & Olson, 2015) enriches the modification history by visualizing the changes within specific time periods to inform users about collaborative patterns and help them organize their work around historical data. *FileBiography* (Lindley et al., 2018) shows that history is also a shared artifact for reflecting, learning, and collaborating among individuals.

Many studies of collaboration assume homogeneous environments, i.e. an aligned artifact ecology (Bødker & Klokmoose, 2012; Larsen-Ledet et al., 2020) where all participants use the same tools. But when multiple users are engaged in a collaborative activity, they may have different *personal* artifact ecologies, i.e. they may not use the same tools as their collaborators. This results in historical data being spread across histories generated by different and often incompatible tools, hindering coordination.

In summary, previous work shows the importance of understanding the full timeline of events to coordinate efficiently. However, it does not address collaborative environments in which users have conflicting artifact ecologies, leaving traces that are inaccessible to their collaborators or incompatible with their tools. We believe this issue can be addressed by defining a unified way to structure historical data and making it shareable among users and across environments.

3. Understanding History Usage in Collaborative Activities

To ground our understanding of users’ behavior and issues regarding historical data usage, we focused on collaborative authoring of text documents. Collaborative writing environments are often used in the literature as a typical case of collaborative work (Olson, Wang, Olson, & Zhang, 2017; Wang et al., 2015) and for studying coordination patterns such as territoriality (Larsen-Ledet, 2019; Larsen-Ledet & Korsgaard, 2019) or the fragmentation of activities in artifact ecologies (Avdic et al., 2021; Larsen-Ledet et al., 2020). Our specific goal is to understand how people work with traces when coordinating their work in this setting.

Larsen-Ledet et al. (2020) describe the artifact ecologies involved in collaborative writing. They observed the fragmentation of collaborative work when users perform tasks on various artifacts to achieve shared goals. This fragmentation is due to the fact that the artifact ecologies of the different users are not fully aligned: users collaborate on shared artifacts in the aligned part of the artifact ecology, but they also manage

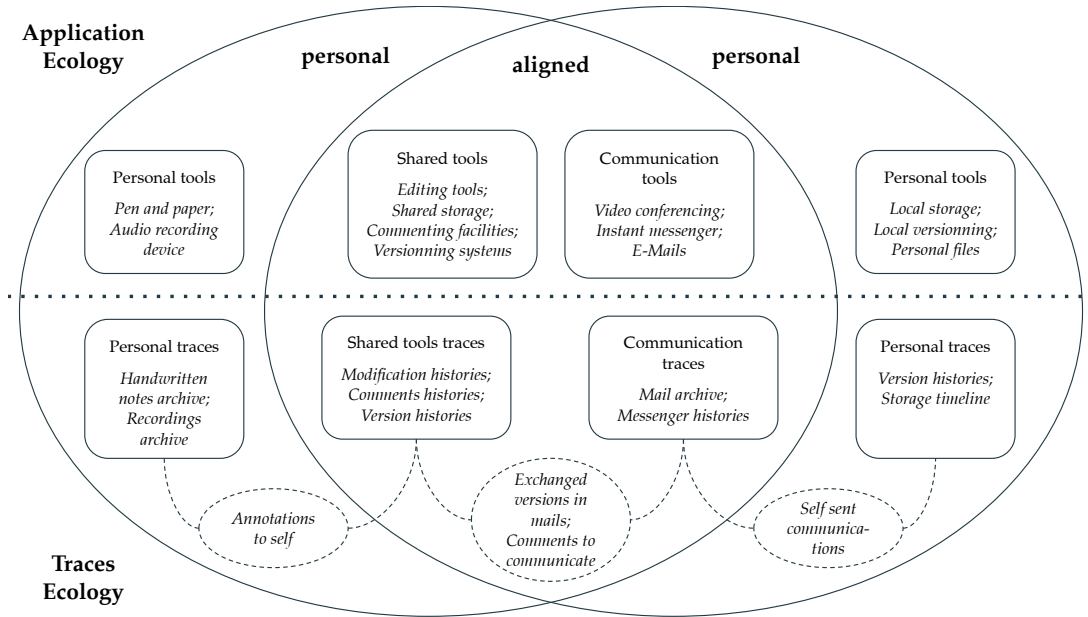


Figure 1. Collaborative writing applications (top half) and traces (bottom half) ecologies. In the bottom part, the rectangles represent the main categories of places where traces about a collaborative document appear and contain typical physical or digital objects holding the traces. The ovals represent traces that belong to the two adjacent categories.

personal artifacts in their respective personal artifact ecology. As a result, each user has to deal with both their personal artifact ecology and the aligned artifact ecology resulting from their collaborative process. Collaborative writing environments therefore offer great diversity in terms of the historical data they generate. To describe this diversity, we build on the framework introduced by Larsen-Ledet et al. (2020), which featured the concepts of personal and aligned artifact ecologies. Whereas the original diagram only depicted activities taking place within or across the different artifact ecologies, we depict the tools involved and the types of traces generated in the context of collaborative writing (Figure 1).

The aligned application ecology does not only involve aligned collaborative editing tools with integrated history facilities, such as *Google Docs*¹ or *Overleaf*², but also communication tools such as email and *Slack*³, shared storage tools such as *Dropbox*⁴, and versioning systems such as *git*⁵, all of which manage their own history. This application ecology is complemented by the personal set of tools used by each participant based on their preferences and habits, such as personal storage and personal editing tools.

Traces are left by each of these tools. They may be integrated into the tool, such as the modification history or the annotations managed by a word processor. They may also be external to it, such as successive versions of a shared document saved as individual files or in a version control system. The traces ecology also includes personal traces and traces of communications among team members. These categories may overlap. For example, annotations in a document may be part of the traces of a

¹<https://docs.google.com>

²<https://www.overleaf.com>

³<https://slack.com>

⁴<https://dropbox.com>

⁵<https://git-scm.com>, <https://github.com>

discussion, and traces of communication could be used as part of one’s personal space, e.g. when sending a note to oneself in an email.

This descriptive framework shows the complexity of working with traces during collaboration, arguably making coordination more difficult. Motivated by this analysis and by previous work on coordination in collaborative writing tasks, we conducted a study to understand how users interact with history tools in this context. The study addresses the following two research questions:

RQ1 How do people use histories to coordinate and keep track of the timeline in a collaborative writing project?

RQ2 What are users’ actual issues regarding history usage in collaborative writing?

3.1. Method

We used a mixed approach for this study⁶. We first conducted story interviews (Mackay, 2020) and then distributed a questionnaire to complement this data.

Participants. We recruited twelve participants for the interviews: eight men, four women; six aged 18-30, two aged 30-40, and four aged 40-50. Six participants were from academia (one HCI Ph.D. student, one biology Ph.D. student, one medical physics Ph.D. student, two biology research engineers, and one biology associate professor) and six from industry (two IT engineers/technical managers, two IT project managers, one scientific writer, and one lead UX designer).

The questionnaire was distributed to twenty-seven participants through research laboratories and HCI community mailing lists. We collected n=27 responses from knowledge workers, mainly from the French HCI community: fourteen men and thirteen women; eighteen aged 18-30, four aged 30-40, two aged 40-50, and three aged 50+.

The participants were not compensated for their participation in the interview study nor for responding to the questionnaire.

Setup. The interviews took place during the COVID-19 pandemic and were conducted remotely, through video conferencing. The questionnaire was administered online through a web-based form.

Procedure. For the interviews, we asked participants to tell us the story of the last document they edited collaboratively. We made them go through their whole process, focusing on historical data usage when necessary. Each interview lasted about one hour.

The questionnaire was composed of five-point Likert items with questions where respondents evaluated their privacy concerns towards sharing their historical data with relevant members of their team and their need for a cross-application history system. The questionnaire is available in Appendix A.

Data Collection. The interviews were audio- and screen-recorded and transcribed for analysis. Questionnaire responses were collected through the web-based form into

⁶The studies reported in this article were approved by our Ethics Review Board and followed our institution’s data protection rules (Inria Coerle; approval number 2022-50). Participants signed an informed consent form approved by the Ethics Review Board before the study.

Table 1. Overview of the five identified themes.

Category	Theme	Key Elements
Practices (RQ1)	T1: Users re-document traces to group them and facilitate coordination	Users group traces to avoid bloated histories Users group traces to share progress status Users gather information from different histories
	T2: Users put personal or collaborative norms in place to better differentiate and understand traces	Making important traces stand out Emphasizing the meaning or context of past actions Customizing traces to browse them more easily
Issues (RQ2)	T3: History data are left in too many places around the object of the collaboration	Traces are left in both personal and aligned ecologies Different roles, different tools, and no shared history Various communication tools and no joint code of conduct
	T4: Too much history data is generated during collaborative activities	Large number of operations, large amount of traces Traces duplication due to complicated access No control over the histories' granularity
	T5: Important history data get lost over time	Traces lost due to tools erasing them Traces' meaning is lost over time due to users' memory

a data table.

Analysis Method. We performed a thematic analysis (Braun & Clarke, 2019; Brown & Stockman, 2013) of the interview transcripts. Two HCI researchers worked together to identify recurring themes, first working separately and iterating on top of each other's categorization, and then working together to merge close themes and discuss disagreements. We analyzed the questionnaire data with summary statistics for each question.

3.2. Results

The thematic analysis of the interviews led to five main themes, divided into two categories according to the two research questions (see Table 1). The first category (themes *T1-T2*) addresses collaborative and individual practices towards traces and the strategies for using them to coordinate with other team members (*RQ1*). The second category (*T3-T5*) addresses the main issues participants face when using historical data that hinder progress in the collaborative activity (*RQ2*).

Theme T1: Participants group traces to improve coordination

We found that participants re-document traces to group them and facilitate coordination. They often group traces to summarize the progress made between successive project milestones and make it understandable. For example, Participant 2 (P2) compiles every annotation made on the shared document, whether it is sent by e-mail or said out loud during a face-to-face discussion, and sends an email to her collaborators before a meeting so that everyone is on the same page. Grouping can also take the form of specific storage places for important and related traces. For example, P10 explains that her team has a specific shared folder for storing the current version of the shared document each time they cross a new milestone.

Theme T2: Participants set up norms to better understand traces

We found that participants define conventions to help them differentiate and understand traces. Traces logged by the same source application do not always have the same importance or the same meaning. Oftentimes, the nature of a trace can be identified through the role of the individual who left it. For example, P2 explained that she is the only one modifying the shared document, while the other members only leave or send her comments and suggestions. But sometimes, participants need more information to understand the meaning of a trace. For example, P3 explained that many of his team members do not use the annotation tool integrated into their word processor. Instead, they add their comments directly to the document's text and set the comments' color based on the importance of the annotation. However, even dedicated tools do not prevent participants from needing such additional information. P9 reported that his team adds labels at the beginning of each annotation to distinguish an urgent modification from a minor one.

Theme T3: Traces are left in too many places

A recurring issue for the participants is that traces are left in too many places around the shared content or documents. Within the same team, people can use different tools to edit the same document, to annotate it or to share files, and the multiplication of histories containing traces can make it difficult to synchronize and integrate timelines. For example, P9 uses two different tools to modify and annotate documents, resulting in some traces being visible in one tool but not the other. The number of communication channels also plays an important role in the difficulties participants face when coordinating. Team members use various channels such as email, instant messaging or even in-document conversations, making it harder to find what has been said about a specific issue. For example, P12 explained that she may “*know [that] a file has been shared*”, but there are numerous communication channels and no “*joint code of conduct*” about what to share and where, resulting in a waste of time spent looking for that information.

Theme T4: Collaboration generates too many traces

Even within a single history, participants feel that too much historical data is generated during collaborative activities. Large numbers of communications or operations on an artifact generate large amounts of historical data and it quickly becomes cumbersome to navigate through it. People also tend to duplicate traces such as document versions or e-mails to consolidate them or to have a different way of accessing them, adding to the volume of traces and creating redundancies. For example, P6 sends himself versions via email in addition to his shared versioning system and his local files. Participants find that current tools do not let them control the granularity of historical data and do not support clustering or summarizing over a given time period. They often have to perform these operations manually and feel they spend too much time doing so. For example, before each milestone and associated meeting, P3 compiles a list of important changes and comments left on the document since the last milestone. It provides a clear agenda of what to discuss that he sends to the team by email.

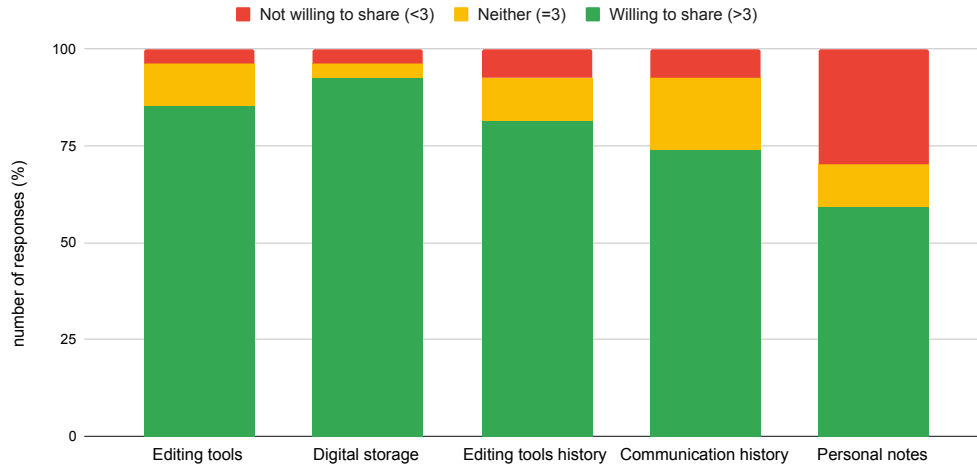


Figure 2. Willingness to share tools and histories (n=27)

Theme T5: Important traces get lost over time

The last key issue we identified is that important historical data get lost over time. They can start disappearing or lose meaning, like traces that fade with time. This often leads to confusion and misunderstandings and requires participants to rely on their memory. One issue is that some tools do not persist relevant data. For example, P3 lost annotations after merging two versions of the same document, and P7 lost them after indicating that the issue had been addressed. More generally, current tools do not record the context of user actions. For example, P7 explained that he often cannot remember why he left annotations whose meaning has become unclear due to lack of context.

Questionnaire: willingness to share tools and histories.

The interview participants improve collaboration by adopting coordination strategies that require users to share relevant historical data. This raises the question of which tools and historical data people are willing to share in the context of collaborative document editing. In the questionnaire, we first asked about the respondents' willingness to share specific tools or data, including shared editing tools and their history, shared digital storage, and shared communication history. We also asked about their willingness to share their personal traces about the project, such as personal notes.

Figure 2 shows each item's scores. Results show that most respondents are willing to use shared and synchronized editing tools (85%; 23/27) and to share a common space to store all their common work (92%; 25/27). To complement their shared editing tools, they are also willing to use the associated facilities to share historical data (81%; 22/27). 74% of the respondents (20/27) are also willing to share the history of their communications about a common project, and more than half (59%; 16/27) are willing to share their personal notes.

Questionnaire: interest in cross-application history tools.

Interview participants reported browsing historical data from different sources to make sense of a project's timeline. However, these sources are not always compatible with

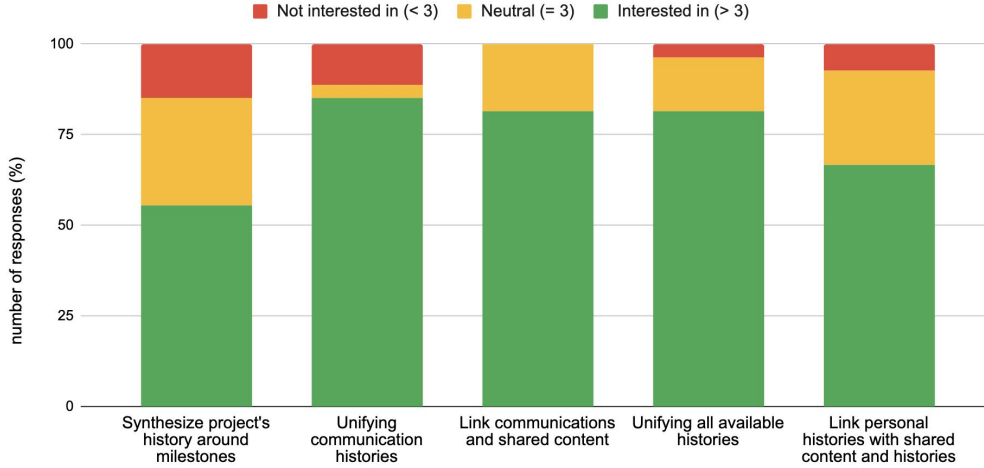


Figure 3. Interest in cross-application history tools (n=27)

each other. Sharing historical data with other team members may also mean sharing data that the other team members do not currently have access to. This raises questions about the relevance of cross-application history systems and tools. In the questionnaire, we asked about the respondents' interests in having cross-application history systems. We also asked about their interest in cross-application features mentioned by some of the interviewees such as cross-referencing different types of historical data or summarizing a project's global history around key moments.

Figure 3 shows each item's scores. A majority of respondents (55%; 15/27) are interested in the possibility of synthesizing a global project's history around specific milestones. Most respondents expressed their interest in unifying their communication histories (85%; 23/27) and in linking their communication histories with shared content (81%; 22/27) for cross-referencing. 81% (22/27) expressed their interest in unifying all histories they have access to during their project, and 66% (18/27) in linking their personal histories with shared content and shared histories for cross-referencing.

3.3. Discussion

We identified two main ways in which users make sense of traces (*RQ1*). First, users *summarize* traces by creating new artifacts from their interaction histories (*T1*) to make them more understandable for them and their teams. They browse across different histories, merge and extract relevant information, and compile it as new content. However, this is hindered by the fact that current tools capture only part of the activity and that histories are separate.

Second, users *augment* traces to make them more valuable (*T2*). They may indicate that a trace is important, annotate its meaning, or add contextual cues. Since current tools do not let them add such information to the history, they develop techniques to customize traces, such as color-coding and name-coding.

Augmenting and summarizing traces help users better understand interaction history and coordinate their actions on shared artifacts. This indicates that historical data are not only defined by static attributes such as source, authorship and time, but also by the *intention* behind the user's actions and the *motivations* behind an event. Both practices require additional work from users because of the lack of sup-

port from current tools. Therefore, trace augmentation and summarization should be facilitated by capturing more contextual information and letting users appropriate historical data.

Users have difficulties using traces to support coordination (*RQ2*) due to how they are collected. Applications collect traces separately (*T3*) and do not let users control the granularity and amount of logged interactions (*T4*). As a result, users must navigate traces in numerous places to identify relevant ones and risk missing important ones. They sometimes copy traces from multiple sources to consolidate them into a single location and avoid being drowned in a deluge of data. However, this adds to the amount and number of locations of history data, adding to the problem it seeks to solve. Finally, traces as collected by current tools are not rich enough. To understand a past action, one must understand its context and its intention. This underlying information is rarely consolidated and made persistent by history tools, therefore users must rely on their memory (*T5*). Users could more easily deal with traces if they were more easily accessible and consolidated in a central location and if they could more easily filter and enrich them with contextual information. Systems should also collect more information with each trace to facilitate navigation and re-finding.

Finally, collaborative settings raise the question of which traces should be shared among team members. Our questionnaire shows that participants are overwhelmingly willing to share historical data, including personal notes, and have a strong interest in tools that facilitate sharing and cross-referencing historical data. However, some participants also want to keep some data private. Therefore users should remain in control over which data is shared and with whom, especially for potentially sensitive information such as communications and personal notes.

4. A Unifying Structure for Historical Data

The interview study shows that the individual histories managed by each tool make it difficult for users to understand the timeline of events, especially when multiple artifact ecologies are involved. Users need historical data to be consolidated across applications and shareable with other team members. They must also be able to create customized collections of historical data that fit their needs. Our goal is to design a cross-application history system that supports these needs.

The key insight is that historical data and collections should be independent from the sources that generated them. Our solution is to *reify* (Beaudouin-Lafon, 2000; Beaudouin-Lafon & Mackay, 2000) historical data into “first-class objects”, i.e. turning the information that constitutes the history into interactive digital objects that users can readily manipulate with appropriate tools. For example, a timeline of historical events can be visualized as such, giving users direct access to past events and past states of a document, as illustrated by *git*’s branching diagrams⁷. By separating historical data from the applications that generated them and reifying historical data into interactive objects, we enable any application to access the global history and make it possible to design new, specialized history tools.

First, we need to define a unified structure for representing historical data. This data structure should contain a set of *core attributes* that any history tool or application can understand and operate on. It should also support personalization by including a set of *context attributes* that users can adapt to their needs.

⁷See, for example, <https://www.sourcetreeapp.com>

The core attributes provide a generic description of a user’s interaction with the system. They are independent of any particular application and apply to any action. They correspond to characteristics of historical data that were often referred to by the participants in the interview study: An interaction is described as a user U performing an operation O on the system S at time T . Therefore, the four core attributes describe who (U) did what (O) where (S) and when (T). We call them *Authorship*, *Interaction*, *Source* and *Time*. Core attributes cannot be modified as this would alter the event they represent.

Context attributes complement the core attributes by providing additional information about the context of the event to help users interpret it. They were sometimes mentioned by the participants in the interview study. They do not necessarily apply to any action in the history. These attributes may be changed by the user, who can also create new ones. For example, a user may add a “keywords” attribute for tagging events in the history so as to find them more easily later. A context attribute can reference another event in the history, creating relationships that can then be used for navigating history or grouping traces. The distinction between core and context attributes is that core attributes are required and read-only, while context attributes are optional and can be modified.

4.1. Workshop: Identifying Context Attributes

The interview study pointed to the potential benefits of consolidating the histories of the tools in an artifact ecology into a single, cross-application history. Based on the activities reported by the participants, we anticipate that such a unified history should support the grouping of traces in various ways to facilitate sense-making and re-finding. These groupings will most likely involve both core attributes and context attributes. To identify a first set of context attributes, we ran a participatory design workshop to observe how people group traces from different sources and what attributes they use to characterize these groupings, such as the intention or the motivation behind a past event. The workshop took place over three participatory design sessions.

Participants. One co-author participated in each of the three sessions. Three additional participants were recruited for each session for a total of nine external participants (six men and three women; aged 20-30; two software engineers, three HCI Ph.D. students, one research engineer, three HCI Master’s students). Each participant had a recent experience with collaborative work (Master’s thesis, research article or technical report).

Setup. For each session, the four participants were split into two groups of two. We provided each group with the same set of traces left across multiple histories during a collaborative project. They had access to a collaborative document, a set of historical data from the actions performed on and around this document, and a scenario explaining the collaborative project. The traces were paper Post-It notes describing a user interaction, with information corresponding to the core attributes identified above.

Procedure. Participants had to create groupings of these traces that made sense to them and that they could communicate to the other group. First, we asked them to create one or more paper-based artifacts by regrouping the historical data. The

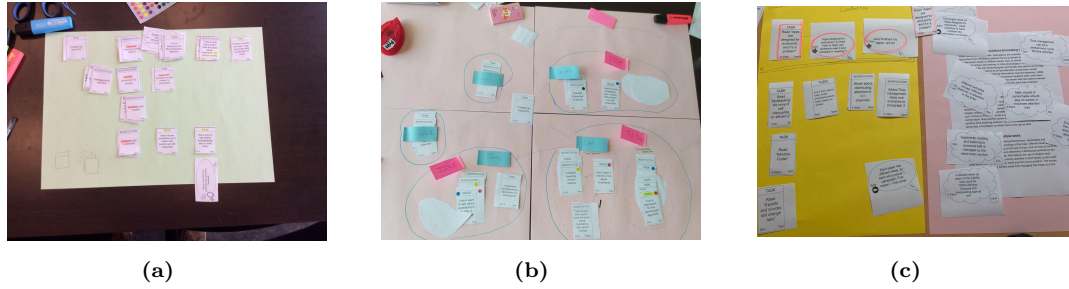


Figure 4. Examples of history artifacts and groupings produced during the participatory design workshop. Each grouping is a sequence of traces. In (a) these sequences can be collapsed under the most important trace of the sequence; in (b) these sequences are themselves grouped into abstract tasks; in (c) these sequences are grouped by spatial context.

groupings had to be meaningful for situations such as resuming work after a long break. They also had to communicate the right information to other people, e.g. to describe progress to their co-workers. The only explicit limitation was that they had to challenge current tools and representations by trying to avoid purely temporal structures such as timelines. We then asked each group to first present their work to the other group to see if they understood each other’s historical data groupings, and then discuss the criteria they used to create these groupings.

Data Collection. We collected the artifacts created by each group (Figure 4). Each session was video recorded.

Results. Participants grouped historical data to express relationships using clusters, but also with links that were not necessarily oriented (Figure 4). They mainly created groupings that expressed sequences of events and causality (Figure 4a). They sometimes grouped these sequences under a more abstract task (Figure 4b), or to express what the user had in mind when doing specific actions. They also grouped traces by the spatial context of the part of the document they related to (Figure 4c), to show the chain of events that led to specific changes in the document.

In all cases, participants expressed the meaning of each grouping, e.g. by labeling it, and were careful in selecting the content of each group. They also pointed out that some traces were more important than others. For example, they created a “collapsed” representation of the groups showing only important data and an “expanded” version showing all relevant traces (Figure 4a).

Discussion. These observations lead us to three important requirements for creating and managing collections of traces. First, users should be able to group traces using labels representing *abstract tasks* or *motivations*. Second, they should be able to express a notion of *sequence* between these data. Finally, they need to be able to control the *granularity* of these collections and highlight certain traces. These findings are consistent with the interview study, where the order of events and the use of some form of tagging for grouping and identifying traces were often reported.

4.2. The Step Structure

The history of an activity or artifact can be seen as a succession of steps taken to reach the present state of the activity or artifact. We therefore call the common digital object encapsulating the structural data shared by all historical data a *Step*. A Step therefore reifies an event or action that took place and constitutes a tangible trace of the activity.

A Step holds two types of attributes (Figure 5):

Core attributes: The core attributes of a Step are set at the creation of the trace. They are read-only and persistent, as they factually describe the action performed. History tools can read these attributes but cannot modify them.

- The *Authorship* attribute contains the “who”, i.e. the user who performed the action;
- The *Interaction* attribute contains the “what”, i.e. the content or description of the command or action that was performed by the user, such as a text modification;
- The *Source* attribute contains the “where”, i.e. the application and/or document in which the action was performed;
- The *Time* attribute contains the “when”, i.e. the timestamp when the logged action was performed.

Context attributes: The context attributes of a Step are those that can be edited by users to convey additional meaning about the event. These attributes can be set at the creation of a Step and edited with dedicated tools. The list below results from the participatory workshop but is not restrictive.

- The *Motivation* attribute contains the “why” of a Step, i.e. the reason behind the user’s action. It can be expressed through different means such as tagging the step with a color or label;
- The *Sequence* attribute specifies whether the Step is part of a sequence of actions and the causality between Steps, for example when one event occurred because of or in response to another event.
- The *Weight* attribute specifies the importance of a Step, e.g. to mark a higher-level task or a milestone.

In summary, Steps are self-contained data structures that can be used independently of their source application. They can be grouped in a variety of ways, not limited to the traditional timeline or list of commands that are common in current applications. Steps are also extensible: the context attributes that we have identified can be complemented with more specialized attributes. Applications that manipulate Steps should simply leave untouched the attributes they do not recognize. Steps therefore provide a sound basis for creating cross-application history systems.

5. OneTrace: a Cross-Application Interaction History System

We created *OneTrace*⁸ and the *OneTrace Desktop* as a proof-of-concept of a shared cross-application history system based on Steps. *OneTrace* is a server that logs any action performed by any user in any compatible application by creating a new Step. The content and granularity of the logged action can be specific to the application, but all Steps have the same structure, as described above.

⁸The prototype was named before the release of Microsoft’s log viewer also called OneTrace, and is not related to it.

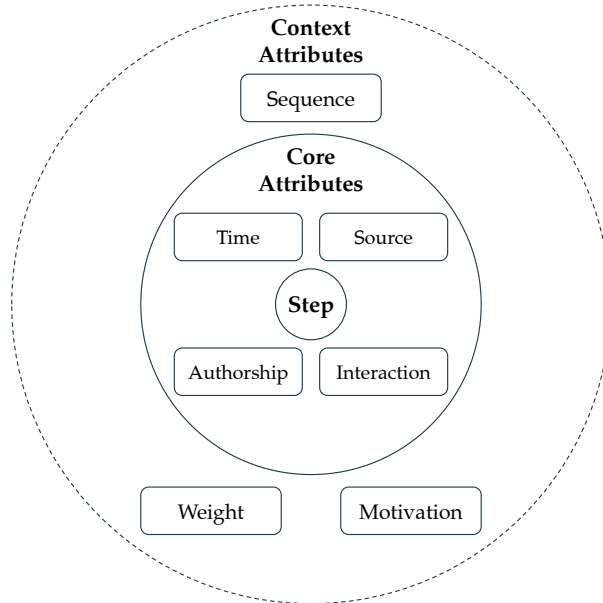


Figure 5. The Step unifying data structure comprises two layers of information: core attributes that can be accessed but not edited, and context attributes that can be edited and extended.

The *OneTrace Desktop* is a web-based system simulating a desktop environment (Figure 6). The user interface features an application dock at the top of the screen, open application windows in the workspace area, and the project’s main timeline in a drawer at the bottom of the screen. The timeline displays the Steps authored by the user and those shared with them. Clicking on a Step magnifies it and displays more information. Users can add information to a Step, which gets stored in the *Motivation* attribute of the Step (the “why”).

Since we are primarily interested in how users group traces together, the *OneTrace Desktop* applications log Steps at a fairly coarse level of granularity:

The WYSIWYG editor logs a new step for each line the user adds to the text document. The source is the document’s name (`<docname>`), the interaction is the description of the added line (`added line:<text of the line>`), the author is the current user, and the time is the current date and time;

The mail client logs a new step for each email being sent. The source is the mail application (`mailapp`), the interaction is the description of the sent email (`sent mail:<text of the email>`), the author is the current user, and the time is the current date and time;

The messaging app logs a new step for each message being sent. The source is the messenger application (`messengerapp`), the interaction is the description of the sent message (`sent message:<text of the message>`), the author is the current user, and the time is the current date and time;

Each application automatically logs Steps when a user interacts with it⁹. Steps are stored in the *OneTrace* server and displayed in real-time on each user’s global timeline. Since this is a proof-of-concept prototype, we limited the implementation to the minimum features needed to simulate a collaborative setting and run the study

⁹See Appendix C for details.

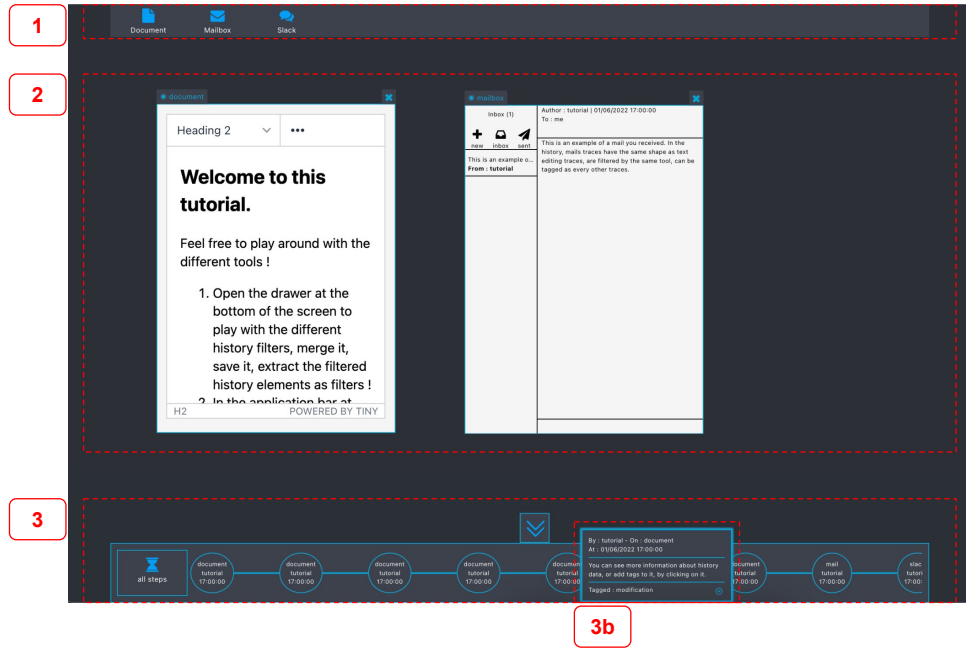


Figure 6. The *OneTrace Desktop* features (1) an application dock, here with a collaborative text editor, a mail client and a messaging app; (2) a workspace with two applications open; and (3) the main timeline where users can magnify Steps (3b).

described in the next section.

The front-end of the *OneTrace Desktop* is implemented with HTML, CSS and JavaScript using the JQuery and JQueryUI¹⁰ libraries and the TinyMCE¹¹ extensible WYSIWYG editor. The *OneTrace* server is implemented with Node.js¹². It logs steps in a JSON file and responds to requests for adding and querying steps.

5.1. The *TracePicker* tool

OneTrace and the *OneTrace Desktop* provide an infrastructure on top of which we can design and implement specific tools to interact with historical data. Based on the participatory design workshop results, we created *TracePicker* to help users organize traces.

TracePicker (Figure 7) is an instrument (Beaudouin-Lafon, 2000; Beaudouin-Lafon & Mackay, 2000) that lets users pick traces in a timeline and pin them together. We call these collections of traces *PickLines*. *TracePicker* lets users express relationships between Steps, thus supporting the (re-)contextualization of historical data. To express causality between traces, *TracePicker* lets users create custom clusters of historical data to organize them in a non-temporal way. Users can label these groupings to document their meaning. Users can also express a hierarchy among traces by marking some as important. Collapsing a *PickLine* hides non-important traces while expanding it shows all traces in the *PickLine*.

We implemented a *TracePicker* prototype (Figure 8) in the *OneTrace Desktop*¹³.

¹⁰<https://jquery.com>, <https://jqueryui.com>

¹¹<https://www.tiny.cloud>

¹²<https://nodejs.org>

¹³A video figure of this system can be found at dx.doi.org/10.6084/m9.figshare.24174006

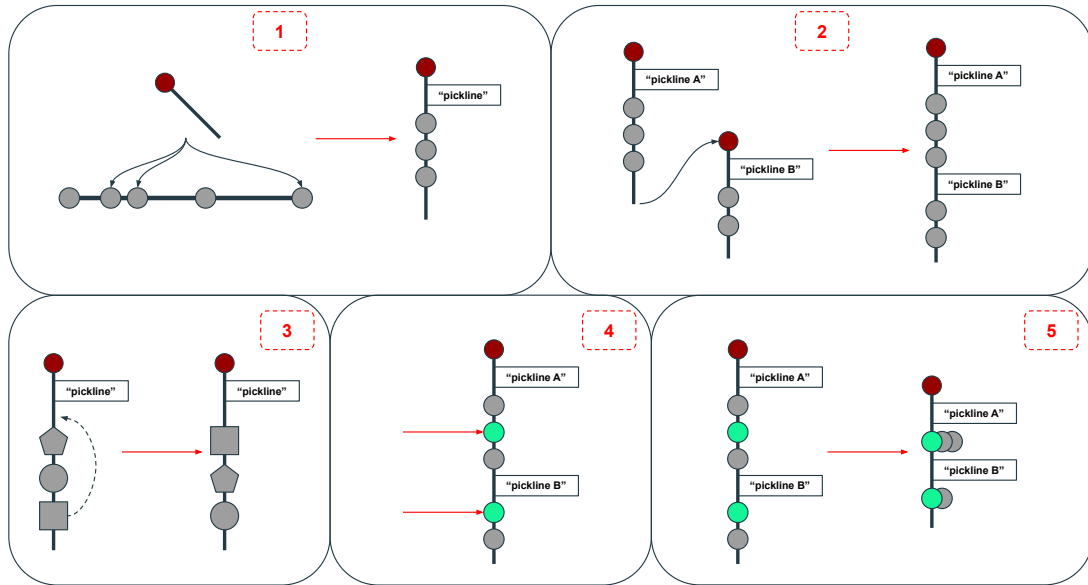


Figure 7. The *TracePicker* concept: (1) The *TracePicker* instrument is used to pick traces and pin them together, creating a *PickLine*; (2) *PickLines* can be joined to create subsets of traces; (3) the content of a *PickLine* can be re-organized; (4) traces can be set as important; and (5) *PickLines* can be collapsed and expanded.

The *TracePicker* tool is enabled by selecting it in the toolbar. It can then be used to pick-and-drop Steps from the timeline into the workspace to form a *PickLine*, or to pick other *PickLines* already in the workspace to form a sub-*PickLine*. Users can further organize the *Sequence* of Steps within a *PickLine* by drag-and-dropping them. Each *PickLine* has a label that users can modify to express the *Motivation* of the group. Double-clicking a Step from the main timeline or the *PickLine* itself toggles it as important and gives it more *Weight*. Clicking the tip of a *PickLine* toggles its display between the collapsed state that only shows the important Steps and the expanded state that shows all Steps. Drag-and-dropping a *PickLine* on the application dock saves it so that it can be accessed and reused by all team members. Finally, the trash tool can delete full *PickLines* or remove individual Steps from a *PickLine*.

6. Assessing Users' Perception of *OneTrace*

OneTrace was created to capture the traces left by multiple applications in a centralized place (theme T3 of the interview study) so that they could persist and not get lost (theme T5). Such a shared history enables the creation of dedicated tools for managing history data. *TracePicker* is such a tool, designed to let users create new history artifacts by building custom groups of historical data (theme T1) from different applications. *TracePicker* lets users augment historical data with annotations and link them together in new ways rather than being constrained by the temporal ordering of a timeline and the scope of a single application. The goal is to help users contextualize historical data for themselves and their teams (theme T2). By letting users reshape these artifacts into a collapsed form, we also aim to reduce the amount of data that users have to browse through (theme T4).

We conducted a questionnaire- and scenario-based study to observe the use of the

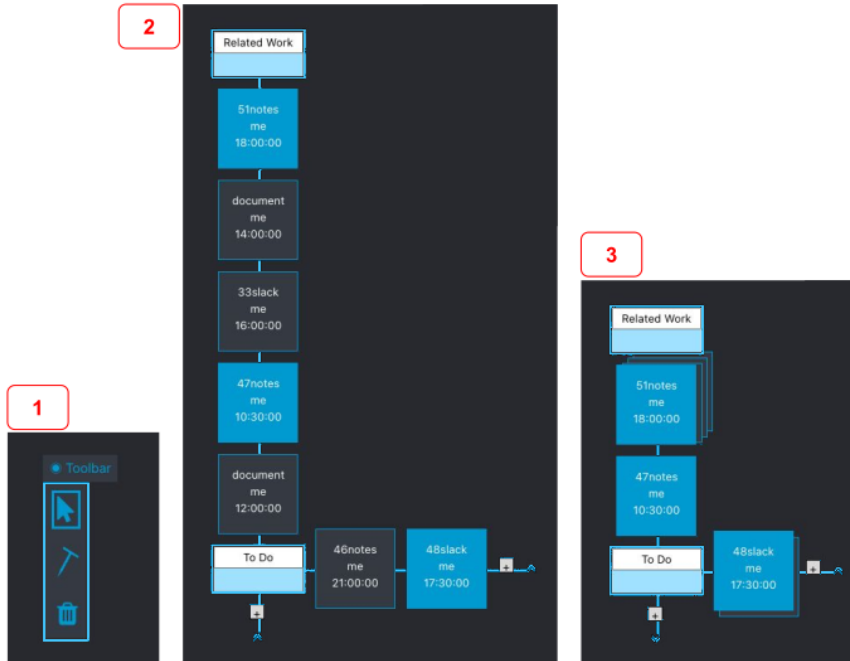


Figure 8. The *TracePicker* prototype features a toolbar to create and delete *PickLines* in the workspace (1). Users can pin Steps and other *PickLines* with the *TracePicker* to form a new *PickLine* (2) and shrink a *PickLine* to display only important Steps (3).

OneTrace Desktop and the *TracePicker* tool. We did not conduct a comparative study for two reasons. First, to our knowledge, no existing system provides a flexible cross-application history system comparable to *OneTrace*, making it difficult to find a meaningful baseline. Second, using real-world applications as a baseline would be unfair because our prototype *OneTrace Desktop* features applications with limited functionality.

The study addresses the following question:

RQ3: What are the users’ perceived benefits of using a cross-application history system such as *OneTrace* for collaborative writing tasks?

More specifically, we want to know whether users think *TracePicker* could help them reduce history bloat and focus on important traces compared to their current practices (study question *Q1*, related to themes T3 and T4); whether users think *TracePicker* could help them better contextualize traces compared to their current practices (*Q2*, related to theme T2); and whether users feel they could resume work more easily with *TracePicker* compared to their current practices (*Q3*, related to themes T1 and T5).

Participants. We recruited eight participants (seven men and one woman, aged 20-25) with a recent collaborative writing experience. Six participants were HCI Master’s students currently writing their Master’s thesis and sharing it with others, including their tutors. The two other participants were Ph.D. students currently writing a research article with other researchers.

Setup Participants used the *OneTrace Desktop* system in a controlled setup, in our lab, on a computer we provided.

Procedure. First, we asked the participants about their usage of historical data by having them fill out a five-point Likert-scale pre-study questionnaire assessing their issues with the systems they currently use¹⁴. In order to ground their answers, we asked them to think of a recent collaborative writing project.

Then, we introduced them to the *OneTrace Desktop* and the *TracePicker* tool with a short tutorial, walking them through the system’s features. After this tutorial, we asked them to follow a scenario (see below) where they had to perform a series of tasks representing different use cases. We prepared historical data for each task by creating a log file filled with steps to match the state of the project corresponding to each task. After going through the scenario, we asked them to fill out a five-point Likert-scale post-study questionnaire to evaluate how *OneTrace* would help them with their history usage. For both the pre- and post-study questionnaires, participants were encouraged to talk aloud to explain their choices. Each session lasted about 60 minutes.

Scenario. The scenario was designed so that it would sound familiar to the participants. Participants impersonate Sarah, a Master’s student writing her thesis report. They have to complete two tasks related to the two aspects we explored during the participatory design workshop: the first task assesses how participants create a *PickLine* and arrange Steps on it to *communicate progress* with history data or to reuse it later; the second task assesses how they use already existing *PickLines* to *understand and contextualize past actions*, typically after a break from work.

For the first task, *Sarah’s two supervisors, Anna and Carl, have recently given her their feedback on her draft, while she also has her own ideas on content to add or modify. Her workday is ending, and she wants to compile information about what she has to do tomorrow.* To perform this task, the participants can freely read the timeline and the traces, and open the applications in the *OneTrace Desktop*. Then, they are expected to create one or more *PickLines* with the *TracePicker* tool to help them better manage their return to work the next day. We created a history with 53 Steps for this task.

For the second task, we set up a situation where participants return to an activity after a long break and must reuse existing *PickLines* to remember the context. *Sarah just returned from 2 weeks of vacation. She had prepared multiple PickLines before leaving to remember what she did and what was left to do by the end of her internship.* To perform this task, the participants must answer a list of questions provided by the examiner about the different things Sarah has to do after returning from her break, using pre-built *PickLines* to find the requested information. Three *PickLines* were provided for this task: one with three Steps, one with five Steps and a more complex one with ten Steps and three branches.

Questionnaires. Both questionnaires feature 5-point Likert-scales (1 = totally disagree; 5 = totally agree) composed of seven items related to the study questions listed above. To answer the first study question (*Q1*), we ask participants if they feel in control over what traces are displayed and available to them in the histories (Item 1/*I1*) and if they feel able to find relevant traces in a large amount of information (*I2*)¹⁵. To answer *Q2*, we ask participants if they feel able to contextualize their own past actions (*I3*) and their teammates’ traces (*I4*). Lastly, to answer *Q3*, we ask participants if they feel able to resume work with the tools at their disposal after a short break of

¹⁴The questionnaires are available in Appendix B.

¹⁵The question does not specify what we mean by “large”. We leave it to the participants’ interpretation.

about an hour to a day (*I5*), a long break of at least a week (*I6*), and in general (*I7*).

In the pre-questionnaire, the statements are about the participant’s use of current tools. For example (Item3/Pre-questionnaire): *With my current tools’ histories, it is easy to contextualize my own past actions.* In the post-questionnaire, the statements are the same but about the potential benefits of *OneTrace*. For example (Item3/Post-questionnaire): *With this system, it would be easier to contextualize my own past actions.*

Data Collection. We took notes during the study and collected the answers to the two questionnaires. Participants were encouraged to think aloud while answering the questionnaires and while reflecting on their actions when performing the tasks. Each session was video-recorded.

Analysis Method. We used a mix of qualitative and quantitative methods. Questionnaire data were analyzed with summary statistics. Think-aloud data were annotated by the researcher conducting the experiment, focusing on feedback and opinions about *OneTrace* and cross-application history systems. Videos were transcribed by the researcher in charge of the experiment.

6.1. Results

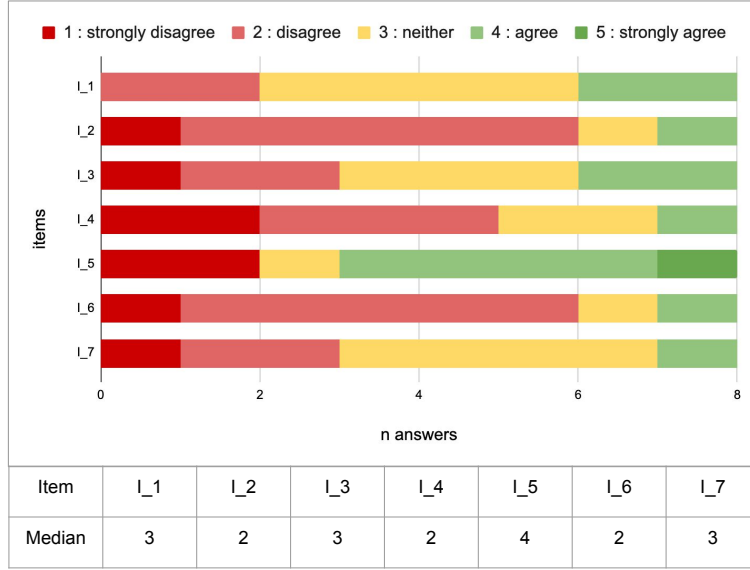
Figure 9 shows the results of the pre- and post-questionnaires. The median rating for each question increases between the pre- and post-questionnaire, except for question *I5*, where it stays the same. Given the small number of participants ($n = 8$), a significance test is not robust. Nevertheless, we report the results of the Mann–Whitney U test (or Wilcoxon rank-sum test), which is significant for all questions except *I1* ($p = .052$) and *I5* ($p = .317$).

The increase in median rating for items *I1* ($3 \rightarrow 4$, $U = 13$, $p = .052$) and *I2* ($2 \rightarrow 5$, $U = 6.5$, $p = .009$) suggests that *TracePicker* helped participants focus on important historical data and reduce data bloat (*Q1*). Participants appreciated that they could mark some Steps as important and only display the most relevant ones. However, they would have liked the ability to add other information, such as color coding, and archive historical data that is unlikely to be used again.

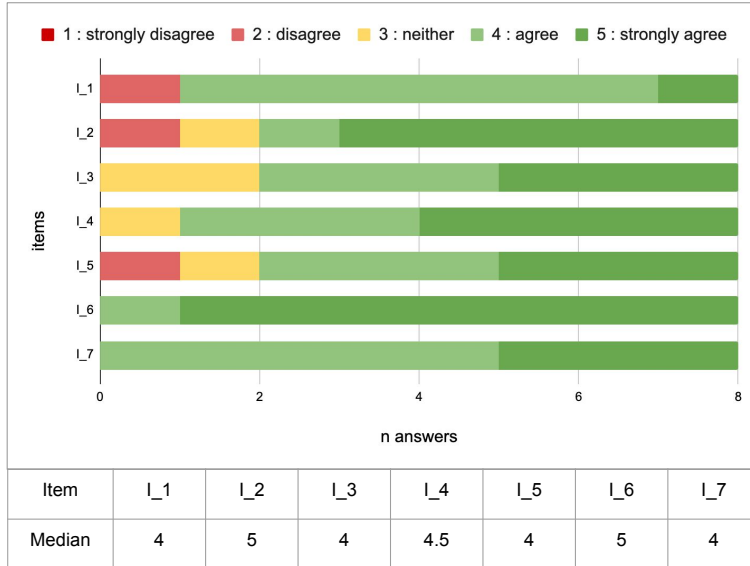
Similarly, the increase in median ratings for the contextualization items *I3* ($3 \rightarrow 4$, $U = 10$, $p = .024$) and *I4* ($2 \rightarrow 4.5$, $U = 3.5$, $p = .003$) show that *TracePicker* seems to make it easier for participants to express and understand the context of past actions in an environment with multiple shared artifacts (*Q2*).

Regarding the items about resuming work, the median rating for resuming after a short break is stable (*I5*, $4 \rightarrow 4$, $U = 22$, $p = .317$) while it shows an increase (*I6*: $2 \rightarrow 5$, $U = 0.5$, $p = .001$; *I7*: $3 \rightarrow 4$, $U = 2.5$, $p = .002$) for resuming after a medium or long break. These results suggest that *TracePicker* improves resuming work except for short breaks (*Q3*). We assume that participants rely on their memory rather than their tools after a short break. Indeed, two participants said that they do not have “*issues remembering things after a short break*”.

In summary, all ratings but one increased between the pre- and post-questionnaire, suggesting that participants valued the features that put them in control of historical data to help them better understand the context of past actions. When resuming work after short breaks, they did not see the benefit of organizing their history rather than simply relying on their memory and some saw it as a waste of time.



(a) pre-questionnaire results



(b) post-questionnaire results

Figure 9. Answers to the questionnaires of the *TracePicker* study. The pre-questionnaire (a) is about participant’s opinion of their existing tools, while the post-questionnaire (b) is about their opinion on the improvements brought by *TracePicker*.

6.2. Discussion

We created the *TracePicker* instrument to enhance historical data contextualization by letting users create custom collections of Steps. Study results suggest that the *PickLines* created with *TracePicker* make it easier to contextualize past actions (*Q2*), resume work after a medium or long break (*Q3*), and reduce bloat by focusing on important historical data rather than details (*Q1*).

Notably, five out of the eight participants only used the *PickLines* to understand the timeline of events and did not refer to the document. They stated that the structure and the labelling of the *PickLines* were sufficient to contextualize the progress on the

document. Six participants explicitly stated that they saw the benefit of using the tool to avoid bloat. Some added branches to their *PickLines* to isolate information from the overall timeline, others found the highlighting and shrinking features sufficient to facilitate synthesizing history. While all participants expressed that the tool would be clearly useful after long-term breaks, they also expressed reservations in the case of short-term breaks. They felt that it would require too much work for the expected benefits.

We also noted that participants liked the ability to create meaningful new artifacts from their history (“*You can just put everything you need there and refer to it later*”). In summary, users found that *TracePicker* facilitated the contextualization of past actions *RQ3*. These findings demonstrate the value of a cross-application history environment such as *OneTrace* to better re-document past actions, understand the timeline of shared content, and enhance coordination.

While *TracePicker* seems to address the issues we identified successfully, there is room for improvement. First, users could have even more control over creating custom history artifacts such as *PickLines* by freely tweaking and reshaping these artifacts and their content. Second, we observed two patterns when participants performed the second task (understanding past actions using a provided *PickLine*). Some participants found that the structure of the *PickLines* (labels and groupings) was sufficient to get the needed contextual information. Others browsed the text document and the main timeline, mostly to be sure not to miss important information. While the latter did not explicitly mention the lack of connection between a *PickLine* and the content it relates to, we believe that establishing such links could improve contextualization, similar to the way the text snippets in *Passages* (Han et al., 2022) remember their provenance and let users navigate back to their origin. This could help users consolidate context around historical data, e.g. by referencing parts of a document in a discussion and including these links in histories. Finally, users expressed reservations about the usefulness of the tool after a short break due to the effort needed to create a *PickLine*. To address this issue, future designs should explore the automated generation of *PickLines*, to lower the threshold for creating *PickLines*.

As with any study, this work has limitations. First, the number of participants was small and the study should be replicated and extended. Second, as a short-term lab study, we could not assess the scalability of the approach to longer periods and larger histories. A long-term field study should address these questions. This would require integrating *OneTrace* with existing tools since the limited features of the applications in our proof-of-concept implementations are unsuitable for real work over an extended period. Third, the scenario was limited in scope to keep the study within about an hour. More realistic scenarios would require a longer study, and could exhibit some limitations of the proposed approach. Finally, the scenario-based approach meant that the participants had to understand the history of a project in which they did not participate beforehand. We therefore could not assess the impact of the participants’ memory on their assessment of the system. On the other hand, this created a situation often encountered in collaborative settings when a new team member joins an existing project and has virtually no knowledge of the actions performed on shared content.

7. Conclusion and Future Work

Knowledge workers must often access historical data to make sense of a collaborative project and coordinate with team members. Yet few tools exist to manage and access

history, especially when the activity involves multiple applications and users. The work presented in this paper makes four main contributions.

The first contribution is empirical. We conducted an interview study with twelve participants that showed that they actively use historical data to keep track of the timeline in collaborative projects. We found that participants navigate, extract and merge historical data and try to regroup them in common places for sense-making and coordination with their team. However, we identified a key problem: current tools generally capture historical data in a proprietary way and make it available only from within the tool itself. This lack of interconnection between histories requires users to navigate numerous places to find the correct information and leads to workarounds that require additional work.

The second contribution is conceptual. In order to solve this problem, we introduced the *Step*, a generic, application-independent data structure that reifies the concept of historical event into a first-class object. A Step includes core attributes set at creation time to describe the who/what/where/when of the logged event and context attributes that users can edit to convey additional meaning about the event. Steps can be managed *outside* the applications that generate them, opening the way to dedicated tools for managing history data.

The third contribution is technical. We developed *OneTrace*, a cross-application interaction history system that collects Steps sent by applications and makes them available to dedicated history tools. This design goes beyond related work by providing users and designers with a way to treat traces as digital material that can be reshaped based on users' needs.

The fourth contribution is about interaction. Based on the results of a participatory design workshop, we created *TracePicker*, an instrument designed to document histories and better express the context of past actions. *TracePicker* lets users create *PickLines* that gather relevant Steps, annotate them, and filter the most important ones. *TracePicker* was integrated into the *OneTrace Desktop*, a web-based simulation of a desktop environment designed to assess the value of our approach. We conducted a questionnaire- and scenario-based user study where participants used *OneTrace* to perform two tasks. This study provided evidence that a unified history and appropriate tools can help users appropriate historical data and create new artifacts for sensemaking and coordination.

In future work, we plan to implement a more robust version of *OneTrace* and refine its design to run a long-term user study. We also plan to create additional instruments to manipulate new history-related artifacts and further study how users appropriate them.

In summary, this work contributes the notion of cross-application history based on the concept of Step, the *OneTrace* server and *TracePicker* instrument to manipulate historical data, and a study demonstrating the value of this approach. It provides evidence that cross-application, cross-user history and associated tools should be integral to collaborative software. This work is of interest to system and application designers, who should integrate history as a “first-class object” in their designs and standardize formats and APIs for interoperability of history across tools. This work is also of interest to researchers in Collaborative Computing and HCI at large, who can build on our results to explore new ways of supporting interaction with history data in interactive and collaborative systems. We hope to see the concept of externalised history widely adopted to enable the design and implementation of advanced history tools.

Acknowledgements

We thank all our participants for their time and their rich insights.

This work was partially supported by European Research Council (ERC) grant n°695464 “ONE: Unified Principles of Interaction”. The authors report there are no competing interests to declare.

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Appendix A. Privacy Concerns and Shared Histories Questionnaires

Introduction:

As a reminder, an activity trace is a piece of information about past actions on the project, which will be left by you or one of your team members.

It will allow you in some cases to keep track of the progress on the project.

It can be, for example, different versions of a document, annotations or comments, modification histories, discussion/communication histories, or even written notes.

It can be data shared between the different actors in the project, or data that you keep personally.

Privacy concerns questionnaire

The following statements are related to your experience, or your feelings towards real-time collaborative work tools (such as Google Doc).

During a collaborative writing project:

- I would be willing to use tools to write text in real time with other members of my team.

1. strongly agree 2. agree 3. neither agree nor disagree
4. disagree 5. strongly disagree

- I would be willing to store our common work around the writing project in a shared environment.

1. strongly agree 2. agree 3. neither agree nor disagree
4. disagree 5. strongly disagree

- I would be willing to share in real-time data such as my modification history or my comments on a shared document.

1. strongly agree 2. agree 3. neither agree nor disagree
4. disagree 5. strongly disagree

- I would be willing to share with the other members of my team the history of discussions I have had around the project.

1. strongly agree 2. agree 3. neither agree nor disagree
4. disagree 5. strongly disagree

- I would be willing to share personal material such as my written notes, or my summaries of meetings about the project.

1. strongly agree 2. agree 3. neither agree nor disagree
4. disagree 5. strongly disagree

Shared histories questionnaire

The following statements are to be rated based on things you felt were missing or needed during the writing project you had in mind for the previous statements.

It would have been necessary for my current tools:

- To be able to synthesize the progress of my team on a project at key moments.
1. strongly agree 2. agree 3. neither agree nor disagree
4. disagree 5. strongly disagree

- To have a common and unique space where to gather all my team's communications about the project.
1. strongly agree 2. agree 3. neither agree nor disagree
4. disagree 5. strongly disagree

- To be able to link the different communication channels with the discussed collaborative documents.
1. strongly agree 2. agree 3. neither agree nor disagree
4. disagree 5. strongly disagree

- To be able to visualize all activity traces in a single space to be able to navigate through them.
1. strongly agree 2. agree 3. neither agree nor disagree
4. disagree 5. strongly disagree

- To be able to link my personal traces (written notes, recordings, non-shared documents...) with my collaborative project.
1. strongly agree 2. agree 3. neither agree nor disagree
4. disagree 5. strongly disagree

Appendix B. *TracePicker* Study Questionnaires

Participant ID :

Pre-study questionnaire

- Q1: With my current tools' histories, I feel in control over what information my histories display.
For example, searching for a specific item/filtering actions.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree
- Q2: With my current tools' histories, it is easy to deal with a lot of history information.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree
- Q3: With my current tools' histories, it is easy to contextualize my own past actions.
Contextualize means associate meaning with actions. For example, you modified your conclusion because your supervisor told you to.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree
- Q4: With my current tools' histories, it is easy to contextualize my team's past actions.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree
- Q5: With my current tools' histories, it is easy to resume work after a short break.
After a lunch break, a day off.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree
- Q6: With my current tools' histories, it is easy to resume work after a long term
After one or two weeks off.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree
- Q7: Overall, it is easy to resume working with my current tools' histories.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree

Participant ID :

Post-study questionnaire

- S1: With this system, I would feel more in control over what information my histories display.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree

- S2: With this system, it would be easier to deal with a lot of history information.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree

- S3: With this system, it would be easier to contextualize my own past actions.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree

- S4: With this system, it would be easier to contextualize my team's past actions.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree

- S5: With this system, it would be easier to resume work after a short break.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree

- S6: With this system, it would be easier to resume work after a long term break.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree

- S7: Overall, it would be easier to resume working with this system.
1- strongly disagree 2- disagree 3- neither agree nor disagree
4- agree 5- strongly agree

Add any additional comments on the system/application here:

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Participant ID :

Additional information

Age :

- 18 - 25
- 25 - 30
- 30 - 35
- 35 - 40
- 40 - 45
- 45 - 50
- 55 - 60
- more than 60
- do not want to answer

Gender :

- male
- female
- not listed :
- do not want to answer

Appendix C. *OneTrace* logging system

Each Step is represented by a plain JavaScript object in the *OneTrace* server according to the Step structure defined in the paper (Figure 5). The list of steps is stored in JSON by the server and can be accessed and modified by the clients of *OneTrace*.

```
//steps.json
{
  "steps": [
    {
      "id" : "0001",
      "source" : "document",
      "content" : "Hello world",
      "tags" : [
        { "name" : "modification" }
      ],
      "author" : "Mark",
      "date" : "01/06/2022 17:00:00",
      "linkfrom" : [
        { "id" : "0002"},
        {...}
      ],
      "linkto" : [
        { "id" : "0003"},
        {...}
      ],
      "priorityon" : [
        { "id" : "0004"},
        {...}
      ]
    },
    {
      ...
    }
  ]
}
```

id is a unique id defined by the server.

source, content, date and author store the core attributes.

linkto and linkfrom store the sequence attribute.

priorityon stores the weight attribute.

tags stores the motivation attribute.

Applications call the following method to log a new step in the system. The server then generates a unique id and pushes a new step onto the JSON file.

```
function addNewStepInHistory(source, content, tags, author,
                             date, linkfrom, linkto, priorityon)
```