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Draft

Tool Support for Knowledge Foraging, Structuring, and Transfer During Online Sensemaking

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Abstract

While modern search engines are excellent resources for finding information on the web, in order to put together that information into a useful mental model for learning or making a decision – such as picking a new car or choosing a JavaScript library – people often need to collect information about the options available and the criteria on which to evaluate the options, synthesize such information from various sources into a meaningful structure, and share and justify the results with others. This sensemaking process, often highly iterative and cyclical, puts a significant cognitive burden on users, and often requires them to externalize their evolving mental models rather than keeping everything in their working memory. However, not only the tools that people use for externalization – such as browser tabs, documents, spreadsheets, or note-taking apps – poorly support the constant shifts between collecting, extracting, organizing, and reorganizing that are needed, but worse yet, even if they do put in the work to organize and share an external representation of their learning outcome or decision rationale (such as creating a list of suitable cars or a table of front-end libraries), it can still be difficult for subsequent users to evaluate whether they can or should trust and reuse that work without wasting it.

In this thesis, I explore interactive systems which bridge the gap between the rapidly evolving mental models in peoples’ heads and the externalization of those models by **exploring opportunities to reduce the costs and increase the benefits of externalization**, thereby capturing more of the cognitive work that users engage in while making sense of information in order to help them as well as subsequent people who might benefit from their work.

To help the initial users forage and structure information, my collaborators and I together designed **Unakite**, a browser extension that enables people to easily collect and organize information into a comparison table in a sidebar as they are searching and browsing, which proved to be able to significantly lowered the friction of externalizing mental models compared to conventional approaches like taking notes and saving screenshots in a separate Google Doc. Building on Unakite, we explored approaches to further reduce the cost of externalization and help people focus on their main activity of reading and making sense of web content, such as by intelligently and automatically keeping track of key information and evidence on behalf of a user (the **Crystalline** system) and leveraging novel lightweight interaction techniques (the **Wigglite** system). To help subsequent users explore and evaluate previous users’ work, I developed both a framework and the **Strata** system that collects and visualizes key signals about the context, trustworthiness, and thoroughness of previous design decisions and rationale.

Despite these advances, the dynamic and evolving nature of sensemaking – particularly in the early stages – means that the structures people created often become obsolete as their mental representations evolve over the course of an investigation. To complete my dissertation, I propose to integrate my existing work together, and in addition, explore what kinds of knowledge organizational structure (e.g., lists, mind maps, affinity diagrams, etc.) are the most appropriate during different stages of sensemaking, and how can tools support users in fluidly and effortlessly transforming these structures to reflect their evolving mental models. Similar to my previous work, I plan to evaluate the new systems through a series of lab and field studies with people solving their real-world problems.

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Chapter 1

Introduction

While modern search engines are excellent resources for finding information on the web, in order to put together that information into a useful mental model for learning or making a decision – such as picking a new mirrorless camera, researching a medical diagnosis, or choosing a JavaScript library to build websites – people often need to collect information about trade-offs from multiple sources, extract and synthesize snippets of information into meaningful structures, or keep track of, share, and justify their decisions and rationale with others or to their future selves.

During this process of sensemaking, people’s mental models constantly evolve as they gather more information about the decision space – the contexts relevant to their goals, the options available, and the criteria or constraints on which to evaluate the options. For example, a YouTuber seeking to upgrade her vlogging setup may learn about many different camera options from various websites. As she discovers them, she prioritizes in her head which she wants to investigate first, looking for video samples and reviews that speak either positively or negatively about those cameras in terms of various dimensions such as sensor resolution, zoom range, color accuracy, battery life, etc. Indeed, estimates suggest that up to 1/3 of the time people spent online [143,186,228], or around 24 billion hours per year (as of 2009) in the US alone [30], are spent performing such complex and cognitively-demanding sensemaking tasks.

This highly iterative and cyclical process puts a significant cognitive burden on users, and often requires them to **externalize** their evolving mental models rather than keeping everything in their working memory. However, the tools that people have access to nowadays for externalization – such as browser tabs, documents, spreadsheets, or note-taking apps -- poorly support the constant shifts between information collecting, extracting, organizing, and reorganizing that are needed. Therefore, *the gap between the quickly evolving mental models in peoples’ heads and the lagging representations of those models in external documents* means that people often abandon their efforts to externalize halfway or avoid doing so in the first place [57,61,114,177], and instead keep everything in their working memory, which, unfortunately, is not unlimited [124,188,261].

Furthermore, even if people do put in the work to organize and share an external representation of their learning outcome or decision (such as creating a list of reasonable vlogging cameras or a comparison table of front-end libraries), *it can be difficult for subsequent users to evaluate whether they can or should reuse that work*. Often, the perceived effort of deciding to reuse someone else’s sensemaking knowledge might exceed that of redoing the sensemaking from scratch – it involves, for example, judging whether the initial knowledge creator’s goals and context match

with that of the subsequent user themselves, if the creator has the proper expertise and has performed a thorough job of surveying the information landscape. For example, a subsequent vlogger can theoretically take advantage of the camera options and reviews that the previous YouTuber has found, but they may have a vastly different budget to begin with, and may need to double check if there are additional alternatives available on the market, etc., and may ultimately prefer to redo their own sensemaking despite of the rich knowledge that the first person has summarized together.

In this thesis, I¹ explore interactive systems which bridge the gap between the rapidly evolving mental models in peoples' heads and the externalization of those models by exploring opportunities to **reduce the costs and increase the benefits of externalization**, thereby capturing more of the cognitive work that users engage in while making sense of information in order to help them as well as others who might benefit from their work.

The research efforts described in this thesis can be divided into four interrelated stages: *helping the initial user (1) forage and (2) structure information, and helping subsequent users (3) evaluate and (4) adapt and reuse the initial users' sensemaking results*. I posit that *the same signals that could help computational tools understand initial people's context and intents can also help subsequent people evaluate and decide whether and how to reuse the artifacts scaffolded by those tools*. Therefore, an overarching goal for this thesis is to understand and explore synergies in making it worth people's effort to provide rich signals about their sensemaking context and mental models to tools that can help them more effectively collect, organize, and refactor information and knowledge, and leveraging those signals to lower the cost for subsequent users to evaluate and adapt the knowledge externalized by previous users. Next, I provide a brief overview of the four prototype systems that constitute my completed work, and then discuss how my proposed work would further contribute to this goal.

1.1 Overview

Capturing and externalizing people's mental models can be challenging for a number of reasons. For example, as mentioned above, people are generally extremely sensitive to the cost structure of the tools they use for making sense of information, and any tool that adds a perceived burden or obstacle to their natural sensemaking process is likely to not be adopted. In addition, people are often uncertain about which information will eventually turn out to be relevant, valuable, and worth capturing, especially at early stages of their learning and exploration when they are overloaded with information. Also, the need for externalization of their mental models are often not discovered until part way through an investigation process, such as juggling much more options, criteria, and trade-offs than initially anticipated, or simply being required to document a decision and the rationale for downstream auditing purposes, etc.

To lay the foundation for people to externalize their mental models, I designed the **Unakite** system, which enables people to collect, organize, and keep track of information about decision trade-offs and build a comparison table, which can be saved as design rationale for later use. To address the potential high interaction and interruption cost of manually collecting and organizing information, I explored automatic approaches by leveraging natural language processing (NLP)

¹Although this thesis proposal is based on research projects that I have personally led, this document predominantly contains the pronoun "we" out of respect to all of my collaborators who have contributed to the research.

and passive behavioral signals that people naturally exhibit while searching and browsing such as mouse movement and dwell time (the **Crystalline** system). In the meantime, I also explored a family of lightweight gestures (which we framed as “wiggling”) that can be used to fluidly collect and annotate information in-situ without much interruption to the primary activity of reading and comprehending web content (the **Wigglite** system). Finally, to help subsequent users explore and evaluate previous users’ work for potential reuse, I both summarized a framework (through interviews) and developed the **Strata** system that collects and visualizes to subsequent users the key signals about the context, trustworthiness, and thoroughness of previous design decisions and rationale.

Despite these advances, the dynamic and evolving nature of sensemaking – particularly in the early stages – means that the structures people created often become obsolete as their mental representations evolve over the course of an investigation. To complete my dissertation, I propose to integrate my previous work together, and explore what kinds of knowledge organizational structure (e.g., lists, mind maps, affinity diagrams, etc.) are the most appropriate during different stages of sensemaking, and how can tools support users in fluidly and effortlessly transforming these structures to reflect their evolving mental models. Similar to my previous work, I plan to evaluate the new systems through a series of lab and field studies with people solving their real-world problems.

To ground the exploration, I primarily focus on two domains: programming and consumer decision making, because both involve frequent learning and research on the web followed by potentially impactful decisions, and are specific enough to engage with deep contextual complexities, yet provide insights that generalize to other sensemaking activities.

1.2 Expected Contributions

The series of work introduced in this thesis points to the importance of having tool support that helps users efficiently organize and manage information as they find it in a way that could also be beneficial to others, and therefore bootstrapping the virtuous cycle of people being able to build on each other’s sensemaking results, fostering efficient collaboration and knowledge reuse.

Specifically, my existing work made the following contributions thus far:

- A thorough review of the background and related research on sensemaking in general and the various tools and systems for foraging, structuring, evaluating, and reusing knowledge (**chapter 2**).
- Unakite, a prototype system that reduces the costs of capturing and organizing online information in-situ and preserves the knowledge as design rationale [131, 177] (**chapter 3**).
- Evidence that it is possible to automatically identify options, criteria, and relevant evidence from web pages that a user is browsing using a set of natural language understanding heuristics [179] (**chapter 4**).
- A set of implicit behavioral signals that users exhibit when browsing the web which can be leveraged for prioritizing and filtering that collected information [179] (**chapter 4**).
- A prototype system called Crystalline that integrates the heuristics and behavioral signals to automatically collect and organize viewed information into list and comparison table views for subsequent decision making [179] (**chapter 4**).

- A novel class of wiggle-based gestures that are cognitively and physically lightweight to perform to collect information, and can simultaneously encode aspects of users' mental context [180] (**chapter 5**).
- A prototype event-driven JavaScript library that implements such wiggle-based gestures and runs in web browsers [180] (**chapter 5**).
- Wigg-lite, a prototype system that takes advantage of the wiggle-based gestures to enable information capturing and classification during sensemaking that works on both desktop and mobile devices [180] (**chapter 5**).
- A synthesized framework for augmenting judgements of appropriate knowledge reuse including three major facets: context, trustworthiness, and thoroughness [178] (**chapter 6**).
- A prototype system called Strata that automatically records, computes, and visualizes many of the appropriateness signals described in the framework [178] (**chapter 6**).
- A series of lab studies showcasing the usability, usefulness, and effectiveness of our tools in reducing the costs and increasing the benefits of externalizing people's mental models when sensemaking.

In the proposed work, I plan to make the following contributions:

- A prototype system that support users to create multiple types of organizational structures and fluidly transform them to reflect their evolving mental model during both early and late stages of their sensemaking processes.
- A lab evaluation of the prototype system that probes its usability, usefulness, and effectiveness.

Chapter 2

Background & Related Work

Sensemaking is widely considered to be the process of searching, collecting, and organizing information to iteratively develop a mental model of an information space in service of a user's goals [220, 234]. A number of models of sensemaking have been proposed, including Russell et al.'s cost structure view [234], Dervin's sensemaking methodology [75], Klein et al.'s data-frame model [150], organizational process views [71, 99], organizational adaptation views [71, 195], and the notional model by Pirolli and Card [219]. At a high level, these models agree that a sensemaking process involves alternating between two phases: **foraging**, which involves people searching for and extracting information, often from various data sources; and **structuring**, the process of integrating the amassed information to form a schema or representation to interpret the space [220]. More recent work has also explored the concept of distributed sensemaking [90, 167], which involves **evaluating** whether to take advantage of and reuse an initial user's decision making results or sensemaking artifacts [90, 106, 245] and **adapting and reusing** them for their own purposes [107, 216]. Below, I briefly discuss the related work for each of these stages.

2.1 Foraging

Prior work has reported that the foraging phase, which involves collecting and extracting information, is where people tend to spend the majority of time during a sensemaking process [47, 55, 185, 219]. Thus, there have been many research and commercial tools that try to help people better capture information during this phase. Some focused on keeping track of entire web-pages or documents, such as SenseMaker [32], browser bookmarks, and reading lists; while others enabled users to capture finer-grain units within a web document, such as Hunter Gather [242], Clipper [148], and Google Notebook [103].

However, foraging can be challenging both *physically*, because the complex structure of web pages can make it hard to select the desired content with exact boundaries and tiresome to repeat the selection frequently [58, 63, 230], and *cognitively*, because in early stages of sensemaking people often are not sure what will actually end up being relevant, useful, and worth collecting [34, 90].

With respect to the physical demand for collecting and extracting information while searching and browsing, prior work has pointed out that users need quick and lightweight interaction techniques, because if the physical cost is too high (such as specifying the boundaries of some

desired content, copying it, switching context to the target tab or window, and transferring the information into the application where it will be stored [89]), users tend not to capture information in the first place [124, 177, 188, 261]. Prior work has explored various ways to lessen the physical cost – on the one hand, multiple approaches have been proposed to make selecting desired content faster by offering pre-defined selection boundaries. For example, systems like Entity Quick Click and Citrine [40, 138, 256] employ techniques like named-entity recognition [184] to pre-process and highlight semantically meaningful entities in a document and allow users to collect and annotate relevant information with a single click. On the other hand, research and commercial products have explored collecting information on behalf of users as they search and browse the web. For example, works such as Thresher [125] and Dontcheva et al.’s web summarization tool [78] let users create and curate patterns and templates of information that they want to collect through examples, and then automatically collect that information from pages that users visit in the future.

With respect to the cognitive cost for collecting and extracting information in-situ, people often have to reason and make a decision about which and how much information to capture despite being uncertain about its future value [53, 58, 118, 148, 282]. In addition, such frequent mental context switches away from reading and making sense of the actual web content can be extra interruptive [124, 148, 239]. Before a user has built a good mental model of an information space, they have to manage the tension between extracting too much information that later turns out to be irrelevant, versus extracting too little information and later having to revisit webpages to collect additional information. Recent work by Chang et al. [58] proposed one potential way of easing the cognitive burden by allowing users to just create “fuzzy” selection of web content on the go and defer the precise specification of what to capture and persist till a second pass.

2.2 Structuring

After collecting and extracting useful information, a user needs to synthesize it into structures that are useful for interpreting the information space and achieving their goals of learning or decision making. The idea of building structured representations of information has a history dating back at least to the visions articulated by Vannevar Bush and others of associative memory, spatial hypertext, and other means of extending the human intellect (e.g., [51, 82, 173, 189, 203]). Since then, there have been many attempts at structuring web content, including lists, tables, graphs, trees, mind maps, argument maps, and panels [278], however, empirical research has found that using such tools can feel like “learning a new language” [146].

Prior work has explored various ways of incorporating lightweight information classification into the foraging phase to leave clues and hints that scaffold later organization. For example, Clipper [148] and Adamite [128] all prompt the user to optionally categorize an information clip after it has just been captured. Spar.tag.us [126] enables users to associate custom tags with individual paragraphs. ForSense [223] leverages natural language processing to automatically cluster information clips based on themes and topics.

There have also been a number of research tools developed to support in-depth organizing and structuring. These include the WebBook and WebForager by Card et al. [54], which use a book metaphor to find, collect, and manage web pages; Butterfly by Mackinlay et al. [182] aimed at accessing articles in citation networks; the Navigational View Builder [200] which combined

structural and content analysis; Elastic Windows, which provided information overview and location context [141]; Webcutter, which collects and presents URL collections in tree, star, and fisheye views [181]; SenseMaker [32] for evolving collections of information; PadPrints [122], a zoomable history browsing interface; and Scatter/Gather [70], a text-clustering interface for iteratively navigating through document collections. Related tools that support aspects of structuring include extraction pattern approaches such as in [78], Stepping Stones and Pathways [72], Cat-a-Cone [120], Data Mountain [226], TopicShop [26, 262], Hunter Gatherer [242], Haystack [142], and Internet Scrapbook [257].

Despite these attempts, the dynamic and evolving nature of sensemaking – particularly in the early stages – means that users often would avoid the cost of structuring or even committing to a particular structure. Even if they do organize information, the structures that they created often become obsolete as their mental representations evolve over the course of their investigation (such as realizing a particular criterion should be prioritized, which prompts an entirely different investigation of several new options, etc.), with no single type of structure likely to remain the most appropriate throughout the whole sensemaking process [90, 119, 148]. Instead, people often would try to keep everything in their working memory, which, unfortunately, is not unlimited [43, 185, 229].

2.3 Evaluating and Reusing

Information and knowledge reuse has become a highly consistent paradigm across a wide range of fields and disciplines to advance their respective frontiers, such as reusing previous engineering best practices on future generations of products [35, 36], taking advantage of schemas and results from previous sensemaking episodes to create new representations and understandings of the world [90, 147, 198, 215], and plugging in previously written and well-maintained design patterns and code snippets to build novel software features and functionalities [4, 16, 96, 97, 155]. Reusing proven information and knowledge promises the benefits of potentially reduced workload and development cycles [35, 155], improved quality and performance [97, 112, 274], and more time for creation and innovation [135, 183, 187, 274].

Despite these benefits, consuming someone else’s sensemaking results can incur significant costs, including deciding whether the initial user’s context is similar enough to their own for that work to be relevant, and evaluating whether the initial user’s trustworthiness and thoroughness are sufficiently high to believe in their results. Prior work has reported various factors that influence the *evaluation* of others’ work, including but not limited to: domain name and URL, presence of a timestamp showing that the information is current or sufficiently up-to-date, authors’ identification and indication of their expertise on the topic, citations to references or scientific evidence, and user ratings or reviews [24, 45, 85, 92, 98, 167, 190, 191, 193, 250, 264, 273]. These factors are common across a wide range of reuse scenarios such as choosing software architectures, libraries, and APIs, purchasing consumer products, handing-off or taking over design and management projects, etc [33, 59, 112, 177, 187, 196, 245, 247, 254].

However, in reality, it has been repeatedly shown that people are often under-prepared and have trouble determining how to evaluate others’ work [29, 190, 192, 240], which is often deemed to be too much effort [190, 245], having a high possibility of missing important details [191, 193]. As a result, users may end up starting from scratch rather than engaging in the potentially costly

consumption of someone else's work if they are uncertain about how relevant and useful that work will end up being [90, 174, 175, 191].

Over the years, many systems have been developed to support knowledge hand-off and reuse during which the current sensemaker (subsequent user) needs to make sense of and evaluate the appropriateness of reusing the results generated by a previous sensemaker (initial user) [187, 245]. Various metadata and properties parallel to the main artifacts of sensemaking have been proposed that would help subsequent users with this process, such as the awareness of the previous sense-making process [79, 215] (e.g., search queries and visited web pages), the level of expertise of the initial user [187, 247], the context of the original sensemaking problem [187], and the initial user's design rationale [159, 160, 252]. However, it is both time and effort intensive for a sensemaker to keep track of their rationale and processes with little immediate payoff, which is also often for the benefit of others rather than themselves [177]. Even in situations where authors have the explicit wish to help, they are often uncertain of what metadata and properties to provide and how those can be instantiated using concrete signals that would be valuable to the consumers in evaluating the reusability of their sensemaking results [245].

Chapter 3

Unakite: Foraging and Organizing Online Information

This chapter was adapted from my published papers:

Michael Xieyang Liu, Jane Hsieh, Nathan Hahn, Angelina Zhou, Emily Deng, Shaun Burley, Cynthia Taylor, Aniket Kittur, and Brad A. Myers. 2019. “Unakite: Scaffolding Developers’ Decision-Making Using the Web.” *In Proceedings of the 32nd Annual ACM Symposium on User Interface Software and Technology (UIST ’19)*. Association for Computing Machinery, New York, NY, USA, 67–80.

Video: <https://youtu.be/UMQ-kWgmbQ4>

Jane Hsieh, Michael Xieyang Liu, Brad A. Myers and Aniket Kittur, “An Exploratory Study of Web Foraging to Understand and Support Programming Decisions,” *2018 IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC)*, 2018, pp. 305-306

3.1 Overview

Knowledge workers spend a significant portion of their time searching for solutions to their problems online. While numerous tools have been developed to support this exploratory process, in many cases the answers to their questions involve trade-offs among multiple valid options and not just a single solution.

In this chapter, we investigate this issue in the domain of programming and developers searching for solutions to their programming problems online. Through interviews, we discovered that developers express a desire for help with decision-making and understanding trade-offs. Through an additional analysis of Stack Overflow posts, we observed that many answers describe such trade-offs. These findings suggest that *tools designed to help a developer capture information and make decisions about trade-offs can provide crucial benefits for both the developers and others who want to understand their design rationale*.

We further probe this hypothesis with a prototype system named Unakite¹ that **collects, organizes, and keeps track of information about trade-offs and builds a comparison table while searching and browsing, which can be saved as a design rationale for later use**. Our evaluation results show that Unakite reduces the cost of capturing tradeoff-related information

¹Unakite is named after a pink and green semi-precious stone, and stands for “User Need Accelerators for Knowledge for Implementations in Technology Environments”.

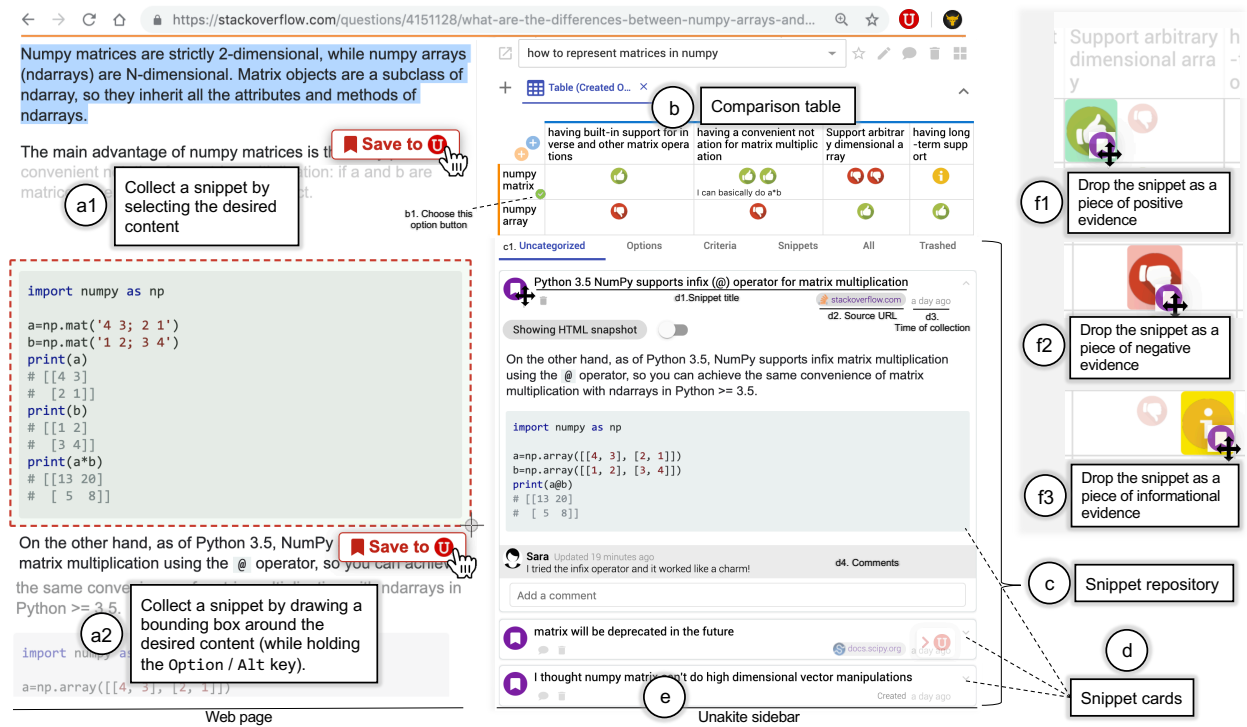


Figure 3.1: Unakite’s user interfaces. With Unakite, a developer collects a snippet by selecting the desired content (a1) or by drawing a bounding box around the desired content (while holding the Option / Alt key) (a2) and clicking the “Save to U” button. The collected snippet immediately shows up under the “Uncategorized” tab in the snippet repository (c) as a snippet card (d) inside the Unakite sidebar (e), which shows the current task at the top (“how to represent matrices in numpy”) along with the drop-down menu to pick other tasks and various tools for the task. The developer can quickly drag the snippet and drop it in one of the cells in the comparison table near the top (b). (f1-f3) show the details of the three parts of each cell in the table where the snippet can be dropped.

by 45%, and that the resulting comparison table speeds up a subsequent developer’s ability to understand the trade-offs by about a factor of three.

3.2 Formative Studies and Design Goals

To gain deeper insights into the barriers developers face about trade-offs, we performed two formative studies.

3.2.1 Study1: Interview with Developers

First, we conducted a series of needs-finding interviews with developers to understand how they currently collect and manage information about trade-offs in programming.

3.2.1.1 Methodology

Participants were a convenience sample of 15 developers (11 male, 4 female) recruited through social media listings and mailing lists. To capture a variety of processes, we chose 5 professional software developers, 2 doctoral students, and 8 master students. While we do not claim that

this sample is representative of all developers, the interviews were very informative and helped motivate the design of Unakite.

We began by asking how frequently participants made decisions about trade-offs when programming. We then explored how they manage these situations. We asked the participants to provide context by reviewing their browser histories and code bases to cue their recollections while retrospectively describing recent projects or problems. We solicited their workflows, strategies, mental models, frustrations, and needs. Finally, we wrapped up with questions probing their experience with understanding programming decisions made by other developers.

3.2.1.2 Results

Making decisions about trade-offs is frequent in programming. Almost all programming tasks described by participants involved some level of decision-making that required them to choose among options. In fact, 13 out of 15 said that they were frequently swamped with exploring multiple possible options while trying to compare them based on various criteria, such as the trade-offs among optimization methods when training neural nets (e.g., “*stochastic gradient descent*”, “*augmented Lagrangian*”, etc.) (P9) and the balance between cost and performance when *picking cryptographic algorithms* to protect users’ sensitive information (P13).

Participants’ browsing patterns and mental models for capturing trade-offs evolve as they dig deeper into the decision space, with a common representation being a comparison table. When approaching decision-making problems like *picking a JavaScript framework to build a web application* (P10), developers generally expected to find a quick-fix style solution at the beginning of their searching process. At this stage, they tended to only curate a short list of solutions that fitted their initial constraints as they queued each in a different browser tab for later reference, without pondering much about the advantages and disadvantages of each. As they dug deeper into the decision space (sometimes voluntarily doing due diligence to investigate multiple options before committing to something permanent (P4, P7), and other times because the previous solution they tried failed), they started to discover new options, criteria, and trade-offs that they were unaware of before. This naturally prompted them to go back to their earlier findings and make comparisons. As reported, their mental models at this stage quickly evolved into a comparison table, with its entries being filled according to information about whether an option satisfied a particular criterion. These findings prompted us to further analyze the applicability of tabular formats in synthesizing the trade-offs in programming problems, which we discuss in the next section.

No matter how organized their tabular mental models might become in the end, most participants reported that their exploration was inherently non-linear and tangled – there was no set pattern that was followed to acquire all the relevant information they needed. For example, as they went through web pages, they discovered new evidence, which in turn drove them to search for or go back to a previous page to read in detail about another option or criterion that they previously missed. This back-and-forth sensemaking process becomes particularly challenging, as evidence is often spread across different web pages on different browser tabs, each with different formats and structures. Additionally, participants often do not realize that there are various trade-offs between options until they dig deeper into the decision space, at which point they are already overloaded with information and lost in browser tabs, and it is hard for them to recall, search for, or go back to previously missed content to fill in the blanks in their mental table. These findings prompted us to offer various features in Unakite to help developers go back to

previously visited content such as automatically keeping track of the source URL and the scroll position when collecting information.

Both making decisions and understanding them later are difficult and cognitively demanding, and developers expressed a strong desire for tool support. 8 out of 15 said they used general-purpose tools and methods like taking notes in Google Docs or using a web clipper (such as that provided by Evernote) and reported problems such as: a high cost associated with collecting content (P7: “...*copy-pasting is just too much work, and I lose all the styling; while Evernote clipper clips the entire page, which is equivalent to not saving anything at all [because] I’d have to re-find it later.*”); maintaining provenance (P15: “...*whenever I save something, I always forget to also save the URL [of the source].*”); synthesizing the new with existing content (P9: “*Evernote dumps everything I clip into a list of notes. There’s no way for me to organize them.*”); and guiding their exploration processes (P1: “... *sometimes there’s just so much [evidence to find] that I often don’t have a clue about what I’m supposed to search next.*”). Additionally, participants reported that another disadvantage of using Google Docs or other applications like Evernote is that they must switch to another browser tab or application to access and organize their collected information. Such frequent context switches are tedious and have been shown to harm developers’ productivity [102, 144, 194]. These findings inspired us to help developers easily externalize their mental models when they are searching and browsing, by providing an easier method of tracking and deciding among available options.

Almost half (7/15) of the participants admitted that they do not document their decisions anywhere. An additional three said that they would only record important source URLs in code comments. Interestingly, participants also discussed the difficulties in code comprehension, particularly when trying to understand code written by others that involved unexpected decisions. They attributed the frustrations primarily to being unable to uncover the context of the decisions and the original trade-offs, and fearing they might accidentally violate important yet hidden constraints that guided the original decision, which is congruent with prior research [152, 158]. This motivated Unakite to automatically keep track of the initial developer’s decision making trails as the design rationale, unlike prior work where developers are forced to manually create documentation of decisions after they are made [212, 267].

3.2.2 Study 2: Analysis of Stack Overflow

Stack Overflow (SO) is an important tool for answering programming questions, and participants cited it as their most frequently visited resource. Given this motivation, we undertook an analysis to assess the proportion of questions on SO which capture trade-offs among multiple options and to determine if the tabular format identified in the interviews is indeed an appropriate structure for synthesizing these trade-offs.

We utilized two sets of posts for this analysis. First, we queried the 50 most viewed questions. We were concerned about this sampling method as it may only represent a narrow set of topics which happen to be the most popular, whereas the average developer may have more niche interests [38]. To obtain a sample of questions with a variety of topics that may be more representative of the interests of the general population, we collected another 90 questions by querying for posts created on a particular day which contained three or more answers. Through manual analysis and construction of comparison tables using spreadsheets, we found that the trade-offs contained in 88% of the 50 most-viewed and 49% of the 90 general population questions along with their answers could be reasonably organized into tables. In fact, we found that some answers already

included tables to summarize the trade-offs among the options, e.g., [8, 9]. Together with the results from the interviews, these findings motivated the design of Unakite’s organization features that let users synthesize information about trade-offs into comparison tables.

3.2.3 Summary of Design Goals

Led by our formative findings and prior research discussed in chapter 2, we hypothesize that an effective interface for decision making about trade-offs while sensemaking should support:

- **Scaffolding:** helping developers form systematic models when approaching decision making problems with trade-offs.
- **Lightweight interactions:** reducing the cost of collecting and organizing content so that the entry barriers for developers to use the tool are low.
- **Summarization:** helping developers synthesize and summarize different pieces of content together and manage them, as suggested by prior work [198, 286, 287].
- **Contextualization:** enabling developers to recreate the context from which information snippets were collected and copied for better sensemaking [215, 234, 248].

3.3 Unakite

Guided by the design goals above, Unakite enables developers (both experienced and novice) to easily collect any content from any web page into *snippets* (pieces of information) and organize them by *options*, *criteria*, and *evidence* as they are searching and browsing the web, and thereby keep track of their decision-making trails for later reference. Unakite is an extension to the Chrome Web browser and a web application.

We first illustrate the experience of using Unakite by describing an example usage scenario that embodies many of the use cases identified in our formative studies.

3.3.1 Example Usage Scenario

Sara, a junior professional developer, is tasked with writing Python code to handle matrix calculations for her company. As the code will be used in production, she wants to determine the best way to represent matrices using numpy [10] before starting the implementation. She decides to use Unakite to help her stay organized during her exploration process.

Sara logs into Unakite, enables it on her current web pages, brings out the Unakite sidebar (Figure 3.1-e), and selects “Create a new task”, entering “how to represent matrices in numpy” as the task name. Next, she starts a Google search on this topic.

As she goes through the search results, she comes across an SO page about the differences between numpy `matrix` and numpy `array`. She then quickly collects text describing both numpy `matrix` and numpy `array` into the task snippet repository by just selecting the text and click the “Save to U” button that pops up (Figure 3.1-a1). The collected snippets immediately appear under the “Uncategorized” tab (Figure 3.1-c).

Continuing on, she comes across several criteria that seem to be good standards to evaluate which of the two options she just discovered is better. For example, she thinks that “having a convenient notation for matrix multiplication like `a*b`” is essential for the readability of the code. Therefore, Sara collects those criteria using the same mechanism.

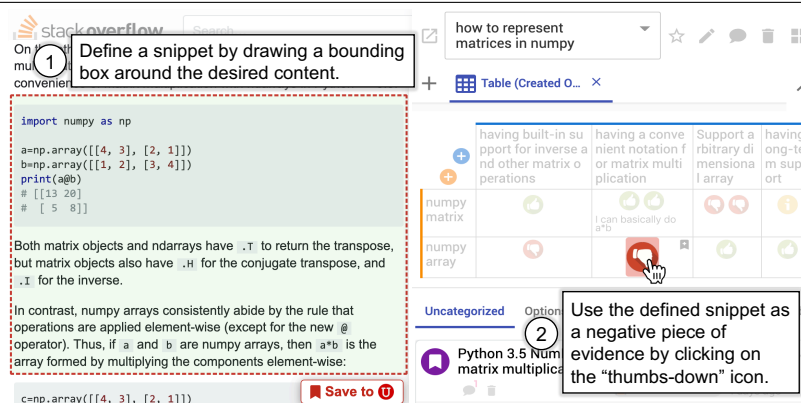


Figure 3.2: “Teleporting” content directly into the comparison table as a piece of evidence.

As the number of collected snippets gets larger, Sara decides to quickly organize them by simply dragging and dropping each snippet into the comparison table (automatically created along with the task) above the snippet repository in the sidebar (Figure 3.1-b). For example, she drags `numpy matrix` into one of the row headers as an option (e.g., a possible solution to solve the task). After a basic table structure is laid out, she realizes that an optimal method should not be deprecated in the future, so she clicks the blue “plus” button to create a new column and types in “having long-term support” as a new criterion. As it’s not one of her immediate concerns, she drags that column to be the last one in the table.

To save a section of the SO page that compares the two options in terms of the criteria she just collected, Sara uses the *snapshot* feature (holding the `Option` / `Alt` key and using the mouse to drag on screen) to draw a bounding box around that section (Figure 3.1-a2). Instead of clicking the “Save to U” button to save it as a snippet and then drag it into the table (which she certainly can), Sara uses the *teleport* feature (Figure 3.2) by clicking on one of the rating icons in the corresponding table cells to directly save the snapshot as a snippet and use it as a piece of evidence. For example, she gives `numpy matrix` a “thumbs-up” (positive rating) for “having a convenient notation for matrix multiplication like `a*b`” and `numpy array` a “thumbs-down” (negative rating) for “having built-in support for inverse and other matrix operations”. Alternatively, developers could also label a snippet as “informational” if it does not have a positive or negative effect on their decision (Figure 3.1-f1,f2,f3).

After filling up the table with options, criteria, and ratings (evidence), Sara now feels clear that `numpy matrix` should be the better choice, so she clicks the green “Choose this option” button (Figure 3.1-b1) next to that option to indicate it was chosen. She wants to document her decision in the company’s internal documentation site. The table she organized, along with all the information snippets she collected, is automatically preserved by Unakite for the current task. She clicks the “Open task detail page” button to open the task in the Unakite dashboard web app, copies the URL from the address bar, and pastes it into her code documentation with “Here’s how I decided to choose `numpy matrix`”.

A year later, Larry comes in and reads the code along with the Unakite table that Sara created. He glances the ratings and checks the evidence snippets by mousing over the rating icons. He quickly understands Sara’s decision, and realizes the opportunity to switch to using a `numpy array` since now the code needs to be able to perform vector operations in arbitrary dimensions and be supported in the long term, both of which are criteria that Sara identified previously.

	having built-in support for inverse and other matrix operations	having a convenient notation for matrix multiplication	Support arbitrary dimensional array	having long-term support
numpy matrix		I can basically do a*b		
numpy array				
	Uncategorized	Options	Criteria	Snippets
				All
				Trashed

Numpy matrices are strictly 2-dimensional, while numpy arrays (ndarrays) are N-dimensional.
 19 hours ago

Keep this in mind when implementing the multiplication function!

Figure 3.3: A snippet used as evidence in multiple cells. Selecting a snippet will highlight its location(s) in the table.

3.3.2 Detailed Design

3.3.2.1 Scaffolding

Unakite provides developers with scaffolding when managing decision making tasks that involve trade-offs by offering the “Option-Criterion-Evidence” (OCE) framework as illustrated in the example scenario. A user can create as many tasks as desired, where typically each task represents a different decision. For each task, the information is organized in a tabular format (Figure 3.1-b) where options are the row headers, criteria are the column headers, and pieces of evidence are spread across the rest of the cells.

We provide this framework for several reasons. As mentioned in the interview study results, developers’ mental model for capturing trade-offs is similar, but less organized, to that described in this framework. Formalizing it provides a concrete framing for developers to think about decisions in a structured way that they are already familiar with. Another aim of providing this structured framework is to encourage developers to think about trade-offs from the start to avoid the unnecessary frustrations later on (as described in the interview results).

3.3.2.2 Lightweight Interactions

Unakite offers various lightweight interactions to collect information and organize them according to the OCE framework. It provides two intuitive ways to collect any content from any web page. The first is selecting the desired content using the cursor in the normal way, and then clicking the “Save to U” button that pops up (Figure 3.1-a1). Another way to collect large pieces of information (code snippets that span multiple lines, columns or sub-sections of tables, pictures, etc.) is to use the snapshot feature: drawing a bounding box around the desired content (Figure 3.1-a2 and Figure 3.2) and clicking the “Save to U” button. These interactions are carefully designed based on developers’ natural habits of copying-and-pasting content and links and taking screenshots without introducing an extra cognitive load of learning a new interaction, and thereby reducing the starting cost for developers to use Unakite.

Unlike previous tools where information was saved either in pure text format [147, 148] or as raw HTML without CSS styling [279], Unakite combines the best of both copying-and-pasting and taking screenshots by capturing, saving and later showing the content of a snippet with its original styling and including the rich, interactive multimedia objects supported by HTML, like images and links. This feature makes the content in snippets more understandable and useful, and also helps developers quickly recognize a particular snippet among many others in the repository by its appearance. Typically, developers will include example code in the snippets as copied from SO and other sources, and Unakite is careful to preserve the formatting of the code, so it can later be copy-and-pasted into the user’s code once a decision to use it has been made.

The collected snippets will be displayed in the current tasks' snippet repository (Figure 3.1-c), which serves as a container that holds all the collected snippets in the form of snippet cards (Figure 3.1-d). One of the benefits of having this repository is that it serves as an information buffer between the web and the comparison table: as recommended by Kittur et al. [148], a “two-stage” model in which information is first saved and then organized, results in a better “structured information space”.

To solve the problem of frequent context switches (identified in the interview study), Unakite brings the ability to access and organize collected information directly into the browser tab that the developer is currently using – Unakite provides a sidebar (inspired by [269, 270]) on the right side of the current window (Figure 3.1-e) containing the comparison table (Figure 3.1-b) and the aforementioned snippet repository. There are several major advantages for developers using the Unakite sidebar. It serves as a comprehensive dashboard that contains both the collected information and the ability to organize them into comparison tables (discussed later in detail) all in a small footprint. Unlike PlayByPlay [279] in which the sidebar lives in a part of the browser UI, Unakite's sidebar is directly injected into the DOM tree and therefore can provide rich interactions with the original web page. The sidebar can be toggled in and out like a drawer using the keyboard shortcut `Ctrl + `` (backtick) or using the “Open/Close Unakite Sidebar” button on the bottom right of the window. When it opens, it automatically shrinks the width of the web page body to make sure nothing is visually hidden.

Unakite provides easy and intuitive interactions such as drag-and-drop, allowing users a variety of ways to quickly organize the collected information into a comparison table. A developer can drag a snippet card from the snippet repository and drop it into the table as either a row header (so it is an option), a column header (as a criterion), or into a cell as a piece of evidence, just as Sara did. Inspired by prior work [198], one can “rate” a snippet as either a positive (shown as a “thumbs-up” rating icon, see Figure 3.1-f1), negative (shown as a “thumbs-down” rating icon, see Figure 3.1-f2), or informational (shown as an “info” rating icon, see Figure 3.1-f3) piece of evidence. Moreover, a snippet can be reused as the evidence in multiple cells. Selecting a snippet (by clicking on it, see Figure 3.3) in the snippet repository will reveal its location(s) in the comparison table, and selecting an icon in the table opens the corresponding snippet in the repository.

There are two additional shortcuts to put snippets directly into a table. To collect some content as an option or a criterion, one can mouse over the “Save to U” button and click the “Option” or the “Criterion” button (Figure 3.4) that appears below. This is modeled after the various options for “liking” in Facebook. In addition to collecting the desired content as a snippet, this will automatically create a new row or column in the comparison table. Another shortcut is the teleport feature that Sara used above (Figure 3.2). These shortcuts are enabled by and add additional benefits to Unakite's always-available sidebar. Together with the other features described above, users have the flexibility to capture and organize their knowledge in various ways and in any order without needing to follow a preset process.

As illustrated in the example scenario, every Unakite task, including all of its snippets and comparison tables, can be accessed in the Unakite web app via a unique URL in any browser. This makes sharing and keeping track of one's decision easier and more powerful: developers can choose to share the link to a task via email to their friends and colleagues to show how and why the decision was made, and the link can be embedded in documentation or comments in code, preserving the actual trade-offs and design rationale in addition to where any example code was copied from.



Figure 3.4: Mousing over the “Save to U” clip button will reveal three additional buttons to collect the desired content specifically as a snippet, an option, or a criterion.

3.3.2.3 Summarization

Unakite introduces several levels of summarization to help developers manage and digest information.

The comparison table provides a high-level summary of the decision making space and the trade-offs among various options. It offers a clear and glanceable picture of the advantages and disadvantages of each option through the “thumbs-up” and “thumbs-down” rating icons without having to expose the nitty-gritty details of the evidence content, which is useful both for the developer making the decision and later code readers, as shown in the example scenario. Additionally, it serves as a presentation of one’s exploration progress that helps users understand which part of the decision space has been explored and which has not (revealed in the interview studies as an important clue developers need when exploring multiple options). For example, the empty cells in the table provide developers with clues about where they need to focus next.

The individual rating icons provide another level of summary of their corresponding supporting evidence. Unlike in previous summarization tools [287] where contents are recursively summarized into words, Unakite encourages the user to parse out the information in a snippet that captures the relationship between an option and a criterion, and represent them as rating icons. We believe this mechanism can usually capture developers’ information needs of whether an option satisfies a specific criterion, as identified in the formative interviews. One can also manually add a rating leveraging their prior knowledge directly in the table by clicking the “Add a snippet” button on the top right of the table cells, and just type or paste. To dig into the detailed evidence of each rating, users can simply click on those icons in the sidebar tables or mouse over the icons in the Unakite web app to reveal the supporting snippet card.

In addition to the built-in summarization mechanisms above, Unakite also enables users to note down their own summaries in various places. Users can easily edit the snippet title (Figure 3.1-d1) in the snippet card to be something more summative. For example, for a long snippet that talks about the performance advantages of React [86] over Angular [104], a user may summarize it as “React apps load faster than Angular ones.” There is also a text box in each table cell for users to summarize all the evidence in that cell or keep track of the evidence that cannot easily be captured by rating icons, such as prices and speed. Moreover, one can add comments to snippets (Figure 3.1-d4), table cells, and tasks about their opinions, thoughts, or the results of their experiments with an option, etc. These were added based on feedback that developers needed more flexibility to add comments and content in many places.

3.3.2.4 Contextualization

Meta information such as the URL of the source web page (Figure 3.1-d2) and the time of collection (Figure 3.1-d3) are automatically recorded along with the snippet and displayed on the snippet card in Unakite. Using this feature, developers are able to go back to the web page where a snippet was collected. Unakite will even help developers to go back to the exact scroll position where the snippet was collected if possible, saving the extra effort of locating it on a web page. The time when a snippet was collected is especially useful in giving developers a rough estimate of the age

of the information and helping them determine whether it is still valid (e.g., API methods might be deprecated or trade-offs might change in newer library versions).

3.4 Evaluation

We conducted two initial user studies of the Unakite system in order to answer the following questions:

- Can developers collect and organize information using Unakite?
- How does Unakite compare to currently available tools like Google Docs?
- Do Unakite tables offer value over just reading through web pages when trying to understand the design rationale?
- How can the design of Unakite be improved?

3.4.1 Study 1 - Authoring Unakite Tables

We carried out a study to evaluate developers' ability to use Unakite to collect and organize information about trade-offs.

3.4.1.1 Procedure

We recruited 20 participants (15 male, 5 female) aged 23-37 ($\mu = 26.75$, $\sigma = 3.49$) from a local research participation pool. The participants were required to be 18 or older, to be fluent in English, and to be experienced in programming. Participants had on average 8.8 years of programming experience, with the longest being around 15 years. 13 participants had professional programming experience, with the rest having experience in college.

In this study, participants were first presented with two tasks each: (A) *how to invoke a function in JavaScript* and (B) *how to create or update a resource using REST APIs*. For each task, they started from scratch without using any information snippets from previous tasks. The study was a between-subjects design, where participants were randomly assigned to either the Unakite or the control condition. In the Unakite condition, participants were given a static web page adapted from a real Stack Overflow page discussing the task topic in each task. Participants were asked to use Unakite to collect and organize information from that single page into a comparison table, and were instructed to inform the researcher when they thought they had finished the task or felt like they could make no further progress. In the control condition, participants were asked to do the same but to build comparison tables using Google Docs instead. We deemed Google Docs as a proper baseline since: 1) it was reported in the formative study as a common tool people use to take notes while making decisions; 2) all participants in this user study were already proficient in using it; 3) compared to other solutions like spreadsheets, it can be easily used to capture richer contexts such as formatted text (example code), images (screenshots of execution results), and links (URLs of documentation and tutorial pages).

All participants were then given a third task in which they were asked to use Unakite to help them understand the trade-offs and make decisions on whatever programming problems they were trying to solve in real life.

Participants in the Unakite condition were given a 10-minute tutorial showcasing the various features of Unakite and a 5-minute practice session before starting. Those in the control condition were given the same tutorial and practice session before the third task. At the end of the study, the

	# manually created snippets / # snippets	# options	# criteria	# ratings	# positive ratings	# negative ratings	# info ratings
Task 1	0.70 (1.34) / 12.10 (3.38)	2.30 (0.67)	2.70 (1.57)	8.80 (4.10)	3.00 (1.89)	1.80 (2.30)	4.00 (3.80)
Task 2	1.20 (3.16) / 17.50 (4.48)	2.60 (0.52)	4.60 (2.07)	13.20 (4.42)	7.70 (4.08)	2.60 (2.46)	2.90 (2.42)
Task 3	2.00 (3.77) / 18.89 (8.31)	3.74 (1.37)	4.74 (2.58)	12.58 (8.87)	6.37 (5.24)	3.84 (4.29)	2.37 (2.52)

Table 3.1: Statistics for various Unakite feature usages in Study 1. Statistics are presented in the form of **mean (standard deviation)** in the table.

researcher conducted a survey and an interview eliciting subjective feedback on the Unakite experience. In particular, participants were asked to list 3 of their favorite features as well as 3 least favorite features or possible improvements of Unakite. The study took about 80 minutes per participant, using a designated MacBook Pro computer with Chrome and Unakite installed. All tasks were screen-recorded for later analysis. All participants were compensated \$20 for their time.

3.4.1.2 Results

All participants were able to complete all of the tasks in both conditions. As shown by the statistics in Table 3.1, the Unakite participants were able to use the various features to collect and organize information into comparison tables.

To examine how Unakite performs compared to the control condition, we opted to compare the *overhead cost* of using both tools to collect and organize information. For the Unakite condition, the overhead cost is defined as the portion of the time participants spent on directly using Unakite features (selecting, snapshotting, dragging snippets into the comparison table, etc.) out of the total time they used for a task, since the rest of the time was spent reading and understanding the Stack Overflow page. Similarly, for the control condition, the overhead cost was calculated as the percent of time participants spent on copy-and-pasting content, making screenshots, and staying on the Google Docs browser tab to organize the table.

We conducted a mixed-effect linear regression with overhead cost as the outcome, condition, task, and their interaction as fixed effects. Since participants may have different abilities in performing the tasks, we included a random intercept for each participant. Results show that the overhead cost when using Unakite is significantly lower (coefficient = -0.22 , $t(18) = -4.81$, $p = 0.0001$) than the control condition, while task (coefficient = -0.05 , $t(18) = -1.40$, $p = 0.1777$) and the interaction term (coefficient = 0.04 , $t(18) = 0.71$, $p = 0.4861$) does not have an effect on the overhead cost. Across both tasks, the average overhead cost was reduced by 45% when using Unakite (Mean overhead cost = 25%, SD = 0.07) compared to using Google Docs (Mean = 44%, SD = 0.12). Thus, using Google Docs did add a lot of extra time, whereas using Unakite, even though unfamiliar, was quick and non-disruptive.

In the survey, participants reported (in 7-point Likert scales) that they thought the interactions with Unakite were understandable and clear (Mean = 6.20, Median = 6.00, 95% CIs = [5.84, 6.56]), they enjoyed Unakite’s features (Mean = 6.00, Median = 6.00, 95% CIs = [5.52, 6.48]), and would recommend Unakite to friends and colleagues doing programming work (Mean = 6.20, Median = 6.50, 95% CIs = [5.75, 6.65]).

Nine of the 20 participants requested that we send them the URL of their third task that they created using Unakite for reference and five of them asked us to help them install Unakite on their computer for personal use and future updates, highlighting both the utility of the system as well as the realism of the tasks they chose. Figure 3.5 shows P13’s table capturing the trade-offs in choosing JavaScript front-end frameworks.

Another highlight in the study is that P3, P10, and P18 decided to either commit or switch to the option they identified as the best option after using Unakite to build comparison tables on



























	Availability of Learning Resources	Popularity	Ease of Integration (with Other Libraries)	Core Features	Usability
React					 
Angular			 	 	
Vue					 
EmberJS	 			 	 

Figure 3.5: Participant P13’s comparison table capturing the trade-offs in choosing JavaScript front-end frameworks.

the topic of their choosing. For example, P3 researched on hybrid AR development frameworks that can take advantage of both ARCore [11] on Android and ARKit [12] on iOS, and found ViroReact [14] to be the best choice. A quick follow-up interview a week later revealed that he had already begun using that framework, and it did satisfy all of his needs so far.

3.4.2 Study 2 - Understanding Unakite Tables

We carried out a second study to evaluate whether developers could understand the trade-offs encapsulated in comparison tables and snippets previously built by others using Unakite.

3.4.2.1 Procedure

We recruited 16 participants (9 male, 7 female) aged 21-32 ($\mu = 25.3$, $\sigma = 3.19$) from the same local participation pool as in Study 1 (but no-one participated in both studies). Participants had on average 7.8 years of programming experience, with the longest being 17 years. None of them were familiar with either the topics involved in this study or Unakite. The study took about 40 minutes per participant, using the same setup as in Study 1. All participants were compensated \$15.

Participants were given a 10-minute tutorial showcasing the various features of the Unakite web app. The study was a within-subjects design, where the participants were presented with two tasks of roughly equal difficulty and were asked to solve one of them with the help of Unakite and the other by reading through a set of web pages, in a counterbalanced order. For each task, participants were given some code written by the researcher to solve a problem, some necessary background information about the problem, and a list of options that were available to solve it. They were then asked to explain why the decision was made to choose the particular option used in the code and the associated trade-offs. In the experimental condition, participants were provided with a previously-built structure (including the comparison table and the snippet repository) through the Unakite web app, while in the control condition, participants were instructed to only read through the set of web pages that the structure in the experimental condition was built from. Specifically, the two tasks were to explain the decision and the trade-offs of:

- Choosing `numpy array` with Python 3.5+ instead of `numpy matrix` or `numpy array` with Python 2.7 to perform some matrix calculations like multiplication, inversion, element-wise multiplication, etc.
- Choosing `numpy array` instead of `Python list` or `Python array` to hold data involved in large-scale numerical manipulations such as regression analysis.

To ensure realism, both tasks were based on actual questions asked and answered on Stack Overflow that are heatedly discussed and well-maintained by real developers.

3.4.2.2 Results

Two researchers each listed all possible explanations to the two tasks independently. After resolving conflicts, we produced a list of possible explanations for each task as the gold standard.

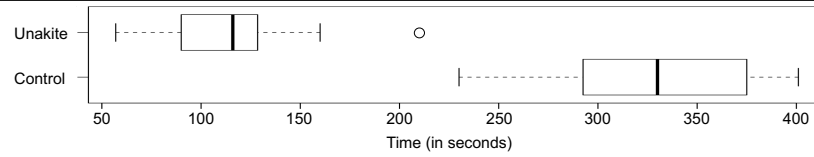


Figure 3.6: Box plot of the average task completion time for the participants under different conditions: Unakite vs. Control in Study 2.

To quantitatively evaluate participants’ performance, we measured the time it took for them to offer three legitimate explanations - those within the gold standard list - in each condition, which all participants were able to accomplish.

A two-way repeated measures ANOVA was conducted to examine the within-subject effects of condition (Unakite vs. Control) and task (A vs. B) on task completion time. There was a statistically significant effect of condition ($F(1, 26) = 25.59$, $p < .001$) such that participants completed tasks significantly faster (almost 3 times faster) with Unakite (Mean = 114.63s, SD = 38.91s) than in the control condition (Mean = 332.56s, SD = 56.26s), as visualized in Figure 3.6. There was no significant effect of task ($F(1, 26) = 0.01$, $p = 0.94$), indicating the two tasks were indeed of roughly equal difficulty.

3.4.3 Evaluation Discussion

3.4.3.1 Usability and Usefulness of Unakite’s features

The snippet collection features, including both the selecting and the snapshot features, were considered highly useful, with 15 participants citing them as one of their favorite features. Participants said they were “*the perfect combination of copy-pasting and taking screenshots*” (P15) with the additional benefits of “*retaining the original styling [of the collected content], especially when there’s code*” (P9), “*keeping track of the [source] URL*” (P7), and “*saving [users] some typing*” (P5). The drag-and-drop interactions were also popular, receiving 13 mentions in participants’ “top three” lists, primarily due to its ease of use (P18: “*it is natural, like picking things up and dropping them in buckets*”). Participants also appreciated that the design of the Unakite UI is clean and easy to learn (12/20), and the overall experience was satisfying (10/20). The sharing via URL feature also received nine mentions, with participants laying out potential usage scenarios like “*putting it in code comments or [their lab’s] internal documentions*” (P11), “*using it for presentations in code reviews*” (P8), “*attaching it in emails that explain my code*” (P5), etc.

Compared with using Google Docs, P15 praised the value of Unakite’s snippet repository functioning as an information buffer: “*It’s like a note-taking space. I can just easily grab as much info that’s related to my topic as I want, and they don’t have to directly fit into the table, but can be something interesting to use later on; whereas in Google Docs, the cost of buffering these interesting snippets somewhere is pretty high.*”

Participants have mixed opinions on how summarization works in Unakite. Most of them (16/20) agreed that summarizing snippets into positive, negative, or informational icons alleviates their burden of having to manually look at the content of each snippet every time, and makes the comparison tables much more skimmable, e.g., “*visual interpretation of thumbs ups and downs provides a quick summary*” (P18). However, P17 also pointed out that “*value comparisons between criteria (columns) are difficult,*” suggesting some notion of weight should be applied differently to the columns when construing the table. P3 indicated that the meaning for the thumbs-up/down icons is open for interpretation in a sense that “*having more thumbs-ups does not necessarily mean [that an option] is better [in terms of a criterion], it could simply mean that the author found more*

positive evidence, unless she specifies that [more means better] in the first place.” Based on these valuable insights, we believe that there are new interface design opportunities for us to explore in Unakite so that the value of the comparison tables could be further improved.

3.4.3.2 Usage Patterns

Similar to what Morris et al. found [198], there was an unbalanced use of the positive and negative ratings in the study: positives (228 in total) are more heavily used than negatives (117 in total). A possible explanation for this asymmetry is that people in general lean towards finding and keeping track of evidence of what “works” rather than what “doesn’t work”.

Participants exhibited two major usage patterns when interacting with Unakite: (1) collecting-oriented: alternating between *long* collecting stages (in which they keep collecting content into the snippet repository) and *short* organizing stages (in which they focus on putting the collected snippets into the comparison table); or (2) organizing-oriented: all snippets going directly into the comparison table immediately after they are collected. We are delighted that interactions in Unakite are flexible enough to support both usage patterns equally well.

3.5 Discussion and Future Work

Seven of the participants (Study 1 & 2 combined) who were involved in decision making processes in the industry suggested that Unakite has the potential to become a collaborative platform for developers to cooperate on decision making processes. This is in line with our vision to add support in Unakite for both asynchronous and synchronous collaborations in the future. Presently, Unakite focuses on recording a static snapshot of a single developer’s decision making trails that is read-only to other developers. In future iterations, one could work on mechanisms that enable later developers to “own” or “contribute” to the structures so that they stay relevant and informative throughout the course of a software engineering project. For example, inspired by Git and other local version control tools such as Variolite [145], one can explore the opportunity of introducing lightweight versioning into Unakite, possibly integrated with code versions, thereby realizing asynchronous collaborations. Suggested by collaborative systems like Search-Together [198] and CoSense [215], additional “awareness” and “division of labor” features can be implemented to transform Unakite into a synchronous collaboration platform.

To support cases in which the needs for collecting and organizing information are not discovered until partway through an investigation process, future research can explore automatically summarizing exploration paths in the background so that developers can retroactively organize their work with reduced overhead. This is, in fact, explored to some extent in our Crystalline system discussed in chapter 4.

One can also investigate the use of Unakite as a pedagogical tool. Many areas of computer science (e.g., data structures, systems) require students to consider different options in terms of trade-offs, rather than determining a single correct answer. Anecdotally, many students find this difficult. The exercise of creating a comparison table to explicitly compare multiple options for a task (e.g., using a stack or a queue to build an undo function) would force students to explicitly determine the criteria necessary for the task, gather evidence to support ratings, and make an educated decision based on these ratings.

Chapter 4

Crystalline: Automating Information Collection and Organization

This chapter was adapted from my published paper:

Michael Xieyang Liu, Aniket Kittur, and Brad A. Myers. 2022. “Crystalline: Lowering the Cost for Developers to Collect and Organize Information for Decision Making.” *In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 68, 1–16.

Video: <https://youtu.be/V0-osTVGuJs>

4.1 Overview

Our previous system Unakite encouraged authors to document their decision making processes and results using the tool’s lightweight collecting and organizing features. However, it remains a laborious process for people to manually identify and clip content, maintaining its provenance and synthesizing it with other content. Prior work suggests that one cause is that people are often uncertain about which information will eventually turn out to be relevant, valuable, and worth capturing, especially at early stages of their learning and exploration when they are overloaded with information [34, 90]. Under these circumstances, people are hesitant to frequently pause and shift their focus from the investigation itself to reasoning about what to capture for later use [58, 124, 148, 239], or they could be too engaged in the sensemaking process and forget to collect anything at all. Furthermore, people’s needs for collecting and organizing information are often not discovered until part of the way through an investigation process, such as realizing there exists much more factors to consider than originally anticipated [68, 80, 81].

In this chapter, we explore the idea of having a system dynamically help users keep track of and organize information by leveraging the content they are browsing and the signals from their browsing behavior. We instantiate this idea in a prototype system called Crystalline¹, which plays the role of a user’s copilot and attempts to automatically identify and keep track of the options, criteria, and the corresponding evidence snippets from the web pages that a user has viewed,

¹Crystalline is named after rocks made up of interlocking crystals. It stands for Clipping Resulting in Your Structure as Tables And Lists Linked to Implicit Notetaking Easily.

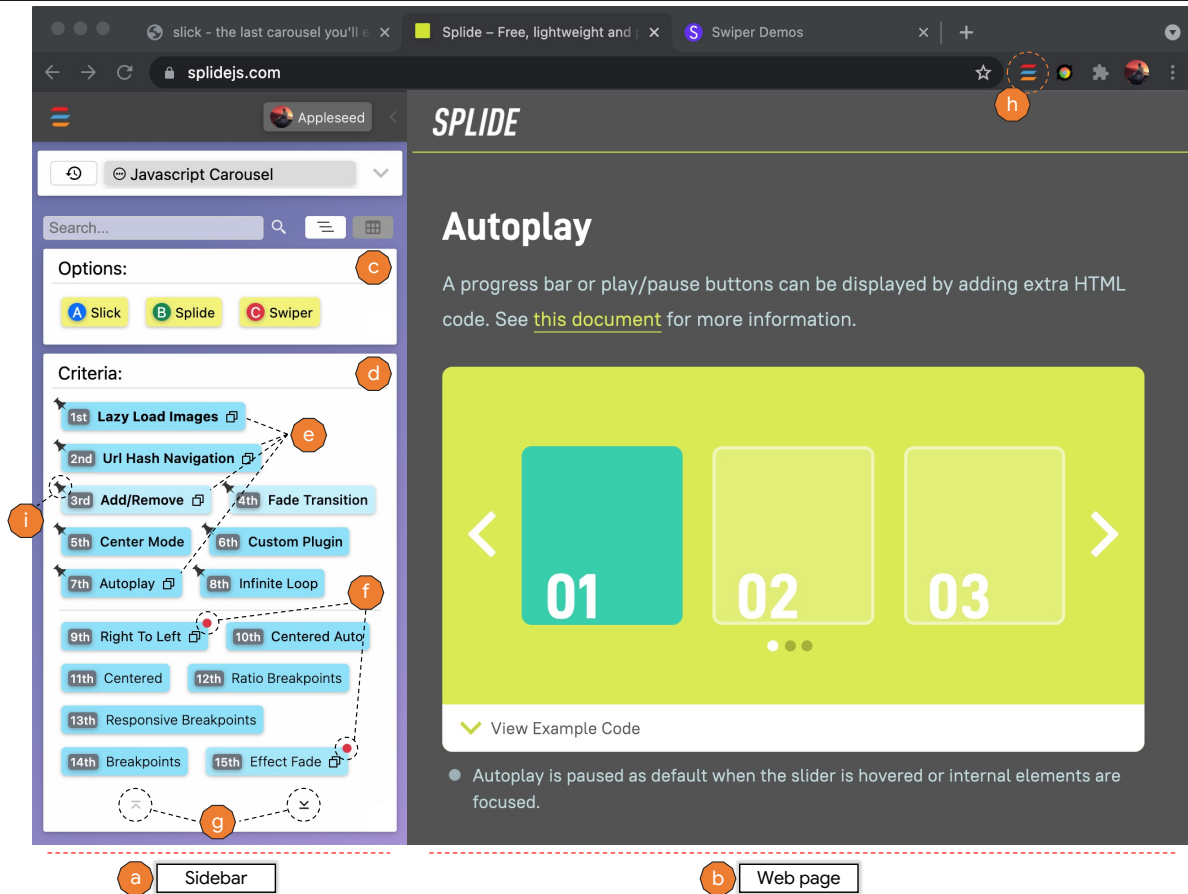


Figure 4.1: Crystalline’s list view UI (a). As the developer browses a web page (b), Crystalline attempts to automatically collect options and criteria from the page, and display them in the options (c) and criteria panes (d) in the sidebar (a). In addition, Crystalline leverages natural language processing to automatically group similar criteria together, as shown by the multiple-pages icon (e). Crystalline uses behavioral signals such as mouse movement and dwell time to try to automatically detect the relative importance of the criteria (shown by the display order, with most important at the top). Users can use the “See more” and “See less” buttons (g) to adjust how many criteria are to be displayed at once. Crystalline will remind users of the existence of additional related evidence through a red notification dot at the top right of a criterion (f). The sidebar can be toggled in and out by clicking the browser extension icon (h). Users may pin (i) important criteria to the top of the list.

and organize the snippets into both list and tabular formats with prioritization. To achieve this, Crystalline mines a variety of behavioral signals while a user browses the web, including scrolling patterns and mouse cursor actions, and employs natural language understanding techniques to automatically classify and organize the collected content. The goal is that users can focus more on reading and understanding web content while occasionally guiding the system when it makes mistakes. Our lab study suggests that users are able to create comparison tables about 20% faster with a 60% reduction in operational cost without sacrificing the quality of the tables.

4.2 Background and Design Goals

To ground our research, we build on the “Option-Criterion-Evidence” framework introduced in our Unakite system. We first briefly review the prior work on implicit behavioral patterns that people naturally exhibit while browsing the web that inspired our investigation. Then we discuss the design goals for the new Crystalline system.

4.2.1 Implicit Behavioral Signals When Using the Web

Prior research has investigated various implicit behavioral patterns that people exhibit when reading and interacting with content on a digital screen. One thread of research has explored using behaviors such as dwell time, cursor movements, clicks, scrolling patterns, and gaze positions as *implicit signals* to approximate user interest on web pages as well as search result relevance [67, 109, 110, 123, 134]. For example, Claypool et al. [67] had participants use a custom-built browser to surf the web and concluded that the time spent on a page, the amount of scrolling on a page, and the combination of time and scrolling had a strong correlation with explicit user interest. In addition, Hijikata [123] discovered that actions such as text tracing and link pointing are decent behavioral indicators for perceived interesting segments of web pages. Similarly, in the domain of web searches, Buscher et al. [48, 49, 50], Guo and Agichtein [109, 110], and Huang et al. [134] demonstrated that eye tracking, as well as interactions like scrolling and cursor hovers, could accurately predict user interests in search results pages.

Building on such empirical understanding, we explore putting a combination of these implicit behavioral signals into use to approximate user visual attention in a working prototype. We used heuristics and pilot testing to devise mechanisms that translate the raw behavioral signals into numeric scores representing the “amount of attention” a user has given to a particular piece of online content. We then use these scores to filter out and rank the content of the evolving comparison table, further reducing the cost for developers to manually manage and prioritize collected information incrementally as they are searching and browsing.

4.2.2 Design Goals

In order to address the limitations of using Unakite as well as other similar sensemaking tools [32, 39, 61, 215] discussed in section 4.1, we formulated the following design goals:

- **Minimize the cost to collect information.** The system should attempt to automatically collect information in the background without the user’s specific attention or direction. This will help users focus on the main task of reading and comprehending the content.
- **Actively filter, organize, and prioritize information.** The system should actively filter, organize, and prioritize the collected information that gets presented to the user and help the user avoid information overload.
- **Reduce the cost of incorrect automation support.** In cases where machine support is incorrect or undesirable, the system should allow users to easily recover from those mistakes [28, 129].

4.3 Crystalline

4.3.1 System Overview

Guided by prior work and our design goals, we designed and implemented Crystalline, a Chrome extension prototype to help developers automatically collect and organize information relevant to their decision making problems.

Users mainly interact with Crystalline through a **sidebar** (Figure 4.1-a) that is injected directly into every web page. As a developer opens and reads web pages, the sidebar will be updated with

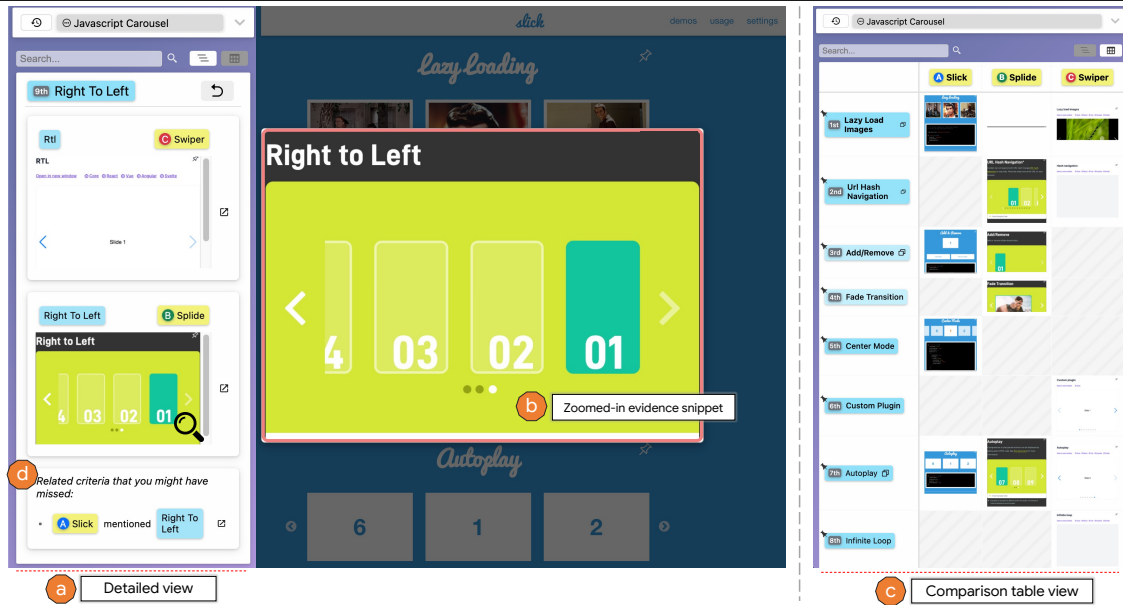


Figure 4.2: Additional Crystalline’s user interfaces. Clicking on one of the criterion in the criteria pane (Figure 4.1-d) will enter a detailed view for that criterion (a), listing out all the collected evidence snippets organized by options. Users can zoom in on an evidence snippet (b) by moving the mouse cursor over it in the detailed view until the cursor becomes a magnifying glass. Crystalline will actively look for and remind users of evidence for the same or similar criteria from pages that users have visited but have not yet paid attention to (d). Finally, similar to Unakite [177], Crystalline offers a comparison table view (c) that summarizes the decision making space and the trade-offs among various options in detail.

the automatically collected options (Figure 4.1-c) and criteria (Figure 4.1-d) in the *list view* (Figure 4.1-c & -d). The list view serves as a concise and glanceable outline that reflects one’s exploration progress — what options one has encountered and what criteria one has looked into. Clicking on one of the criteria will enter a detailed view for that criterion (Figure 4.2-a), listing out all the collected evidence snippets organized by options; similarly, clicking on an option will enter the *detailed view* for that option, which lists all the related criteria and the corresponding evidence associated with that option. Details on how we currently implemented the automatic collection and organization features are discussed in section 4.3.2.

In addition, developers can also switch to the *comparison table view* (Figure 4.2-c) that summarizes the decision making space and the trade-offs among various options in detail. The order in which a criterion gets presented both in the list and the comparison table view are based on the *estimated importance* of the item to the user, which we approximate by the *amount of attention* a user has given to it. This, in turn, is derived from the user’s implicit behavioral signals, which we will discuss in detail in section 4.3.2.2. To examine a particular piece of evidence in the detailed view or a comparison table cell, users can hover on it to zoom in (Figure 4.2-b), or click on it to *teleport* to the original web page and scroll position from where it was previously collected.

Similar to previous systems [128, 177, 223], the sidebar can be toggled in and out like a drawer by clicking the extension icon (Figure 4.1-h) or using a keyboard shortcut. Developers can passively monitor the sidebar as they are searching and browsing to make sure the system performs correctly, and quickly correct or dismiss the mistakes that the system makes. In addition, developers are free to hide the sidebar to have an unobstructed view of the web page, knowing that all the features for automatic information collection and organization are still running in the background even if the sidebar is in the hidden state.

4.3.2 Detailed Design

We now discuss how the different features in Crystalline are designed and implemented, and how they support our design goals.

4.3.2.1 Collecting information about options and criteria

In Crystalline, we explore having the system *automatically* collect relevant information in the background without the user having to explicitly perform the action of collecting information. This has the benefit of minimizing the distraction and cost of keeping track of information as an extra step in addition to thinking about the content on a web page, which, in turn, maximizes a user’s attention to reading and understanding the content itself.

Specifically, Crystalline collects information about options, criteria, and their associated evidence snippets as discussed previously, which was reported by prior work as the key aspects developers look for when solving decision making problems [131, 159, 177]. Currently, to automatically recognize the *options*, Crystalline employs the following techniques: (1) it looks for the word or phrase between any instances of “vs.” (or other variants like “v.s.”, “versus”, etc.) in web page titles and opening paragraphs and adds them as potential options. For example, the Medium.com article titled “Tensorflow vs Keras vs Pytorch: Which Framework is the Best?”² would yield “Tensorflow”, “Keras”, and “Pytorch” as three potential options; (2) it first runs noun phrase and entity extractions using the Google Cloud Natural Language API [105] on the web page title, section headers as well as the column and row headers of any HTML tables, then checks if the identified entities are mentioned in the titles of other visited pages. In addition, it also checks if the identified entities would frequently come up in each other’s Google autocomplete results (the Google “vs” technique is described in [94, 178], which issues queries in the form of “[option_name] vs” to the Google Autocomplete API to get a list of autocomplete results that can be interpreted as potential alternatives to “[option_name]”. An earlier version of this technique was launched as an experimental feature named Google Sets [65]). Furthermore, it checks if the identified entities are mentioned repeatedly across the main content of the current web page. All potential options will go through a final deduplication process to produce the final list of options presented in the *options pane* (Figure 4.1-c) in the sidebar. We chose and tuned these heuristics based on our internal usage and pilot testing results. In the future, more advanced NLP techniques could be used to augment the current set of heuristics.

Crystalline uses a similar set of heuristics to identify *criteria* from the web pages, with an emphasis on examining section headers and table headers (and entities extracted from them) rather than website titles. In this work and in the context of programming, we focus on using such heuristics to identify the criteria directly mentioned in the content, such as extracting “learning curve” from “React is widely considered to have quite a steep learning curve.” We leave the extraction of latent criteria for future work, which are more commonly seen in domains other than programming, such as extracting “price” from “I bought this mp3 player for almost nothing” [222].

Further, users can always edit the options and criteria names, delete unwanted options or criteria, or manually select and collect any text as either an option or a criterion using the popup menu (Figure 4.3) as a backup.

²<https://medium.com/@AtlasSystems/tensorflow-vs-keras-vs-pytorch-which-framework-is-the-best-f92f95e11502>

Implicit Behavioral Signal	Selected References in Prior Research	Descriptions	Strength of indication of user attention	Score Function W
Copying content	Developers frequently copy sample code from the web to use in their own code [46, 116, 117]	Triggers when the user copies some text from a content block b . This typically happens when a developer copies sample code from web pages to try out in their own code.	Strongest	40 for each triggering
Text highlighting	People tend to highlight text while reading to help focus their attention [231]	Triggers each time when some text in a content block b gets selected. Triggerings where the selected text is shorter than 5 characters are disqualified.	Strong	20 for each triggering
Clicking	Clicking on content, such as widgets and links, is considered to be a decent behavioral indicator for perceived interesting elements on web pages [123]	Triggers when the user clicks on a content block b . This accounts for situations where the developer interacts with content on a page, such as live demo widgets. Clicks that are part of text highlighting are excluded.	Strong	20 for each triggering
Cursor hovering	People tend to use the cursor to guide their attention while reading web pages [64, 111, 123, 134, 227].	Triggers each time when the mouse cursor hovers over a content block b for at least 2 seconds. This accounts for situations where the developer naturally moves the mouse cursor onto the content that is currently being read to guide his or her attention [64, 133, 227]. However, a cursor hover triggering will be disqualified when the system detects an extended period of idling (2 minutes) without any user actions.	Weak	$0.5t$, where t is the duration (measured in seconds) of the cursor's stay within the bounds of content block b . The maximum score is 10. In our pilot testing, users rarely spend more than 10 seconds reading a text block.
Content dwelling	The longer some content stays visible, the more likely that the user is interested in it [67, 134].	Triggers each time when a content block b gets scrolled into and stays in the visible view port for at least 2 seconds. This indicates that the developer has at least paid attention to b . However, a dwell triggering during idling is disqualified.	Weak	$0.2t$, where t is the duration (measured in seconds) of content block b 's stay in the visible browser viewport. The maximum score is 4. In our pilot testing, users rarely stay at one location for more than 10 seconds.

Table 4.1: Implicit behavioral signals used in Crystalline to track user attention. Column 1 lists the implicit signals; column 2 provides evidence from selected prior research on the efficacy of the signals; column 3 describes how the signals are used in Crystalline; column 4 indicates the relative strength of a signal in terms of predicting user attention; column 5 details the scoring function used to translate signal triggerings into numeric scores based on the relative signal strengths. The scoring functions were empirically determined through iterative pilot testing.

4.3.2.2 Organizing and prioritizing information

Not all options or criteria are equally useful to a particular developer. Prior work has suggested that a programming decision usually comes down to how well each option matches the developer's goals and criteria that he or she deemed important [100, 161, 163, 178, 213, 217, 224, 235]. In this work, we explore using the amount of attention that one pays to a particular criterion to approximate its perceived value or importance. To operationalize this, for each web page that a developer visits, Crystalline processes all the content blocks (HTML block-level elements, such as `<p>`, ``, `<pre>`, and `<div>`, etc.) to detect what options and criteria are associated with each block. Specifically, it prioritizes verbatim mentioning of options and criteria within a block, then possible options and criteria identified from section headers above the block, then web page titles. If no options are detected, the page title is used as a placeholder.

Next, Crystalline tracks each triggering of five implicit behavioral signals (*copying content*, *text highlighting*, *clicking*, *cursor hovering*, and *content dwelling*) listed in Table 4.1 on any content block and translates it into a numeric score (using column 5). The final attention score A_c representing the amount of attention that a user pays to a particular criterion c is then calculated using equation (4.1):

Performance and Development

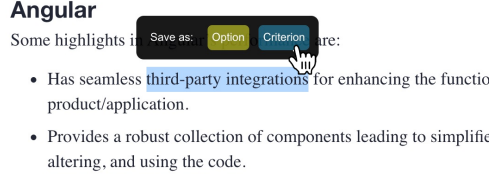


Figure 4.3: Using the selection popup menu to manually collect options and criteria.

$$A_c = \sum_{t \in T} I(t, c) \times W(t) \quad (4.1)$$

where T is the set of all implicit signal triggerings; t is a particular triggering; $I(t, c)$ returns 1 if t was triggered on a content block that is associated with the criterion c , and returns 0 otherwise; and $W(t)$ is the corresponding scoring function found in the last column in Table 4.1. The scoring functions were empirically determined through iterative pilot testing.

To accommodate various behavioral patterns exhibited by different users, we iteratively recruited four batches of participants with diverse backgrounds and job responsibilities both within our lab and externally. We followed a diary study approach [225] by monitoring their online searching and browsing behavior related to programming through a custom chrome extension that logs triggerings of the above behavior signals and ranks the importance of the associated content blocks accordingly (the initial score functions were determined through our heuristics). At the end of each sensemaking episode, we prompted them to review how well the system did in inferring what they thought was important, and tuned the score function heuristics accordingly (favoring recall over precision). We leave more advanced and adaptive scoring models for future work to investigate.

By default, the system shows the top 15 criteria ranked by decreasing attention scores in both the list and the table view. Users can use the “See More” and “See Less” buttons to adjust how many criteria that they would like to see at the same time (Figure 4.1-g). As the user browses more content and spreads his or her attention on different content blocks, the order of these criteria changes accordingly in real-time, which provides the user with an ambient awareness of what the system thinks are important. To provide users with the flexibility to override the system’s ranking, they can right-click on a criterion and use the “pin this criterion” feature to pin it at the top (Figure 4.1-i). They can additionally specify their own order of preferences by dragging and dropping to reorder the criteria in the table view, which will automatically pin a criterion if it is not already pinned. Each time an implicit behavioral signal triggering is detected, Crystalline also collects the target content block as an evidence snippet, which is presented with its original styling [177] in the detail views and the comparison table view as mentioned above.

4.3.2.3 Managing connections and relationships.

One way for Crystalline to actively manage the relationships among the collected information is to automatically merge similar criteria together into *criteria groups* (indicated by a “multiple items” icon at the end, see Figure 4.1-e). To achieve this, we leverage recent advances in transformer machine learning models such as Universal Sentence Encoder [56] and BERT [76] that can encode textual content into semantically meaningful vector representations called embeddings [101], i.e., two or more semantically close pieces of content will also be close in the embedding vector space (measured by a distance metric, e.g., the cosine similarity distance between vec-

tors [253]). Crystalline computes an embedding for every criterion as the average of its own embedding and its corresponding evidence snippet, and automatically merges criteria that are within a specified semantic distance threshold to each other into a group. For example, as shown in Figure 4.2-a, the system automatically merges “Right to Left” (taken from the option “Splide”) and “RTL” (taken from the option “Swiper”) together since they are semantically similar. The distance threshold was determined empirically through iterative pilot testing. This has the benefit of reducing clutter while helping users make connections among the information that they have seen, which is reported by prior work as one of the difficult steps during sensemaking and schematization [90, 220, 234]. In case the system fails to automatically group similar criteria together, users can use drag and drop to manually make the grouping. Similarly, users can easily split a criteria group by right-clicking on the group and hitting the “split this criteria group” menu item.

In situations where a user reads and investigates some criterion at one location, Crystalline will also actively look for evidence for the same or similar criteria from other pages that the user has visited (including the current page) but has not (yet) paid attention to according to the implicit signals. Crystalline will remind the user of the existence of this additional evidence through a red notification dot at the top right of a criterion (Figure 4.1-f) as well as in the detailed views (Figure 4.2-d). This then serves as an additional way for the system to help users uncover and manage unseen relationships among the information space, as well as a springboard for users to jump directly to the “overlooked” information for further investigation.

4.3.3 Implementation Notes

To produce the content embeddings, we used *bert-as-a-service* [76] and the uncased_L-12_H-768_A-12 pre-trained BERT model to implement a REST API that the extension can query on-demand. The embedding calculations are known to incur significant computational costs and delays. Therefore, to ensure a smooth user experience, they are better suited to run on a remote server with the necessary resources rather than locally in an end-user’s browser.

Unlike other systems [84, 218] that help users find more information from new sources, Crystalline only collects information from the web pages that a user has explicitly visited. This is an intentional design choice we make in the current implementation: the major role of Crystalline is to remove the burden for users to actively keep track of relevant information that they have personally seen and investigated so that it is easier for them to revisit and recall. We leave the design space of automating the discovery of new relevant information for future research to explore.

4.4 Evaluation

We conducted an initial lab study to evaluate the usability of the Crystalline system in helping developers collect and organize information.

4.4.1 Participants

We recruited 12 participants (7 male, 5 female) aged 22-35 ($\mu = 27.6$, $\sigma = 3.7$) years old through emails and social media. The participants were required to be 18 or older, fluent in English, and experienced in programming. Participants had on average 6.9 years of programming experience, with half of them currently working or having worked as a professional developer and the rest having programming experience in universities.

4.4.2 Procedure

The study was a within-subjects design, where participants were presented with two tasks and were asked to complete one of them using Unakite (baseline condition) and the other using Crystalline (experimental condition), in a counterbalanced order. For each task, participants were presented a programming decision-making problem, a set of four web pages, some necessary background of the problem, and a list of three options available to solve the problem that they were required to investigate. The provided web pages were either documentation pages of specific options or comprehensive review articles reviewing several options together. Participants were instructed to read through the provided web pages, and use either Unakite or Crystalline to collect and organize information into a comparison table containing all the given options and at least 8 different criteria in the order of their perceived importance. We imposed a 20-minute limit per task to keep participants from getting caught up in one of the tasks. However, they were instructed to inform the researcher when they have collected 8 criteria as well as the associated evidence. If they wished to continue beyond this checkpoint, they were allowed to, until they felt like they could make no further progress. Specifically, the two tasks were to use the corresponding system in each condition to build a comparison table of:

- (A) Choosing a JavaScript carousel library to build a photo sharing web application. The available options were: Splide.js [20], Slick [19], and Swiper [21].
- (B) Choosing a front-end framework to implement a basic personal portfolio website. The available options were: React.js [86], Angular [104], and Vue.js [22].

We chose Unakite over other commercially available tools such as Google Docs as the baseline condition because: 1) it can be easily used to capture richer contexts such as formatted text (example code), images, and links; 2) similar to Crystalline, it also provides a sidebar that allows participants to view and organize the collected information directly rather than switching context over to another browser tab or application to paste in and structure information; and 3) Unakite was shown to be easy to learn and use in prior research and incurs significantly less overhead cost than using Google Docs [177].

In addition, rather than letting participants search for their own pages to research, we provided them with the predefined set of pages to ensure a fair comparison of the results, and since helping to find relevant web pages is not a goal of Crystalline. Requiring participants to only read the predefined pages (each contains on average 7 screenfuls of content) also helps ensure that the two tasks are of roughly equal difficulty in terms of reading and cognitive processing effort. Furthermore, to ensure realism and participant engagement, the tasks were selected based on actual questions asked and discussed on programming forums and websites. We specifically simplified the requirements and background of task B to match that of task A, since otherwise, choosing a JavaScript framework (e.g., to build interactive industry-level web applications) would arguably be more substantial and involve deeper and much more careful comparisons and team discussions that are beyond the scope of this lab study. In fact, as shown in section 4.5.1 there was no significant difference by task.

Each study session started by obtaining consent and having participants fill out a demographic survey. Participants were then given a 10-minute tutorial showcasing the various features of Unakite and Crystalline and a 10-minute practice session on both systems before starting. At the end of the study, the researcher conducted a survey and an interview eliciting subjective feedback on the Unakite and Crystalline experience. Each study session took approximately 60 minutes, using a designated MacBook Pro computer with Chrome, Unakite and Crystalline installed. All participants were compensated \$15 for their time.

	Manually select information and capture	Rename an option / criteria	Delete an option / criteria	Manually put information snippets into the table	Remove a snippet from the table	Merge criteria into groups	Split criteria groups	Pin or reorder criteria	Overall
Task A	27.0 (6.42)	1.67 (1.97)	0.67 (1.03)	16.5 (5.43)	0.50 (0.84)	N/A	N/A	6.00 (2.19)	52.3 (13.7)
Task B	26.2 (5.56)	1.83 (1.60)	1.50 (1.38)	14.5 (5.28)	0.33 (0.82)	N/A	N/A	6.00 (1.79)	50.3 (14.3)
Average	26.6 (5.74)	1.75 (1.71)	1.08 (1.24)	15.5 (5.21)	0.42 (0.79)	N/A	N/A	6.00 (1.91)	51.3 (13.4)
(a) Unakite condition									
	Manually select information and capture	Rename an option / criteria	Delete an option / criteria	Manually put information snippets into the table	Remove a snippet from the table	Merge criteria into groups	Split criteria groups	Pin or reorder criteria	Overall
Task A	0.83 (0.75)	2.17 (1.17)	0.50 (0.84)	0.17 (0.41)	0.33 (0.52)	2.33 (0.82)	0.83 (0.75)	5.33 (1.97)	12.5 (3.02)
Task B	1.00 (1.26)	1.67 (0.82)	0.50 (0.55)	0.33 (0.52)	0.33 (0.52)	1.83 (0.75)	0.67 (0.82)	5.50 (2.74)	11.8 (3.31)
Average	0.92 (1.00)	1.92 (1.00)	0.50 (0.67)	0.25 (0.45)	0.33 (0.49)	2.08 (0.79)	0.75 (0.75)	5.42 (2.27)	12.2 (3.04)
(b) Crystalline condition									

Table 4.2: Statistics for the average number of interactions performed by users to perform the tasks in the user study. Standard deviations are included in the parentheses.

4.5 Results

4.5.1 Quantitative Results

All participants were able to complete all of the tasks in both conditions, and nobody went over the pre-imposed time limit. Figure 4.1, together with Figure 4.2, shows an example table built by one of the participants in the study for task A.

To examine how Crystalline performs compared to the baseline Unakite condition, we measured the time it took for participants to finish each task. A two-way repeated measures ANOVA was conducted to examine the within-subject effects of condition (Crystalline vs. Unakite) and task (A vs. B) on task completion time. There was a statistically significant effect of condition ($F(1, 20) = 8.06$, $p = 0.01$) such that participants completed tasks significantly faster (21.6% faster) with Crystalline (Mean = 611.8 seconds, SD = 144.6 seconds) than in the Unakite condition (Mean = 780.3 seconds, SD = 137.6 seconds). There was no significant effect of task ($F(1, 20) = 0.11$, $p = 0.74$), indicating the two tasks were indeed of roughly equal difficulty. These results suggest Crystalline helped participants build up comparison tables faster overall, even the majority of their time was necessarily spent reading through the material in both conditions.

To account for this reading time, we also compared the *overhead cost* (see section 3.4.1.2) of using both tools to collect and organize information. For the Crystalline condition, we calculated the overhead cost as the portion of the time participants spent on directly interacting with Crystalline (scrolling through the list and table view to examine the evidence collected so far, splitting and merging criteria, pinning important criteria, manually collecting information, etc.) out of the total time they used for a task (vs. reading and comprehending the web pages). Similarly, in the Unakite condition, the overhead cost was calculated as the percent of time participants spent on directly using Unakite features (selecting and collecting snippets, drag and dropping them into the comparison table, etc.), in the same way as was done to compare Unakite to Google Docs.

A two-way repeated measures ANOVA was conducted to examine the within-subject effects of condition (Crystalline vs. Unakite) and task (A vs. B) on overhead cost. There was a statistically significant effect of condition ($F(1, 20) = 77.5$, $p < 0.001$) such that the overhead cost was significantly lower (almost 60% lower) in the Crystalline condition (Mean = 11.6%, SD = 0.04)

than in the Unakite condition (Mean = 28.4%, SD = 0.07). Again, there was no significant effect of task ($F(1,20) = 0.53$, $p = 0.48$). Thus, using Crystalline resulted in reduced overhead costs of collecting and organizing information.

To gain deeper insights into *why* the overhead cost was significantly lower in the Crystalline condition, we tallied the number of interactions performed in each task while collecting and organizing information to build the comparison tables (Table 4.2). Here, we notice that the majority of interactions in the Unakite condition are to manually collect information snippets (on average 26.6 times) and place them into the comparison table (on average 15.5 times). In contrast, in the Crystalline condition, the majority of interactions are to merge criteria into groups (on average 2.08 times) and pin or reorder the criteria in the table (on average 5.42 times). This suggests that, to some extent, Crystalline has transformed the previously active capturing and organizing work into passive monitoring and error-fixing, which explains the lower overhead cost.

In the survey, participants reported (in 7-point Likert scales) that they thought the interactions with Crystalline were understandable and clear (Mean = 6.17, SD = 0.39), Crystalline was easy to learn (Mean = 6.08, SD = 0.79), and they enjoyed Crystalline’s features (Mean = 6.25, SD = 0.45). In addition, compared to Unakite (Mean = 5.75, SD = 0.45), they thought using Crystalline (Mean = 6.08, SD = 0.29) would help them solve programming problems more efficiently and effectively, and would recommend Crystalline (Mean = 6.17, SD = 0.58) over Unakite (Mean = 5.58, SD = 0.51) to friends and colleagues doing programming work, both differences were statistically significant under paired t-tests.

4.5.2 Qualitative Observations

4.5.2.1 Usability and usage patterns

Overall, participants appreciated the increased efficiency afforded by various Crystalline features. Many (9/12) mentioned that the perceived workload to collect and organize what they have investigated was minimal, saying that *“I feel like I got a table for free”* (P3), *“the fact that I can see what I’ve paid a lot of attention to automatically bubbles up to the top is quite magical”* (P9), and *“It feels as if I was sitting in the passenger seat and not having to do all the steering and maneuvering”* (P7). Some (3/12) participants also reported having taken advantage of the overlooked information reminder feature (Figure 4.2-d) to guide their research. Furthermore, participants reflected that Crystalline relieves them of the burden of trying to anticipate the value of a particular piece of information before collecting it since *“the important bits will eventually be at or near the top, hopefully”* (P12), and they could *“focus on reading the page itself and not context switch to bookkeeping mode again and again”* (P5).

However, some did voice concerns about the system’s ability at the beginning of the tasks, arguing that they were *“skeptical if it will actually collect the right things”* (P1), and reported that they would *“skim through the list view and the table view quite frequently at the beginning”* (P7). However, as they progressed through the tasks, their confidence in Crystalline increased, and they only occasionally checked the sidebar. We observed that three of the 12 participants ended up not examining and editing the system’s output until they felt like they had finished reading and processing all the given pages, and they made minimal edits to the results.

4.5.2.2 Working with machine suggestions

Participants generally thought that the benefits of automating the collection and organization process outweighed the costs of dealing with occasional unhelpful machine suggestions, such as incorrectly merging criteria together or prioritizing unimportant criteria at the top of the list. For example, P7 reflected, *“it feels like a mind reader. I know it’s not perfect, but I also don’t expect it to be, and would actually prefer occasionally peeking into what it’s been doing and fixing whatever that’s not correct than grabbing everything by myself all the time.”*

Some did raise concerns about the ordering of criteria getting changed too frequently (*“they [the criteria] were jumping around”*, P7) at the beginning. This is likely due to the fact that users were skimming through a web page without paying particular attention to anything at the beginning, causing their attention scores to be relatively indistinguishable. For future iterations of the system, we could experiment with less frequent UI update intervals under these circumstances so it would cause less distraction.

4.5.3 Evaluation Discussion

Similar to what was reported in prior work [223], since our participants were not explicitly told how the system worked to automatically collect and rank information, they had to form their own mental models and hypotheses about how the system works and how they could affect it with their behavior. For example, P8 noticed that *“it looks like if I spend a little bit more time on a particular place on a page, the corresponding criterion would get picked up and bumped up quickly; and if I click on that part a bunch of times, which happens to be what I typically would do when I try to focus my attention on something now that I’m thinking about it, it’s [the corresponding criterion] going to go up even faster.”* This suggests that our implicit signals were working, and further, that with experience users might adapt to *explicitly* steer the system towards their goal of collecting and prioritizing information, resulting in, to some extent, a mixed-initiative collection approach that still would require much less effort than the baseline methods. Future research could explore the costs and benefits of a wide variety of interactions and signals that lie on the spectrum between implicit behavioral signals to full manual direct manipulations, and any differences caused by directly instructing users about the implicit signals being used.

Though the current version of Crystalline mainly focuses on reducing the cost for developers to collect and organize information, which was exactly what we tested in the lab study, we were also interested in making sure that the *quality* of the comparison tables built using Crystalline does not degrade as seen in other automation scenarios [108, 251]. Since there is not a gold standard comparison table, we evaluated the correctness of Crystalline’s automatic approaches by how much editing participants had to do in order to fix Crystalline’s mistakes and make sure that all the content in the table was eventually filled out and ranked correctly according to their understanding as per the study protocol. As shown in Table 4.2(b), participants only had to perform on average 12.2 edits to the automatically generated comparison tables, compared to the 51.3 actions that they had to manually perform in the baseline Unakite condition (the difference is statistically significant, $p < 0.01$). Among these, edits that are related to collecting information, such as manually selecting information and capture (0.92 times), renaming (1.92 times), and deleting information (0.50 times) were minimal, suggesting that our combination of NLP and behavioral signal heuristics was working effectively to collect information that the users thought was important. However, participants pinned or reordered the criteria that were automatically ranked by Crystalline on average 5.42 times (SD = 2.27 times). One possible explanation is that

the universal scoring functions (in Table 4.1) did not necessarily apply to every single participant, suggesting the need for a more sophisticated and personalized scoring mechanism in future iterations of Crystalline and systems that leverage signals from users’ natural browsing behavior.

In addition, we asked and coded their opinions about *using* these tables as if they were the subsequent developers trying to *understand* the design rationale. In general, participants were excited about using comparison tables automatically built by Crystalline. For example, P10 highlighted scenarios where Crystalline would be useful for his own purposes, saying that “*it’s sort of like a never-erased whiteboard that would most likely help me remember what I looked at three months ago.*” In addition, some reflected that compared to having no clue of why a decision was made in a particular way in the first place, they would appreciate at least having access to a Crystalline table even if it was not actively monitored and maintained during the initial developer’s sensemaking process. For example, P4 said: “*I think being able to read something like this [Crystalline table] is going to make a big difference when you’re banging your head against the wall trying to understand why this particularly old API was chosen, I mean, especially when the guy who wrote the code was long gone, I could at least ‘read a transcription of his mind’ in some sense.*” Here, we see preliminary evidence that our approach of automatically collecting and organizing information on behalf of developers is useful and valuable. We leave the formal evaluation of the quality of fully automatically built comparison tables with possibly more advanced versions of Crystalline for future work.

4.6 Discussion and Limitations

Currently, Crystalline works best on a limited set of web pages in the programming domain, including documentation pages that are dedicated to a particular library or a set of APIs, as well as review articles or question answering pages that discuss and compare several options together. We chose to optimize for these types of web pages in the current prototype as they are reported in prior work [131, 177] as well as our formative discussions with developers as some of the most frequently consulted programming resources when it comes to making decisions. However, the performance reported on the web pages used in the study is not necessarily representative of how Crystalline would operate even on web pages of these types for users in general. In addition, Crystalline currently relies heavily on the overall structure of the web pages being standard, meaning that a page uses HTML tags appropriately according to their semantics (e.g., enclosing headers and list items in `<h>` and `` tags rather than wrapping everything with `<div>` tags) and that there is a strong semantic coherence between a section header and its corresponding content. Though this is sufficient to demonstrate the idea of automatic collecting and organization and the benefits they offer, future research is needed to make Crystalline-style tools work on a more diverse set of web pages, as well as how to be clear upfront about its limitations in parsing web pages that do not follow appropriate web standards.

In addition, our lab study has several limitations. Given the short amount of training and practice time participants had, some might not have been able to fully grasp the various features of Crystalline, or they might have been confused about what Unakite (the baseline system) has to offer. The study tasks might not be what participants typically encounter in their daily work, depending on whether they are in a position to make decisions, and thus they may not be equipped with the necessary motivation or context that they would otherwise have in real life. We mitigate these risks in the study setup by: 1) having participants perform a practice task for each condition simulating what they would have to do in the real tasks; 2) choosing the study tasks

based on actual questions that are discussed by developers on Stack Overflow and other popular programming community forums; and 3) providing participants with sufficient background information and context to help them get prepared. In fact, 7 out of 12 participants reported that the tasks were indeed similar to what they would deal with in their daily work. One further address these limitations in the future by having developers use Crystalline on their own work and personal projects, which would provide them with sufficient motivation as well as experience with Crystalline enriched over time.

Furthermore, the overhead cost measurement in the study could be conservative, as we did not account for the time participants spent simply glancing or looking at the sidebars without any explicit interactions with it. However, from our observations during the study, participants rarely spent any extended time doing this. Nevertheless, we would like to take advantage of more advanced tools such as eye tracking [42, 210, 211, 227] in the future to more accurately account for the proportion of time when a participant’s gaze is fixated on the user interface of the tools rather than on actual web content.

Last but not least, automation afforded by systems like Crystalline enable people to focus their attention on reading and comprehending the web pages rather than splitting attention with having to collect and organize the information at the same time. However, prior work in learning science, such as Bransford et al. [69], found that people who *personally* performed the actions of collecting, categorizing, and organizing information were more likely to be able to recall it correctly and in detail, and exhibited increased confidence in the final outcome. This raises an interesting tension and trade-off between full-on automation and direct manipulation — future research would be required to examine the long term effect on people’s learning outcome as well as confidence in their decisions using systems like Crystalline, and determine the appropriate levels and circumstances when automatic information bookkeeping should be applied.

Chapter 5

Wigglyte: Lightweight Gestures for Collection and Triage

This chapter was adapted from my published paper:

Michael Xieyang Liu, Andrew Kuznetsov, Yongsung Kim, Joseph Chee Chang, Aniket Kittur, and Brad A. Myers. 2022. “Wigglyte: Low-cost Information Collection and Triage.” *In Proceedings of the 35nd Annual ACM Symposium on User Interface Software and Technology (UIST '22)*. Association for Computing Machinery, New York, NY, USA, 67–80.
Video: https://youtu.be/_MH81Zuyj64

5.1 Overview

Consumers conducting comparison shopping, researchers making sense of competitive space, and developers looking for code snippets online all face the challenge of capturing the information they find for later use without interrupting their current flow. In addition, during many learning and exploration tasks, people need to externalize their mental context, such as estimating how urgent a topic is to follow up on, or rating a piece of evidence as a “pro” or “con,” which helps scaffold subsequent deeper exploration. However, current approaches incur a high cost, often requiring users to select, copy, context switch, paste, and annotate information in a separate document without offering specific affordances that capture their mental context.

To summarize, we frame a fundamental sensemaking challenge for people trying to research and make decisions online as the high friction involved in capturing: (1) the content that they want to keep track of, which can range from a word, a phrase, an image, to a paragraph or multiple blocks of mixed multimedia content, (2) which option or topic that content corresponds to and its perceived priority for further investigation (which is called “triaging”), and (3) whether the evidence they find about that option or topic is positive or negative regarding its suitability for the user’s goals (which is called “valence”) [177].

Our vision in this chapter is to create a technique that reduces the friction for the transfer of a user’s internal mental judgements while they are processing information into an external system that will capture those judgements and scaffold sensemaking and exploration. While it is a challenge for the cost of this transfer to be zero, we aim to reduce the overhead significantly by exploring a new interaction technique called “wiggling,” which can be used to fluidly collect,

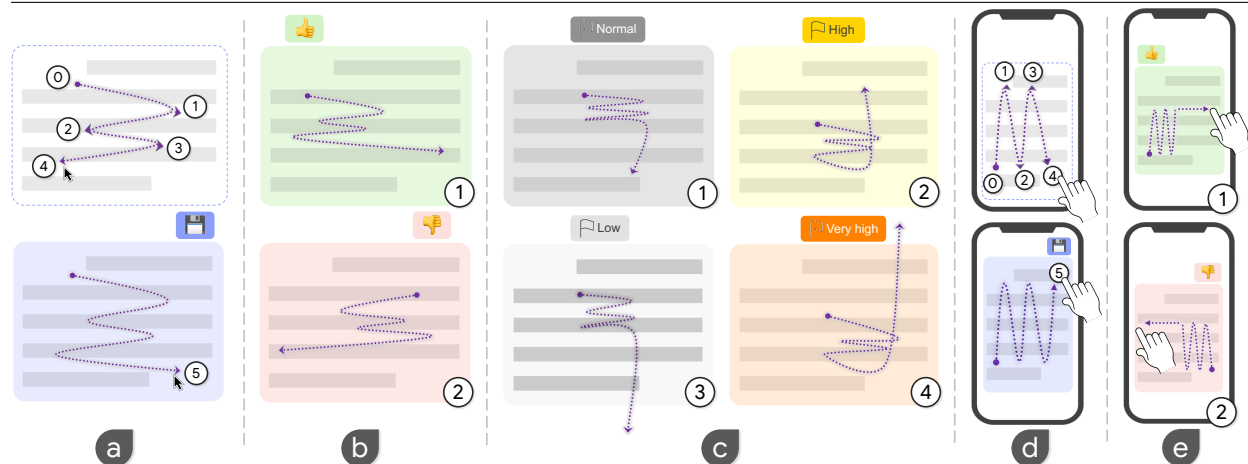


Figure 5.1: We introduce the “wiggling” technique: rapid back-and-forth movements of a mouse pointer on desktop (a) or a finger on mobile devices (d) that do not require any clicking to perform, yet are sufficiently accurate to select the desired content, while at the same time supporting an optional and natural encoding of valence rating (positive to negative) (on desktop: b1-2, on mobile: e1-2) or classification of priority (to facilitate triage) (c1-4) by ending the wiggle with a swipe in different directions.

organize, and rate information during early sensemaking stages with a single gesture. Wiggling involves rapid back-and-forth movements of a pointer or up-and-down scrolling on a smartphone, which can indicate the information to be collected and its valence, using a single, light-weight gesture that does not interfere with other interactions that are already available. Through implementation and user evaluation, we found that wiggling helped participants accurately collect information and encode their mental context with a 58% reduction in operational cost while being 24% faster compared to a common baseline.

5.2 Related Work

5.2.1 Recognizing and Using Gestures

The wiggle gesture we use in Wigglite (as shown in Figure 5.1) has a similar form to a scratch-out gesture in some previous systems used for undo [280], edit [232], or delete. Wiggling has also been used by some window managers, for example, Microsoft Windows 7 in 2009 introduced “Aero Shake” [265] where grabbing the title bar with the mouse and shaking the window left and right minimizes all other windows, or restores them. However, these gestures all require that the mouse button first be depressed, while our approach, on the contrary, is specifically designed to work when with none of the mouse buttons are depressed. In addition, macOS has an accessibility feature that supports shaking the mouse to make the size of the pointer much larger to help locate the pointer [259]. Importantly, our testing shows that those features do not interfere with our browser-based implementation of wiggle-based gestures.

Over the years, many complex gesture *recognizers* have been developed, such as the Rubine recognizer [232], which extracts multiple features from a trajectory and uses a linear classifier for recognition. However, these parametric recognizers are difficult to control with respect to the variances in gestures to be supported. Another approach is template-based gesture recognition, such as the \$1 recognizer [281] and the Protractor recognizer [172], which compare new trajectories to the pre-defined gesture templates, and is more lightweight without sacrificing too much

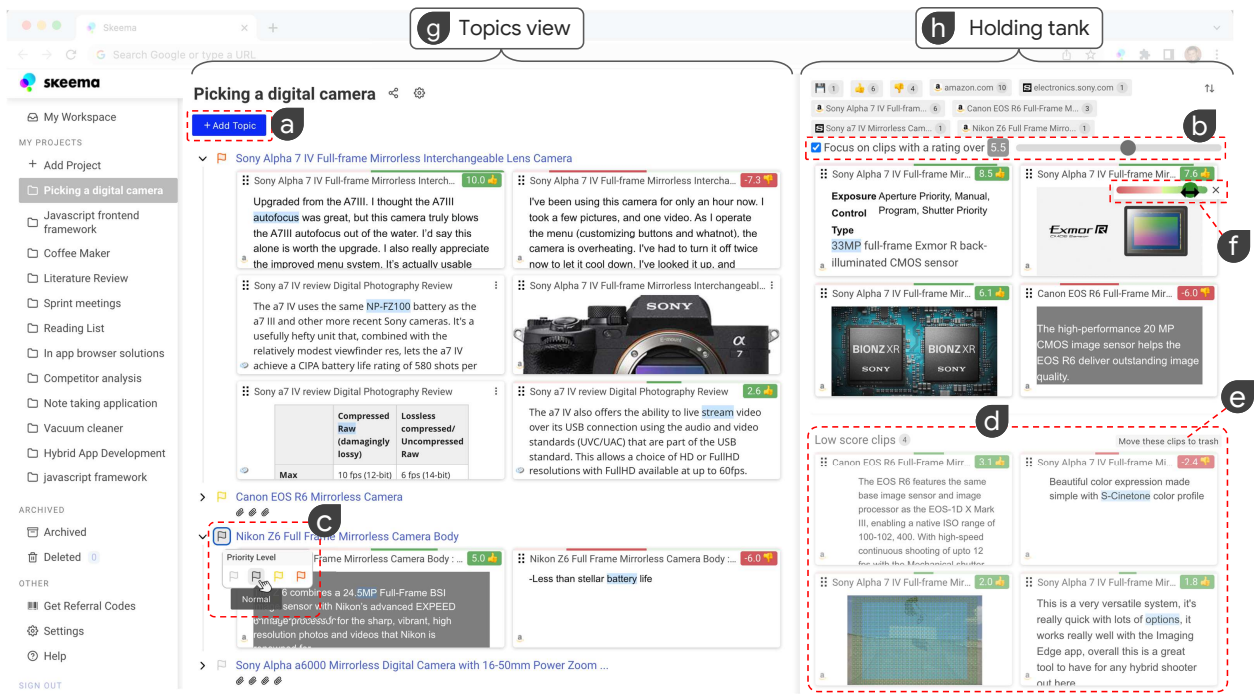


Figure 5.2: Wigglyte’s UI built on top of SKEEMA. On the left is the topics view (g) where users can create a topic (a) as well as change its perceived priority (c). On the right is the holding tank (h) that holds the collected information, in which users can filter out information with a lower rating using the slider (b). As a result, clips with rating scores lower than the set threshold would be automatically grouped together at the end and grayed out (d), and users can easily archive or put them in trash by clicking a button (e). In addition, users can manually adjust the valence rating of an information clip (f).

accuracy. However, these recognizers can be both time and resource intensive, especially on mobile devices where the computing power and resources are usually limited. In our work, we built a heuristics-based ad-hoc recognizer (see section 5.4), allowing the system to perform real-time eager recognition [233] without impacting the performance of other UI activities on both desktop and mobile devices. In addition, building on prior evidence that people can accurately perform swipes to as many as eight different directions [52, 156], we support ending the wiggle gesture with a directional swipe to further classify the collected information or encode people’s mental context in situ.

5.3 Background and Design Goals

To ground our research, we build on an existing information and task management system called SKEEMA. First, we briefly describe SKEEMA and its features related to the context of this work, then discuss the design goals and processes for the wiggling gesture for the new Wigglyte system.

5.3.1 The SKEEMA system

SKEEMA is a Chrome browser extension designed to support people’s need to collect and organize information and manage their tabs during online sensemaking. Different from general web clippers that typically only support saving entire pages of web content into an individual note within a notebook [84], SKEEMA enables people to save an arbitrary amount of web content as

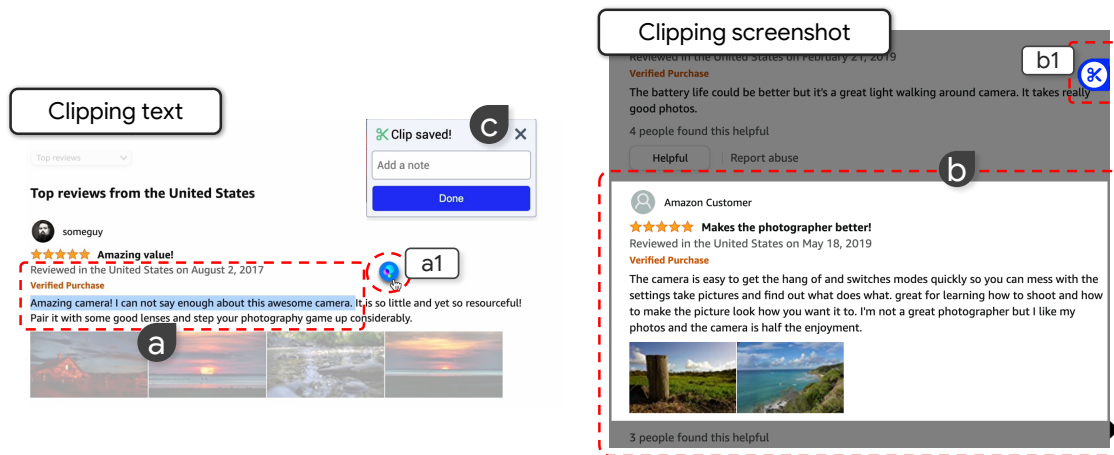


Figure 5.3: Two clipping mechanisms that SKEEMA supports: clipping text (left) and clipping screenshot (right).

information clips (Figure 5.5-c) into a holding tank (Figure 5.2-h), and later organize them into topics in the topics view (Figure 5.2-g). For clipping, SKEEMA offers two methods:

- **Clipping text:** Users can select arbitrary content using the cursor and click the clipping button that pops up to collect the selected texts (see the left part of Figure 5.3).
- **Clipping screenshot:** Users can use the screenshot feature to drag out a bounding box to save the desired content (see the right part of Figure 5.3).

To help users express whether a piece of evidence that they collected is positive or negative with regard to their own goal, SKEEMA allows users to add a valence rating from -10 to +10, with negative values indicating a “con” and denoted by a “thumbs-down” emoji and positive values indicating a “pro” and denoted by a “thumbs-up” emoji (see Figure 5.5-c1).

SKEEMA allows users to organize information into thematically related topics in the topics view (Figure 5.2-g). To achieve that, users need to manually create a topic (Figure 5.2-a), enter a name, and drag the desired information cards from the holding tank and drop it into the topic. Users can also set priority to a topic to indicate its perceived utility and how much they want to follow up on it, which defaults to be “Normal”, but can also be set to “Low”, “High”, or “Very high” (Figure 5.2-c).

Although SKEEMA has the support for collecting finer-grain content (which research has shown to be the unit of information that people usually think in and work with during sensemaking [188, 241]), there is still a high cost in specifying the collection boundary and adding ratings and priorities to the collected information and topics (which users would have to switch to the SKEEMA tab to do). In addition, clipping text in SKEEMA loses the text’s original CSS styling, which might be helpful for quicker recognition later on [177], and SKEEMA does not gracefully support collecting consecutive blocks of mixed content (e.g., consumer review text of a camera followed up some sample photos, such as shown in Figure 5.3-b).

5.3.2 Design Goals for Low-cost Information Capturing and Triaging

Guided by prior work and well as the limitations of SKEEMA discussed above, we set out to provide an interaction that could simultaneously reduce the cognitive and physical costs of *capturing* information while providing natural extensions to easily and optionally *encode* aspects of users’ mental context during sensemaking. We hypothesize that such an effective interaction should have the following characteristics:

- (1) **Accuracy:** It needs to be accurate and precise enough to lock onto the content the users intend to collect.
- (2) **Efficiency:** It should be quick and low-effort to perform, and minimize interruptions to the main activities that users are performing, such as learning and active reading.
- (3) **Expressiveness:** It should be extendable to provide natural and intuitive affordances for users to express aspects of their mental context at the moment. In the scope of this work, we would like to have wiggling support encoding valence ratings as well as topic priorities.
- (4) **Integration:** It should be a complement to and not interfere with the existing interactions that users already use, such as using the pointer to select text and pictures or click on links.

Below, we present a brief overview of the iterative design exploration leading to the current wiggle-based interactions.

5.3.3 Iterative Design Exploration

To begin our exploration, we took a desktop-first approach and brainstormed various interactions that would address these four design goals. To ground our explorations, we also prototyped these candidate interactions using JavaScript in a browser, which is where a large portion of the reading and collecting happens [58, 114]. Like previous approaches, collecting the desired content, including text and/or images, can be broken down into two main phases: *(a) identifying the desired target* and *(b) triggering the collection*.

One of the interactions we first explored was simply clicking on the desired content (or in the gutter to the left or right) to capture it into the system, similar to existing interactions supported by some text editors such as Microsoft Word. Although straightforward, this interferes with existing selection methods, and would require users to first enter a “grabber” mode, possibly through a special hotkey combination, which violates both design goals (2) and (4). Next, we experimented with hovering the pointer over the target content and keeping it still for a period of time in order to trigger a collection. This has the benefit of not interfering with existing interaction methods as there is no clicking required, satisfying goal (4). However, research has shown that when heavily engaged in active reading and sensemaking tasks, people often need to select and save information frequently within short time intervals [58, 275], and waiting for a noticeable amount of time will add an inherent cost to every collection operation a user wants to perform and therefore is likely to interrupt the user’s main activity, violating design goal (2).

Next, we experimented with using non-click gestures (satisfying goal (4)) performed on the desired target to trigger the selection, since gestures are considered intuitive to perform and widely used in both commercial and academic systems [157, 162, 166, 233, 268]. One of the promising ideas was to use the mouse pointer to sketch out a certain shape over the desired target to trigger a collection. In addition, by varying the shape, it could theoretically support encoding different aspects of users’ mental model, such as sketching a “+” for marking it as a “pro” and “-” as a “con” [281], supporting design goal (3). However, similar to using keyboard shortcuts, it is hard for users to learn and memorize the different shapes without special affordances [162, 290]. Furthermore, making sure one sketches out the correct gesture may require non-trivial physical as well as cognitive demand, violating goal (2), and even so, these shapes can have a high false recognition rate, violating goal (1).

We then experimented with gestures that do not require special training or practice in order to perform accurately. One that worked particularly well is wiggling the mouse pointer, i.e.,

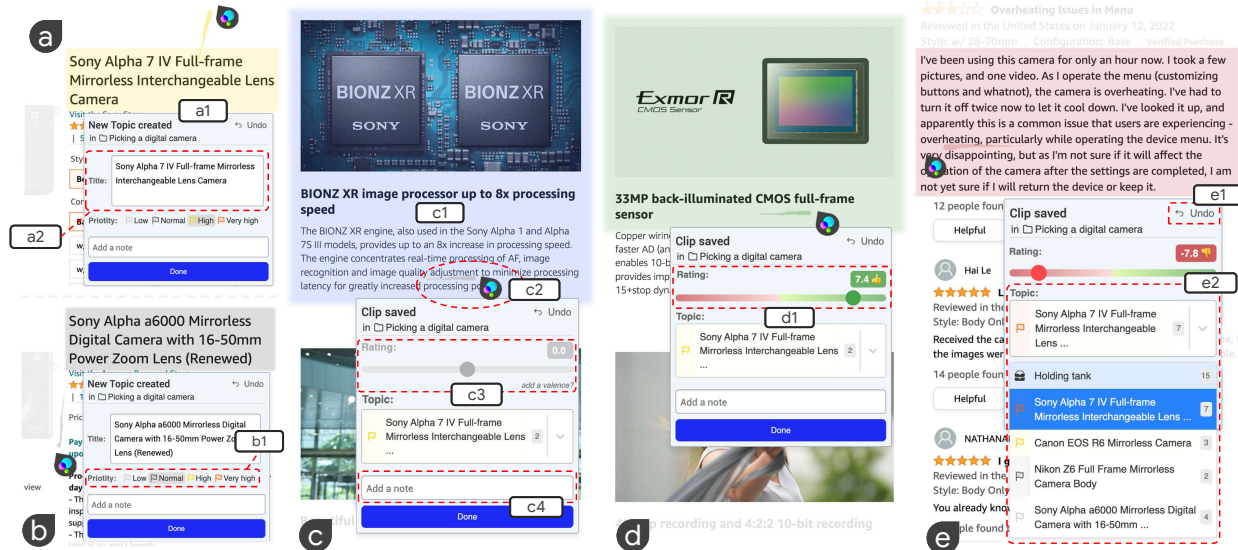


Figure 5.4: Using wiggling to collect information as well as encode priorities and valence ratings. Specifically, as shown in (c), users can wiggle (c2) over the desired content (c1) to collect it into the information holding tank (Figure 5.5-c). A popup dialog will be presented near the just collected content to allow users to optionally add a valence rating (c3), pick a topic that the content should go into (e2), add notes (c4), as well as undo the collection (e1). In addition to regular collection, users can also end the wiggle with a swipe right to encode a positive rating (d) or left to encode a negative rating (e), which can also be changed in the popup dialog (d1). Furthermore, by ending a wiggle with a swipe up (a) or down (b), users can create a new topic with different priorities (b1), and can change the title of the topic directly in the popup dialog (a1).

making small ballistic back-and-forth movements, on top of the desired collection target (Figure 5.1-a). Here, the choice of a target could be determined from the average or starting location of the mouse pointer during the gesture, and the user continues to perform the same back-and-forth motion until reaching a certain threshold to trigger the collection. Indeed, prior work has suggested that people naturally use the mouse pointer to guide their attention while reading [124], or even unconsciously have the pointer follow their eye gaze [134], so the pointer could be readily available to initiate a wiggle in place.

This has some additional benefits, such as it seemed natural and intuitive like scratching off something [232, 280], it can be activated without clicking, which can be both cognitively and physically costly [148], and is robust against false positives since only a very specific motion pattern could trigger a collection. Furthermore, it can be chained with optional operations such as swiping in different directions that not only are consistent with the wiggling gesture itself but also intuitively map to users' mental context (such as swiping left/right for negative/positive and up/down for various levels of importance, and even leveraging the amount of distance traveled of a swipe to encode a continuous value).

Since there is no mouse pointer on mobile devices such as smartphones, and using fingers to move left and right in browsers triggers page navigation back and forth, whereas up and down is used for scrolling, we decided to take advantage of these small up-and-down scroll events, since they are not currently in use by any existing interactions. Therefore the wiggling counterpart on mobile devices became using the finger to quickly scroll up-and-down while the finger is over the desired collection target (Figure 5.1-d).

5.4 The Wigglite System

5.4.1 Wiggle-based Gestures

For desktop computers with a traditional mouse, trackpad or trackball input device, the wiggle interaction consists of the following stages, as illustrated in Figure 5.1-a,-b,-c:

- (1) **Acquiring the collection target:** To initiate, users move their mouse pointer onto the target content that they would like to collect (Figure 5.1-a0) and initiate the wiggling movement specified in the steps below. Wigglite uses an always-on wiggle gesture recognizer to automatically detect the start of a wiggling gesture. This avoids the requirement of an explicit signal like a keyboard key or mouse down event, which might conflict with other actions, and has the benefit of combining activating and performing the gesture together into a single step, therefore reducing the starting cost of using the interaction technique.
- (2) **Wiggle:** To collect the target content, users simply move the mouse pointer left and right approximately inside the target content. To indicate that the system is looking to detect the wiggling gesture, it will display a small “tail” (e.g., Figure 5.4-c2) that follows the pointer on the screen, and replaces the regular pointer with a special one containing the SKEEMA icon. Wigglite also adds a dotted blue border to the target content to provide feedback about what content will be collected, and the blue color grows in shade as users perform more lateral mouse movements (Figure 5.1-a1–4). This is analogous to half-pressing the shutter button to engage the auto-focus system to lock onto a subject when taking photos with a camera. To assist with collecting fine grain targets, ranging from a word to a block (e.g., a paragraph, an image), Wigglite allows users to vary the average size of their wiggling to indicate the target that they would like to collect: if the average size of the last five lateral movements of a pointer is less than 65 pixels (a threshold empirically tuned that worked well in our pilot testing and user study, but implemented as a customizable parameter that individuals can tune based on their situations), Wigglite will select the word that is covered at the center of the wiggling paths; while larger lateral movements will select a block-level content (details discussed in section 5.4.3.2). In addition, users can abort the collection process by simply stopping wiggling the mouse pointer before there are sufficient back-and-forth movements.
- (3) **Collection:** As soon as users make at least five back and forth motions (optimized for the amount of physical effort required and the number of false positive detection through pilot testing, but is also implemented as a parameter that can be customized by individuals in practice, details discussed in section 5.4.3.1), the system will commit to the collection, and gives the target a darker blue background showing that a wiggle has been successfully activated (as shown in Figure 5.1-a5). If users want to collect multiple blocks of content, they can just naturally continue to wiggle over other desired content after this activation. Or, they can stop wiggling. However, if users have selected the wrong target, an undo button appears, which can be clicked to cancel the collection (Figure 5.4-e1).
- (4) **Extension:** Instead of just stopping the wiggle motion after collection, users can leverage the last wiggle movement and turn it into a “swipe”, either horizontally to the right or left to encode a positive or negative valence rating (as shown in Figure 5.1-b1,b2), or vertically down or up to specify a topic and priority for that topic (as shown in Figure 5.1-c1–4). Feedback for the extension uses different colors for the background of the target content to provide visual salience (details discussed in section 5.4.2).

Similarly, on a mobile device with touch screens:

- (1) **Acquiring collection target:** To initiate, a user’s finger touches the target content that should be selected.
- (2) **Wiggle:** To collect the target block, the user keeps the finger on the screen and starts making small up-and-down scrolling movements. Similar to the desktop scenario, the system adds a dotted blue border to the target content to provide feedback that the wiggling is being detected (Figure 5.1-d0–4). Note that due to the limitations of the large size of the finger with respect to an individual word [58] as well as the unique use cases of mobile devices (e.g., quickly consuming and collecting blocks of information on the go [137, 276]), Wigglite for mobile only supports selecting block-level content such as paragraphs or images.
- (3) **Collection:** As soon as the user makes at least five up-and-down motions, the system will commit to the collection by giving the target a darker blue background (Figure 5.1-d5). Now, the user can stop wiggling and lift the finger from the screen. Similar to the desktop version, an undo button pops up that lets the user cancel the collection in case of an error. Note that due to the limited screen real estate that typical mobile devices afford, additional blocks of content will have to be first scrolled into view for users to then capture them, which would make the interaction less fluid. Therefore, collecting multiple blocks of content is currently not supported by Wigglite on mobile.
- (4) **Extension:** Instead of stopping the wiggle motion after collection, users can end the wiggle with a horizontal swipe to the left or right to achieve similar encoding capabilities described for the desktop version. After the system detects the wiggle, it turns off other actions until the finger is lifted, so the swipes do not perform their normal actions. (But the normal swipes, scrolling, and other interactions still work normally when not preceded by a wiggle.) Currently, since Wigglite already uses the vertical dimension for detecting wiggling movement on a mobile device, and large cross-screen vertical movements are difficult to perform, especially when holding and interacting with a single hand, we opted not to make a mobile equivalent of encoding topic priorities.

5.4.2 An Overview of The Wigglite System

Wigglite enables users to collect and triage web content via wiggling. First of all, after a regular wiggle with no extension (Figure 5.4-c), Wigglite presents a popup dialog (augmenting the original SKEEMA popup) directly near the collected content to indicate success. In addition to SKEEMA’s notes field (Figure 5.4-c4), users can attach a valence rating (Figure 5.4-c3) and pick the topic that this piece of information should be organized in (Figure 5.4-e2), as opposed to post-hoc organization using drag and drop as required by SKEEMA. By default, it goes into the last topic the user picked or the holding tank if none was picked initially. Unlike SKEEMA where information was saved in pure text format or an inflexible screenshot with limited resolution, Wigglite leverages the technique introduced in [177, 179] to preserve and subsequently show the content with its original CSS styling, including the rich, interactive multimedia objects supported by HTML, like links and images. This makes the content more understandable and useful, and also helps users quickly recognize a particular piece of information among many others by its appearance [177].

Of course, a more fluid way to encode user judgements than what was described above is to leverage the natural extension of the wiggle gesture discussed in the previous section: to encode a valence rating in addition to collecting a piece of content, users can end a wiggle with a horizontal “swipe”, either to the right to indicate positive rating (or “pro”, characterized by a green-ish color that the background of the target content turns into, and a thumbs-up icon, as shown in Figure

5.4-d), or the left for negative rating (or “con”, characterized by a red-ish color that the background of the collected block turns into, and a thumbs-down icon, as shown in Figure 5.4-e). Optionally, users can also turn on real-time visualizations of “how much” they swiped to the left or right to encode a rating score representing the degree of positivity or negativity, and can adjust that value in the popup dialog (Figure 5.4-d1) or from the information card (Figure 5.2-f). Under the hood, Wigg lite calculates this score as the horizontal distance the pointer traveled leftward or rightward from the average wiggle center divided by the available distance the pointer could theoretically travel until it reaches either edge of the browser window. This score is then scaled to be in the range of -10 to 10 to match with the existing values provided by SKEEMA.

Alternatively, to directly create a topic and encode it with a priority from wiggling, users can either end the wiggle with a swipe up (encoding “high”, characterized by a yellow-ish color that the background of the target content turns into, as shown in Figure 5.4-a) or down (encoding “normal”, characterized by a gray-ish color that the background of the target content turns into, as shown in Figure 5.4-b). Optionally, if the user swipes all the way up or down to the edge of the browser window, Wigg lite will additionally encode two more levels of priorities, “urgent” and “low”, indicated by a bright orange and a muted gray color (Figure 5.4-b1), which can be adjusted in the popup dialog (Figure 5.4-b1) as well as in the topics view (Figure 5.2-c). In this case, the content will instead be used as the default *title* of the newly created topic (which users can change in the popup dialog directly as shown in Figure 5.4-a2 or later in the topics view).

To help users better manage the information that they have gathered in the holding tank, Wigg lite offers several additional features on top of the original SKEEMA system. First, it enables users to sort the information cards by various criteria, such as in the order of valence ratings or in temporal order (Figure 5.5-b). Second, it offers category filters (Figure 5.5-a) automatically generated based on the encodings that users provided using wiggling (or edited later) and the provenance of information (where it was captured from). Users can quickly toggle those on or off to filter the collected information. For example, in Figure 5.5-b, the information with a “positive rating” or “negative rating” and collected from “amazon.com” was filtered and shown, as indicated by the dark gray background of the corresponding filters (if none of the filters are enabled, all the information cards will be shown). Third, users can quickly filter out information with a lower rating (e.g., indicating that it was less impactful to a user’s overall goal and decision making) by adjusting the threshold using the “Focus on clips with a rating over threshold” slider shown in Figure 5.2-f. As a result, clips with rating scores lower than the set threshold would be automatically grouped together at the end and grayed out (Figure 5.2-d), and users can easily archive or put them into the trash in a batch by clicking the “Move these clips to trash” button (Figure 5.2-e). These organizational features further help users reduce clutter in the holding tank, and provide a scaffold for them to start dragging and dropping clips into their respective topics.

Due to the limited screen size and use cases of a mobile device, we chose to only let users view the clips along with their valence in the holding tank (Figure 5.5-c).

5.4.3 Design and Implementation Considerations

Here, we discuss important design and implementation considerations made through prototyping Wigg lite with JavaScript in a browser to achieve the design goals specified in section 5.3.2.

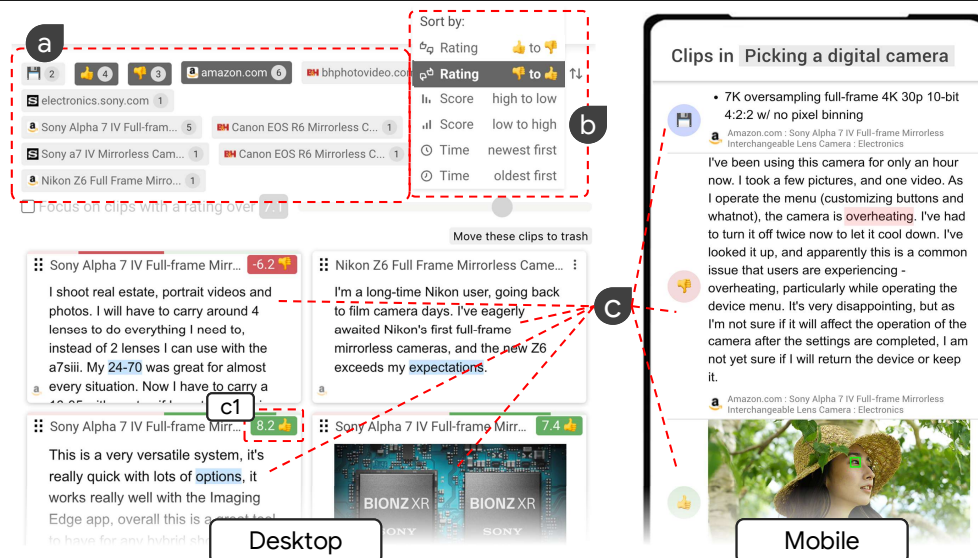


Figure 5.5: Wigglyte’s information holding tank shown both on desktop and on mobile, which houses content that users collected through wiggling in the form of information cards (c). In addition, on desktop, users can apply different filters (a) and sorting mechanisms (b) to the information cards.

5.4.3.1 Recognizing a wiggle gesture

For accurately recognizing the wiggle pattern, we explored several options. One way is to use an off-the-shelf gesture recognizer such as the \$1 [281] or the Protractor [172] recognizer. Although these recognizers may be lightweight and easy to customize, they are fundamentally designed to recognize distinguishable shapes such as circles, arrows, or stars, while the path of our wiggle gesture does not conform to a particular shape that is easily recognizable (and we argue that it should not conform to any particular shape, the sketching of which would increase the cognitive and physical demand). A second option we investigated was to build a custom computer vision based wiggle recognizer using transfer learning from lightweight image classification models such as MobileNets [130]. Though these ML-based models improved the recognition accuracy in our internal testing, they incurred a noticeable amount of delay due to browser resource limitations (and limitations in network communication speed when hosted remotely). This made it difficult for the system to perform eager recognition [233] (recognizing the gesture as soon as it is unambiguous rather than waiting for the mouse to stop moving), which is needed to provide real-time feedback to the user on their progress.

To address these issues, we discovered that a common pattern in all of the wiggle paths that users generated with a mouse or trackpad during pilot testing share the characteristic that there were at least five (hence the activation threshold mentioned in section 5.4.1) distinguishable back and forth motions in the horizontal direction, but inconsistent vertical direction movements. Similarly, on smartphones, wiggling using a finger triggers at least five consecutive up and down scroll movements in the vertical direction but inconsistent horizontal direction movements. Therefore, we hypothesized that only leveraging motion data in the principle dimension (horizontal on desktop, and vertical on mobile) would be sufficient for a custom-built recognizer to differentiate intentional wiggles from other kinds of motions by a cursor or finger.

Based on our implementation using JavaScript in the browser, we found that it successfully supports real-time eager recognition with no noticeable impact on any other activities that a user performs in a browser. Specifically, the system starts logging all mouse movement coordinates (or scroll movement coordinates on mobile devices) as soon as any mouse (or scroll) movement

is detected, but still passes the movement events through to the rest of the DOM tree elements so that regular behavior would still work in case there is no wiggle. In the meantime, the system checks to see if the number of reversal of directions in the movement data in the principle direction exceeds the activation threshold, in which case a “wiggle” will be registered by the system. After activation, the system will additionally look for a possible subsequent wide horizontal or vertical swipe movement (for creating topics with priority or encoding valence to the collected information) without passing those events through to avoid unintentional interactions with other UI elements on the screen. As soon as the mouse stops moving, or the user aborts the wiggle motion before reaching the activation threshold, the system will clear the tracking data to prepare for the next possible wiggle event.

5.4.3.2 Target Acquisition

In order to correctly lock onto the desired content without ambiguity, we explored two approaches that we applied in concert in Wigglyte. The first approach is to constrain the system to only be able to select certain targets that are usually large enough to contain a wiggling path and semantically complete. For example, one could limit the system to only engage wiggle collections on block-level semantic elements [1], such as `<div>`, `<p>`, `<h1>`–`<h6>`, ``, ``, `<table>`, etc. This way, the system will ignore inline elements that are usually nested within or between a block-level element. This approach, though sufficient in a prototype application, does rely on website authors to organize content with semantically appropriate HTML tags.

The second approach is to introduce a lightweight disambiguation algorithm that detects the target from the mouse pointer’s motion data in case the previous one did not work, especially for a small `` or an individual word. To achieve this, we chose to take advantage of the pointer path coordinates (both X and Y) in the last five lateral mouse pointer movements, and choose the target content covered by the most points on the path. Specifically, we used the same re-sampling and linear interpolation technique introduced in the \$1 gesture recognizer [281] to sample the points on a wiggle path to mitigate variances caused by different pointer movement speeds as well as the frequency at which a browser dispatches mouse movement events. On mobile devices, since the vertical wiggling gesture triggers the browser’s scrolling events, the target moves with and stays underneath the finger at all times. Therefore, we simply find the target under the initial touch position.

When Wigglyte is unable to find a target (e.g., when there is no HTML element underneath where the mouse pointer or the finger resides) using the methods described above, it does not trigger a wiggle activation (and also not the aforementioned set of visualizations), even if a “wiggle action” was detected. This was an intentional design choice to further avoid false positives as well as to minimize the chances of causing distractions to the user.

5.4.3.3 Integration with existing interactions

Notice that the wiggling interaction does not interfere with common active reading interactions, such as moving the mouse pointer around to guide attention, regular vertical scrolling or horizontal swiping (which are mapped to backward and forward actions in both Android and iOS browsers) [197, 261]. In addition, wiggling can co-exist with conventional precise content selection that are initiated with mouse clicks or press-and-drag-and-release on desktops or long taps or edge taps on mobile devices [63, 230]. Furthermore, unlike prior work that leverages pressure-

sensitive touch screens to activate a special selection mode [58], wiggling does not require special hardware support, and can work with any kind of pointing device or touch screen.

5.4.4 Implementation Notes

We implemented the wiggling technique as an event-driven JavaScript library that can be easily integrated into any website and browser extension. Once imported, the library will dispatch wiggle-related events once it detects them. Developers can then subscribe to these events in the applications that they are developing. All the styles mentioned above are designed to be easily adjusted through predefined CSS classes. The library itself is written in approximately 1,100 lines of JavaScript and TypeScript code.

The Wigglite browser extension is implemented in HTML, TypeScript, and CSS and uses the React JavaScript library [86] for building UI components. It uses Google Firebase for backend functions, database, and user authentication. In addition, the extension is implemented using the now standardized Web Extensions APIs [199] so that it would work on all major browsers, including Google Chrome, Microsoft Edge, Mozilla Firefox, Apple Safari, etc. However, we primarily targeted Google Chrome and Microsoft Edge to minimize testing efforts during development.

The Wigglite mobile application is implemented using the Angular JavaScript library [104], the Ionic Framework [136] and works on both iOS and Android operating systems. Due to the limitations that none of the current major mobile browsers have the necessary support for developing extensions, Wigglite implements its own browser using the InAppBrowser plugin from the open-source Apache Cordova platform [31] to inject into webpages the JavaScript library that implements wiggling as well as custom JavaScript code for logging and communicating with the Firebase backend.

5.5 User Evaluation

We conducted an initial lab study to evaluate the usability and usefulness of Wigglite in helping people collect information as well as encode aspects of their mental context while doing so. Specifically, we aimed to address the following research questions:

- **RQ1 [Accuracy]:** Are wiggle-based interactions sufficiently accurate to help users collect what they want?
- **RQ2 [Efficiency]:** Are wiggle-based interactions sufficiently low-friction to perform without interrupting the primary reading and sensemaking activities?
- **RQ3 [Expressiveness]:** Are the proposed extensions of marking priorities and valence useful in helping people encode their mental contexts?
- **RQ4 [Integration]:** Do wiggle-based interactions interfere with existing interactions that people are already using?

5.5.1 Participants

We recruited 12 participants (6 male, 6 female; 3 students, 3 software engineers, 2 UX designers, 1 UX researcher, 1 medical doctor, 1 administrative staff member, and 1 entrepreneur) aged 21-38 years old (mean age = 28.5, $SD = 4.5$) through emails and social media. Participants were required to be 18 or older and fluent in English. All participants reported experience reading and making

sense of large amounts of information online for either professional or personal purposes on a daily basis, and had tried or were using commercially available web clipping and organization tools and systems, such as the Evernote Clipper, OneNote, or Notion.

5.5.2 Study Methodology

The study was a within-subjects design with each participant engaging in two tasks, one using Wigglyte with SKEEMA in the experimental condition, and the other just using SKEEMA in the control condition, counterbalanced for order. For our control condition, SKEEMA provided the affordances of a web clipping tool, which would provide a more conservative and matched baseline than no tool support. Specifically, our control condition enabled participants to capture text through a popup button (Figure 5.3-a1) to save highlighted text and a screenshot clipper instead of the wiggle interaction. After saving the information, participants could set the priority of topics and the valence of information in the workspace view (Figure 5.2), versus being able to encode them as a continuation of the wiggle in Wigglyte.

For each task, participants were presented with a product category they needed to research, and a set of three Amazon pages from which they were required to collect information. Participants were instructed to read through the provided webpages, collect information, and organize the information clips into topics, such as by different options or different criteria in which the options should be evaluated. They were required to at least collect 10 information clips as well as create a minimum of 3 topics with priority for each task. Participants had 15 minutes to complete the task, but could inform the experimenter to move on if they finished early.

The two tasks were:

- (A) Choosing a digital mirrorless camera: participants were told to imagine that they were to purchase a new mirrorless camera to take photos of their spouse and young kids on their weekend road trips.
- (B) Buying a vacuum cleaner: participants were told to imagine that they were to buy a new vacuum cleaner in preparation for moving into a new house with a newborn baby and their two pets.

In order to minimize differences between tasks and participant decision making, we provided a fixed set of web pages per task, each with approximately eight screens of content. As described in the results, the two tasks took approximately the same amount of time for participants to finish, and were counterbalanced in order and randomized across conditions.

Each study session started by obtaining consent and having participants fill out a demographic survey. Participants were then given a 10-minute guided tutorial showcasing the various features of Wigglyte as well as the baseline system, and a 10-minute free-form practice session to familiarize themselves with the features of both systems. At the end of the study, participants completed a survey and engaged in a semi-structured interview about their experience with the tool. The interview focused on participants' perceptions of using the wiggle-based interactions. The questions probed the perceived effectiveness of wiggling, their current practices around collecting information, and scenarios where they thought wiggling would be useful and how they would modify it to be more useful. The interviews were audio-recorded and transcribed, after which qualitative coding and thematic analysis [62] were performed.

Each study session took approximately 60 minutes to complete, using a designated MacBook computer with Google Chrome and Wigglyte installed as well as a Logitech MX Master 2S mouse.

	Condition	Overhead cost	Time (seconds)	<i>n</i> of clips collected	<i>n</i> of topics created using wiggling	<i>n</i> of topics created separately in the workspace view	Total <i>n</i> of topics created
Task A	Baseline	33.0% (8.60%)	713.7 (76.0)	21.0 (7.03)	N/A	4.17 (1.17)	4.17 (1.17)
	Wigg-lite	14.0% (7.89%)	558.7 (76.5)	38.3 (5.28)	7.50 (1.05)	0.50 (0.84)	8.00 (1.89)
Task B	Baseline	30.40% (7.31%)	692.0 (131.4)	19.5 (6.81)	N/A	4.67 (0.52)	4.67 (0.52)
	Wigg-lite	12.8% (2.74%)	515.7 (54.3)	37.3 (8.64)	7.17 (1.17)	0.50 (1.22)	7.67 (2.39)
Average	Baseline	31.7% (7.73%)	702.8 (102.9)	20.3 (6.68)	N/A	4.42 (0.90)	4.42 (0.90)
	Wigg-lite	13.4% (5.67%)	536.8 (67.0)	37.8 (6.85)	7.33 (1.07)	0.50 (1.00)	7.83 (2.07)

Table 5.1: Statistics of the performance measures in the study. Standard deviations are included in the parentheses.

5.6 Results

All participants were able to complete each task within the specified 15 minute time limit. Below, we compile together both quantitative and qualitative evidence to evaluate Wigg-lite with respect to our four design goals and research questions.

5.6.1 RQ1 [Accuracy]

First, evaluate if the wiggling gestures are accurate enough to help users collect and express what they want. Specifically, we looked for cases where: (1) participants hit the undo button to dismiss an incorrect wiggle activation and redo the wiggling due to Wigg-lite picking up the wrong target content, which turned out to be on average 0.67 (SD = 0.65) times per person per task, and only accounted for 1.48% of the 45.16 (SD = 8.82) total wiggle actions participants on average performed per task; (2) participants had to use the popup dialog to immediately edit the valence or topic priority because Wigg-lite picked the wrong swipe direction, which turned out to be 0; (3) participants had to redo the wiggling gesture because the previous one they performed did not activate at all, which turned out to be on average 0.92 (SD = 0.67) times per person per task, and only accounted for 2.01% of the total wiggle actions participants on average per task.

This evidence suggests that the wiggling technique provided by the current Wigg-lite system is sufficiently accurate and robust, at least with ample amount of training and practice. It would be interesting for future work to explore how it performs in the wild, potentially without much upfront practice, and examine whether and how people’s wiggling accuracy and performance evolve over time.

5.6.2 RQ2 [Efficiency]

Second, we are interested in understanding if Wigg-lite creates a more fluid experience when collecting and triaging information with less interruption compared to the baseline condition. For this comparison, we opted to measure two key metrics: the *overhead cost* of using a tool to collect and triage information, and the total amount of *time* it took for participants to finish each task. For the Wigg-lite condition, we calculate the overhead cost as the portion of the time participants spent on directly interacting with Wigg-lite (performing wiggling gestures, interacting with the popup dialog if necessary, filtering the information clips, organizing them in the workspace view, etc.) out of the total time they used for a task (vs. reading and comprehending the web pages) [177, 179]. Similarly, in the baseline condition, the overhead cost accounts for situations where participants use the highlighting or screenshot feature to collect information, organize them in the workspace view, etc.

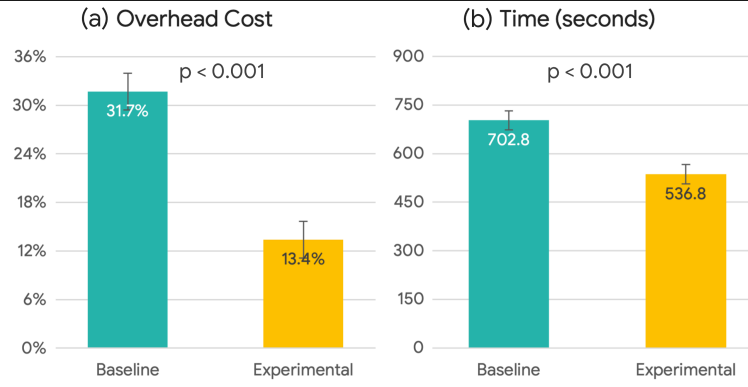


Figure 5.6: Using Wigglyte incurred significantly less overhead cost (a) and helped participants finish the tasks significantly faster (b) when compared to the baseline condition in the user study.

We conducted a two-way repeated measures ANOVA to examine the within-subject effects of condition (Wigglyte vs. baseline) and task (A vs. B) on overhead cost. There was a statistically significant effect of condition ($F(1, 20) = 40.7, p < 0.001$) such that the overhead cost was significantly lower (58% lower, as shown in Table 5.1 and Figure 5.6-a) in the Wigglyte condition (Mean = 13.4%, SD = 0.06) than in the baseline condition (Mean = 31.7%, SD = 0.08). There was no significant effect of task ($F(1, 20) = 0.46, p = 0.51$). In addition, a two-way repeated measures ANOVA was conducted to examine the within-subject effects of condition (Wigglyte vs. baseline) and task (A vs. B) on task completion time. There was a statistically significant effect of condition ($F(1, 20) = 20.8, p < 0.001$) such that participants completed tasks significantly faster (23.6% faster, as shown in Table 5.1 and Figure 5.6-b) with Wigglyte (Mean = 536.8 seconds, SD = 67.0 seconds) than in the baseline condition (Mean = 702.8 seconds, SD = 102.9 seconds). Again, there was no significant effect of task ($F(1, 20) = 0.77, p = 0.38$).

As the condition had a statistically significant impact on both the overhead cost as well as the task completion time (with faster completion and lower overhead cost in Wigglyte conditions), Wigglyte indeed helped participants reduce the overhead costs of collecting and triaging information and speed up their sensemaking process overall, even though the majority of their time was necessarily spent reading and understanding the material in both conditions.

Furthermore, in the post-study interview, participants overall appreciated the increased efficiency afforded by Wigglyte, especially using the wiggling gestures. Many (9/12) mentioned that the perceived workload to collect information that they have encountered was minimal, saying that *“It felt like I didn’t do anything to get those snippets into the system”* (P3), and was fluid enough that it did not interrupt their flow of reading the task pages, such as *“I just wiggle and move on, in fact, when I am wiggling on something, my eyes are already onto the next paragraph, no more stopping to do the regular clipping thing any more”* (P11). Therefore, Wigglyte did offer a more fluid experience when collecting and rating information with less interruption.

5.6.3 RQ3 [Expressiveness]

Third, we are also interested to know to what extent Wigglyte induces changes in people’s behavior, especially given the natural extension that wiggling affords to encode priorities and valence.

As shown in Table 5.1, participants collected significantly more information using wiggling (on average 37.8 clips, SD = 6.85) than when using the conventional selecting or screenshot workflow (on average 20.3 clips, SD = 6.68) ($p < 0.01$), despite spending less time on the tasks. Among the collected information clips using wiggling, 75.3% of them were encoded with either a posi-

tive or negative valence. Similarly, participants created significantly more topics using Wigg-lite (on average 7.83 topics, $SD = 2.07$) than in the control condition (on average 4.42 topics, $SD = 0.90$) ($p < 0.01$), where topics were required to be created separately in the workspace view. It is also worth noting that using wiggling to create topics (7.33 times, $SD = 1.07$) almost eliminated the need to separately (0.50 times, $SD = 1.00$) create topics (granted that most participants did at least edit the title of the topics in the popup dialog or in the workspace view to make them more succinct and easier to read). This evidence suggests that participants indeed were able to use Wigg-lite to externalize the perceived utility of a particular piece of information as well as their mental judgements of how it aligned with their goals in situ.

Furthermore, in the post-study interviews, some (4/12) participants reflected that Wigg-lite would enable them to express their perceived utility in a way that is also useful for subsequent sorting and ranking. For example, P5 mentioned that *“I really enjoyed the threading [creating topics with priorities] feature, being able to say something is important or extra important on the spot would help me stay on top of my todo list.”* However, perhaps due to the limited scale of the lab study, we did not observe significant differences in the types of information participants used as topics—most of them are about the different options as well as some criteria to evaluate a product. Future and potentially larger-scale investigations are required to understand the types of information users collect using a lightweight gesture like wiggling versus using conventional capturing methods.

5.6.4 RQ4 [Integration]

Last but not least, we would like to understand if the wiggle gesture would interfere with participants’ normal behaviors during web browsing, such as unconsciously using the mouse pointer to guide their attention [134], clicking [123], or scrolling (false positives). To measure this, we looked for cases where participants hit the undo button to dismiss a wiggle activation due to Wigg-lite had wrongfully recognized some regular mouse movements as a wiggle, which turned out to be 0 across the board. This provides evidence that the wiggling gestures added by Wigg-lite do not interfere with the existing interactions and user behaviors.

5.6.5 Other Subjective Feedback

In the survey, participants reported (in 7-point Likert scales) that they thought the interactions with Wigg-lite were understandable and clear (Mean = 6.25, $SD = 0.45$), Wigg-lite was easy to learn (Mean = 6.42, $SD = 0.67$), and they enjoyed Wigg-lite’s features (Mean = 6.25, $SD = 0.62$). In addition, compared to the baseline condition (Mean = 5.75, $SD = 0.62$), they thought using Wigg-lite (Mean = 6.17, $SD = 0.39$) would help make their information collection and triaging processes more efficient and effectively ($p = 0.017$), and would recommend Wigg-lite (Mean = 6.33, $SD = 0.49$) over the baseline version of Wigg-lite (Mean = 5.92, $SD = 0.29$) to friends and colleagues ($p = 0.007$), both differences were statistically significant under paired t-tests.

In addition, some participants reflected on the playfulness and attractiveness of the wiggle interactions and how it encouraged them to collect information compared to what they normally have to go through. For example, P8 said: *“It’s fun, you know? I didn’t quite believe it at the beginning, but it actually made grabbing stuff so much fun”*, and P1 suggested that *“somehow with this, I don’t think going through something that I’m not familiar with would be as daunting as it used to be”*. Four of the participants even went on to ask when Wigg-lite will be released publicly so that

they could use it for their own work and personal tasks, and wondered if they could customize the system, such as by “*writing some sort of plugin, like the one I wrote for Obsidian [206], to map the different directional swipes to what I want depending on the situations that I’m in*” (P11).

5.7 Discussion and Limitations

One potential limitation to wiggling is the suitability of its rapid back-and-forth movements to user populations with motor impairments or advanced age, for example, users with hand tremors. There are several ways in which wiggling might be more suitable than expected or relatively easily adapted to such populations. First, since wiggling uses the initial mouse location as its selection anchor, a user can take their time adjusting to arrive at the correct area (which would still require less accuracy than traditional highlighting). Once there, they could initiate selection without clicking, which could address mouse slip while clicking, a common problem with advanced age or motor impairment [87,88,266]. If issues with tremor lead to lower accuracy, one approach that might be investigated is smoothing mouse movement using generative models trained on a user’s individual behavior (e.g., [277]). More generally, additional research is needed to understand the suitability of wiggling across a variety of user capabilities, contexts, and devices [164,165].

While sensemaking in various domains might exhibit different characteristics and therefore lead to different information foraging behavior patterns, we chose both the study tasks to be in the domain of comparison shopping to at least make sure that the tasks are roughly of equal difficulty. In addition, product comparison shopping embodies many of the common sensemaking properties and needs that people have, for example, it is information dense so that users would potentially have to read and process lots of information and collect quite a few items, and users would often have to interpret the information based on their own goals and context, so that there is a need for them to externalize their mental context alongside the collected information. Nevertheless, we would like to address this limitation by evaluating Wigglite in a variety of domains where sensemaking usually occurs, such as students conducting literature reviews, patients researching medical diagnoses, and programmers learning unfamiliar APIs.

Finally, due to the limited set of capabilities of the Wigglite mobile application and the similarity of features with its desktop counterpart, we did not evaluate the mobile app in our lab study, and therefore could not directly compare the wiggle-based collection and triaging techniques for sensemaking to a baseline. Informally in our pilot testing, using wiggling to collect information and optionally encode a positive or negative valence was much faster and more convenient than any common information capturing methods that people currently use on mobile devices, such as copying and pasting text and taking screenshots or photos [260]. Nevertheless, we would like to evaluate the wiggle-based techniques and Wigglite for mobile in a formal lab study in the future.

Chapter 6

Strata: Evaluating and Reusing Summarized Knowledge

This chapter was adapted from my published paper:

Michael Xieyang Liu, Aniket Kittur, and Brad A. Myers. 2021. “To Reuse or Not To Reuse? A Framework and System for Evaluating Summarized Knowledge.” *Proc. ACM Hum.-Comput. Interact.* 5, CSCW1, Article 166 (April 2021), 35 pages.
Video: <https://youtu.be/NuL-jtf710E>

6.1 Overview

As the amount of information online continues to grow, a correspondingly important opportunity is for individuals to reuse knowledge which has been summarized by others rather than starting from scratch. However, appropriate reuse requires judging the relevance, trustworthiness, and thoroughness of others’ knowledge in relation to an individual’s goals and context.

In this chapter, we explore augmenting judgements of the appropriateness of reusing knowledge in the domain of programming, specifically of reusing artifacts that result from other developers’ searching and decision making. Through an analysis of prior research on sensemaking and trust, along with new interviews with developers, we synthesized a framework for reuse judgements (Table 6.1). The interviews also validated that developers express a desire for help with judging whether to reuse an existing decision. From this framework, we developed a set of techniques for capturing the initial decision maker’s behavior and visualizing signals calculated based on the behavior, to facilitate subsequent consumers’ reuse decisions, instantiated in a prototype system called Strata. Results of a user study suggest that the system significantly improves the accuracy, depth, and speed of reusing decisions. These results have implications for systems involving user-generated content in which other users need to evaluate the relevance and trustworthiness of that content.

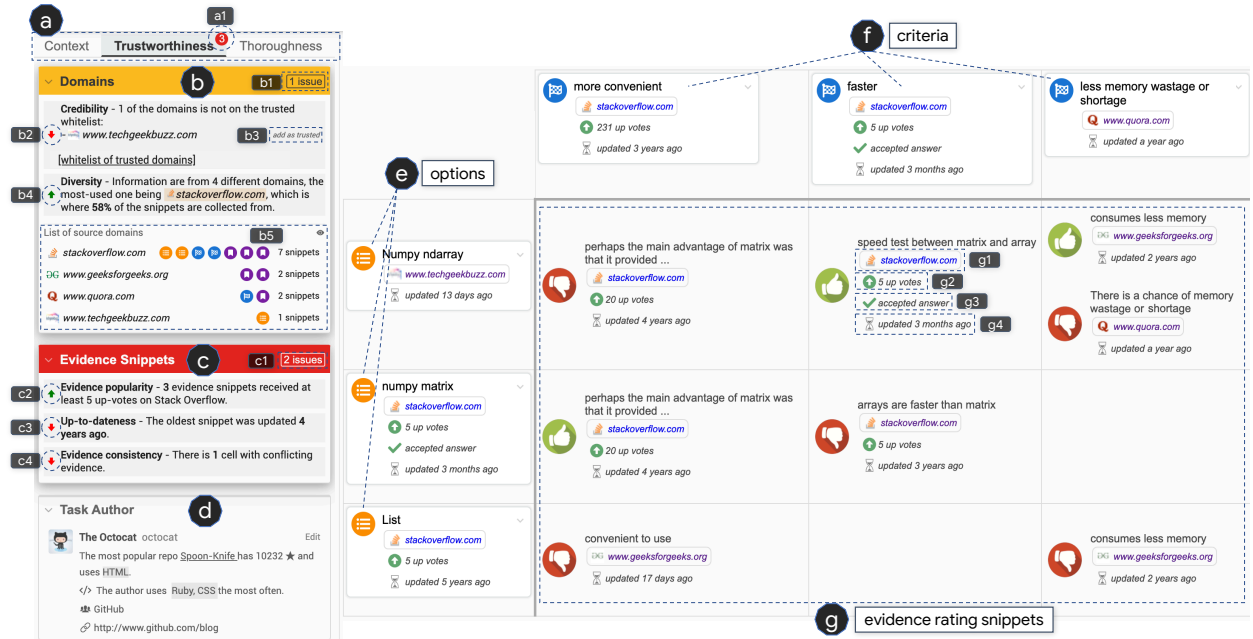


Figure 6.1: Strata’s user interface. Strata helps developers evaluate three main facets of appropriateness of reusing a Unakite comparison table with options (e), criteria (f), and evidence (g) through three overview panels: (a) the *Context* panel, the *Trustworthiness* panel, and the *Thoroughness* panel. Each panel contains the *groups* (such as (b), (c), (d)) of appropriateness properties to directly address developers’ information needs. Developers will also be alerted of any potential issues with respect to each facet (e.g., b2, c3, c4).

6.2 Background and Formative Investigations

Although Unakite has been shown through lab studies to help the initial developer in making a programming decision, it displays few of the signals suggested by the research discussed above on trust and sensemaking handoff that could help consumers of the table decide whether it is appropriate for them to reuse it. For example, the initial table creator may or may not have been thorough in their research; may or may not have the same context and environment; or may or may not care about the same goals as the consumer. Although we use Unakite as a specific context, there are many similar examples of developers creating comparison tables in code documentation, blogs, and Stack Overflow [8, 9], which are typically even sparser in terms of signals for reuse appropriateness, with no supporting interactivity or drill-downs possible.

6.2.1 Formative Interviews

To characterize the prevalence and types of issues developers have with knowledge reuse, specifically with reuse of programming decisions, we conducted semi-structured interviews with 15 developers (5 female, 10 male). Participants were recruited through mailing lists, social media postings, and word-of-mouth. To capture a variety of processes, we chose 8 professional developers, 3 doctoral students, and 4 master students. While we do not claim that this sample is representative of all developers, the interviews informed and motivated the development of the subsequent framework (Table 6.1) and the design of the Strata system.

We began by asking participants about their experiences in reusing someone else’s decisions when programming and how frequently would that situation occur in their work. We then explored how they manage these situations and their information needs, in particular, what ques-

Facet	Information Need	Selected References in Prior Research	Sample Quotes in Formative Study	Selected Supporting Features in Strata
Context	Goals of the original decision	<ul style="list-style-type: none"> Search queries are useful for encoding task goals & contexts in various settings like asynchronous collaborations [39, 198, 215, 216, 247, 283]. 	<ul style="list-style-type: none"> <i>"This looks like it's trying to pick a speech recognition API, but what I want is actually text to speech."</i> 	<ul style="list-style-type: none"> Keeping track of the author's search queries to reflect his or her task goal.
	Explanation or contextualization of information	<ul style="list-style-type: none"> Recontextualization of information helps with understanding [177, 187]. Clarity and informativeness of website content improves understanding [92, 264]. 	<ul style="list-style-type: none"> <i>"What does this 'very efficient' mean, is it 'memory' or 'time' efficient?"</i> <i>"Is it [a sorting algorithm] 'fast' only when there're a few hundred data points or also when there are millions of data points?"</i> 	<ul style="list-style-type: none"> Keeping track of the surroundings along with the information snippets and presenting them as contextual explanations.
	Situational awareness	<ul style="list-style-type: none"> Awareness of common ground facilitates sensemaking handoff [66, 245, 247]. Users need awareness of each others' actions in order to perform their tasks better [27, 198, 201, 215]. 	<ul style="list-style-type: none"> <i>"I want to solve it with pure JavaScript, but it seems that most of the answers here are actually written using jQuery?"</i> <i>"I'm using Python 2.7 at the moment, which is fairly old, does this example also use this version?"</i> 	<ul style="list-style-type: none"> Detecting information about languages, frameworks, and their versions mentioned in information snippets with a predefined yet easily extensible list of detectors.
Trustworthiness	Source credibility and diversity	<ul style="list-style-type: none"> Source credibility affects trustworthiness of information [74, 85, 92, 191, 264]. Sources similar to what a consumer usually uses are more likely to be deemed credible [193, 244]. 	<ul style="list-style-type: none"> <i>"If it's from Stack Overflow, I'm usually fine with it. But if it's from some random blog posts written by some random guy, I would think twice."</i> <i>"I wonder if all of these just came from the official documentation or there're also other developer forums."</i> 	<ul style="list-style-type: none"> Visualizing the distribution of information snippets across different domains (websites). Alerting consumers of potential untrusted domains.
	Information up-to-dateness	<ul style="list-style-type: none"> Information currency affects its perceived credibility [24, 45, 191]. 	<ul style="list-style-type: none"> <i>"Is this speed comparison [between React, Angular, and Vue] up-to-date now that Angular 9 was just released?"</i> 	<ul style="list-style-type: none"> Extracting and surfacing the last updated time of information snippets.
	Information popularity	<ul style="list-style-type: none"> People apply the endorsement heuristic to evaluate credibility [191]. People seek social proof when evaluating credibility [244]. 	<ul style="list-style-type: none"> <i>"If there're a lot of other devs [who] also think this is a good idea, then I'm much more comfortable to use it."</i> 	<ul style="list-style-type: none"> Extracting and surfacing signals showing information popularity, such as the up-vote count of an answer on Stack Overflow.
	Information consistency	<ul style="list-style-type: none"> People apply the consistency heuristic to evaluate credibility [191]. People seek more than one source to verify information [190]. 	<ul style="list-style-type: none"> <i>"It claims PyTorch is much easier to learn than Tensorflow, but I wonder if there're people suggesting otherwise."</i> 	<ul style="list-style-type: none"> Alerting consumers if there are conflicting (both positive and negative) ratings in any of the table cells.
	Author credibility	<ul style="list-style-type: none"> The author's level of expertise affects information trustworthiness [74, 149, 244]. Disclosing patterns of past performance helps people evaluate trustworthiness [149, 250, 258]. 	<ul style="list-style-type: none"> <i>"Does the table author know what he's doing?"</i> <i>"Is the author saying all the nice things about Caffe because he has lots of experience with it or because he's biased?"</i> 	<ul style="list-style-type: none"> Surfacing credibility and bias signals from the table author's Github profile, such as their primary programming language, number of stars on their repositories, and affiliation.
Thoroughness	Research process and effort	<ul style="list-style-type: none"> External representations handed off should indicate prior investigative process and insights [215, 216, 289], how much work had been done, and how mature the representation was [245, 247]. 	<ul style="list-style-type: none"> <i>"How much effort was put into making this decision?"</i> <i>"What did the author focus on?"</i> 	<ul style="list-style-type: none"> Keeping track of and visualizing the author's activities on an interactive timeline view, including search queries, pages visited, duration of stay on the pages, information snippets collected, etc.
	Alternatives or competitors	<ul style="list-style-type: none"> Knowledge and sensemaking results should indicate their coverage and scope [74, 191]. 	<ul style="list-style-type: none"> <i>"I heard anecdotally that Svelte gives you much better performance than all these big (JavaScript) frameworks [React, Angular, and Vue]. I should take a look at that before I decide."</i> 	<ul style="list-style-type: none"> Finding and surfacing commonly searched-for alternatives mentioned in Google autocomplete suggestions.
	Usable artifacts	<ul style="list-style-type: none"> Developers need help finding and reusing code examples [46, 208, 221]. 	<ul style="list-style-type: none"> <i>"Which option was chosen in the end?"</i> <i>"[Are there] any code snippets that I can immediately plug into mine and test?"</i> 	<ul style="list-style-type: none"> Extracting and surfacing code examples from information snippets.

Table 6.1: A framework summarizing the three major facets (column 1) when evaluating the appropriateness to reuse knowledge, including people's specific information needs (column 2), selected evidence from prior work (column 3), sample quotes from our formative study interviews (column 4), and features we devised to support the information needs in the subsequent Strata system (column 5).

tions do they have when evaluating the appropriateness to reuse and how answers to those questions may affect their final verdicts on reusability. In addition to eliciting facts on their past experiences, we also presented them with a set of decision tables in the running Unakite application (which were directly adapted from real tables online, e.g., [243]) as well as the corresponding background situational context, and asked them to judge if they could reuse these tables in those given situations. We asked them to speak about any questions they had and perform any inquiry they wanted to answer those questions (e.g., checking the sources, searching for evidence online, etc.). Finally, we wrapped up with questions probing their experience with explaining their design rationale to others, and whether and how do they convince others that their decisions are appropriate to be reused.

Interviews were conducted either in person or remotely by the first author and lasted 30 minutes. They were audio-recorded and then transcribed. In addition, screenshots of participants' computers were taken for later analysis when applicable. Then, the first author went through the transcriptions and coded them via an open coding approach [62], which included multiple iterations of discussions with the research team. Our key findings are presented below.

6.3 Framework

Data from the formative study suggested that developers would benefit from support in evaluating the appropriateness of reusing decisions. For example, there are many indicators that could be beneficial to surface to help users make these judgements, ranging from the expertise of the author to the quantity and legitimacy of the sources used. Although there has been little prior work characterizing the most important factors for decision reuse specifically by developers, as listed above there has been significant work discussing frameworks and measurements relevant to evaluating and reusing knowledge, such as online information credibility judgement [190, 191, 192, 193], asynchronous collaboration [198, 216], and sensemaking handoff [90, 245, 246, 247]. From these research papers, we extracted properties and signals that would be important and relevant to decision reuse for developers.

By coding and synthesizing the aforementioned prior work as well as the formative study results through affinity diagramming, we identified three major clusters, that we call *facets*, when evaluating the appropriateness for reuse in programming: the original author's decision making *context*, and the *trustworthiness* and *thoroughness* of the resulting decision. We used these as a guide in developing an integrated framework, shown in Table 6.1, consisting of the three identified facets (column 1), specific information needs of developers with regard to each facet (column 2), selected evidence for the importance of these information needs as well as possible solutions to address them from prior work (column 3), and sample quotes from our formative interviews (column 4). These insights together inspired the features for our subsequent Strata system (column 5). We now discuss the framework in detail, along with the support from the prior work and the formative interviews. The design of Strata follows in section 6.4.

6.3.1 Context

Although in prior work the importance of understanding the trustworthiness of information often outshines everything else when evaluating the appropriateness to reuse [149, 187], we were surprised to find out that, at least in the domain of programming decision reuse, developers often ask questions about the *context* of a previously-made decision before they proceed to assess

trustworthiness (9/15). Cited reasons include that one needs to know *“how relevant it is to what I am doing”* (P5) first, and if the context of the original decision does not align very well with the problem at hand, one would often stop the evaluation process and move on to look for new solutions. For example, if a developer is working in Java, solutions that only work in JavaScript may not be worth investigating.

6.3.1.1 Goals of the original decision

When evaluating context, most (12/15) participants asked questions about the goals and purposes of the author of the decision in order to compare those with their own. For example, *“this looks like it’s trying to pick a speech recognition API, but what I want is actually text to speech,”* (P14) and *“people say they want to do one thing, but after taking a closer look, they really are doing this other thing, which often makes me a tad frustrated”* (P7). Indeed, prior research suggests that the goals of decisions are often treated as “self-evident” given the results, and therefore are often not kept track of by the authors [159, 160]. On the other hand, goal mismatch does not always prevent developers from further evaluating a decision; instead, it can become a *“learning opportunity”* for them to *“know more about a new technology or design pattern”* (P11).

Furthermore, when asked about their experience of making decisions, participants reported that their goals may very well evolve with their exploration process rather than remaining fixed from the beginning (7/15). For example, *“I started out trying to choose a framework to build a mobile app for both Android and iOS, but later I stumbled upon this progressive web app thing that totally fulfills all of my requirements, so I ended up trying to learn more about that, and sort of abandoned the mobile app route that I was originally planning to take”* (P3). This motivated us to develop features (e.g., keeping track of all of the search queries used) to capture not only an author’s original goal but also the evolving nature of that goal, so that later knowledge consumers could have a better grasp of how the author’s goal changed throughout a decision making process.

6.3.1.2 Explanation or contextualization of information

One of the frustrations that participants reported having is that they often have trouble understanding the meaning of some of the criteria and evidence used in online decision tables (8/15). For example, *“what does this ‘very efficient’ mean, is it ‘memory’ or ‘time’ efficient?”* (P10). In some other circumstances, they suspect that evidence may not hold true when external constraints or requirements change: *“is it [a sorting algorithm] ‘fast’ only when there’re a few hundred data points or also when there are millions of data points”* (P1). Indeed, prior work suggests that clarity and informativeness of information have a significant impact on how well it is understood [92, 264], and presenting information along with its original context (recontextualization) is considered a good way to help people understand its meaning and the conditions in which it is correct or accurate [91, 177, 187].

In addition, it was also suggested by participants that it is not always easy to recontextualize information, especially when the context is not available (6/15). Unakite partially addressed this by allowing users to create a snippet out of a large block of information in its original HTML format as well as automatically recording the corresponding source URL for later retracing [177]. In Strata, we build on that by introducing the concept of a *context snapshot*, which, at capture time, automatically keeps track of the *surroundings* of an information snippet in addition to the snippet content itself and its source URL. When consumers are reviewing a snippet, they will be

able to benefit from the possible explanations such as code examples and performance metrics contained in the surroundings that would otherwise be missing from the snippet content.

6.3.1.3 Situational awareness

An essential part of context is the situation in which the information will be reused. In programming, this corresponds to the languages, libraries, and platforms being used, which are often referred to as *dependencies*, and participants reported checking if a given decision shares the same language or library usage as to what they have to work with (8/15). For example, P7 asked *“I want to solve it with pure JavaScript, but it seems that most of the answers here are actually written using jQuery.”* Furthermore, version mismatch has been a frequent issue for reuse in programming. With the continuous rise of the open source software development model [112] and the increasing number of frameworks, libraries, languages, and patterns [3, 5, 13], version and dependency mismatches and errors can cause troubles from missing features to breaking dependent downstream applications [15]. Indeed, participants reported checking for versions before they commit to adopting a certain solution (6/15). For example, *“I’m using Python 2.7 at the moment, which is fairly old; does this example also use this version, or is it using Python 3.5?”* These inspired us to try to automatically detect the language, library, platform, and version information whenever possible when an author collects information online, and surface this to the consumer to directly address their information needs.

6.3.2 Trustworthiness

As mentioned, information trustworthiness or credibility is often used as a surrogate for verifying information correctness [127], and is one of the most reported and researched facets during the evaluation of the appropriateness to reuse knowledge across many domains [187, 191]. Our interview data shows that it plays a crucial role in the domain of reusing decisions in programming as well.

6.3.2.1 Source credibility and diversity

As suggested by prior work, source credibility has a significant impact on the trustworthiness of information [74, 85, 92, 191, 264]. Not surprisingly, all participants in our study reported this same belief – they are more inclined towards trusting information from sources that are official (e.g., API documentation websites) or with a very good reputation within the community (e.g., Stack Overflow), and are more likely to reject information from sources that they have little experience with, echoing the *reputation heuristic* and the *expectancy violation heuristic* [193, 244] that people generally use to assess trustworthiness. For example, P12 said: *“if it’s from Stack Overflow, I’m usually fine with it. But if it’s from some random blog posts written by some random guy, I would probably think twice.”*

It is worth noting that in addition to credibility, source diversity also plays a role in trustworthiness, according to 7 of the 15 participants. They thought that the more diverse the sources used are, the more likely that the evidence in the table has been *“peer reviewed”* or *“confirmed by a bunch of other devs”*, and *“seeing essentially the same thing independently said on a couple of different sites and forums”* gives them *“peace of mind”*. We believe that source diversity also works in concert with information popularity and consistency, which we will discuss in detail in the upcoming sections. This motivated us to provide source domain information as a direct

signal for each of the information snippets collected as well as a visualization of how all the collected snippets are distributed across the different domains, enabling users to easily assess source credibility and diversity.

6.3.2.2 Information up-to-dateness

There was a consensus among the participants that in order to make a correct decision, the evidence used must be up-to-date (11/15). Indeed, prior work also suggests that information currency is another crucial element contributing to its credibility, with the intuition that the older a piece of information is, the more obsolete it gets, which implies a lower level of trustworthiness [24, 45, 191]. This is especially true in today’s software development world, where languages and libraries are constantly being updated and older versions are quickly rendered obsolete by newer versions. For example, P6 was keen to stay on top of the state of the art of the JavaScript frontend framework competition: *“Is this speed comparison [between React, Angular, and Vue] up-to-date now that Angular 9 was just released?”* However, the above heuristic can be taken with a grain of salt by some participants, citing reasons that software that was updated a long time ago does not necessarily mean that it is obsolete. As P4 put it, *“the last release of Haskell was like 10 years ago, but it’s still the latest version, and I still use it all the time in my work.”* Nevertheless, we elect to provide users with direct access to at least the last updated timestamp information of each snippet that the author collected in an effort to help consumers assess up-to-dateness faster. In addition, the separate information about versions, as mentioned above, allows users to use whichever property is most relevant.

6.3.2.3 Information popularity

Echoing what has been reported in prior work that people seek social proof when evaluating information credibility [191, 244], participants (8/15) said that the popularity of information also plays an important role in its trustworthiness, with the general rule suggesting that the more people that stand behind a solution, the more trustworthy it is. For example, P9 said: *“if there’re a lot of other devs [who] also think this is a better idea, then I’m much more comfortable to use it.”* This is similar to the *endorsement heuristic* [193], which suggests that people are inclined to perceive information and sources as credible if others do so too. This inspired us to directly present consumers with popularity signals (such as an answer’s up-vote number on Stack Overflow, or the number of claps of an article on Medium.com) from where snippets are collected.

Also included in the endorsement heuristic is that people sometimes follow others’ endorsements without much scrutiny of the site content or source itself [193]. However, some of our study participants suggest quite the opposite (7/15) — they often put much more emphasis on source credibility over the popularity of specific information snippets from that source. For example, *“in retrospect, if an answer is taken from Stack Overflow, I don’t really care about its up-vote number or if it’s the officially accepted one, I’ll just trust it and use it”* (P3), or *“I don’t really look at how many people clapped over a Medium article, the fact that it’s from Medium.com is usually good enough for me”* (P8). Though seemingly inconsistent with prior work, we do not claim that this is typical in the domain of programming — one possible explanation is that websites like Stack Overflow by default rank the most up-voted posts at the very top with the specific intention to present the most popular information to readers.

6.3.2.4 Information consistency

In addition to source credibility, diversity, up-to-dateness, and popularity, a few participants (5/15) suggested that having more corroborating evidence implies that a piece of information is more trustworthy. For example, P6 said: *“This [deep learning library comparison chart] claims that PyTorch is much easier to learn than Tensorflow, but I wonder if there’re people suggesting otherwise? I kind of want to see at least one other expert that has experience with both and also says PyTorch is better.”* Prior research has also found that people will apply the *consistency heuristic* to evaluate credibility, validating information by checking different websites to make sure that the information was consistent [190, 193]. Meanwhile, consistency also implies the converse — having contradicting evidence will undermine the trustworthiness of an existing piece of information.

6.3.2.5 Author credibility

Prior work has shown that the author’s level of expertise impacts the credibility of information [74, 244]. This is especially significant in the domain of programming, where there is a substantial difference between novice and expert developers in their experience and ability to evaluate code and libraries [37]. For example, when shown with a comparison table on the topic of choosing a deep learning framework, P11 asked: *“Does the author know what he’s doing? I’d rather take advice from someone who’s an expert rather than some random undergrad.”* However, participants (4/15) also reported that there is no easy way to tell the level of expertise of a table author or if that expertise matches with the topic of the table in the current Unakite system.

Another factor that impacts the credibility of an author is if he or she is biased, possibly due to his or her affiliation or personal preferences — for instance, P12 asked: *“is the author saying all the nice things about Caffe [a deep learning framework] because he has lots of experience with it or because he’s biased?”* However, one participant also acknowledged that sometimes these “biases” may not be as negative as it sounds — it could be an indication that an author is highly experienced with one particular option and therefore gives favorable evidence for it. To address the above concerns, prior research suggests that disclosing patterns of an author’s past performance may be a good indication of his or her expertise as well as possible biases [149, 250, 258]. This motivated us to at least allow the author to provide a link to his or her GitHub profile, and Strata will automatically compute and show relevant expertise metrics (contribution activities, most proficient programming languages, etc.) and affiliation information to the consumer.

6.3.3 Thoroughness

Another important facet when evaluating the appropriateness to reuse knowledge is thoroughness, which deals with the process and the amount of effort used when creating the knowledge, its coverage and scope, as well as any usable artifacts discovered or produced in the process.

6.3.3.1 Research process and effort

Prior work in sensemaking handoff recommends that when knowledge is handed-off from the author to the consumer, it should let the consumer be aware of the prior investigative process and insights [215, 216, 289], such as how much work has been done, and how mature the knowledge representation is [245, 247]. We also found relevant evidence from the interviews: three participants recalled similar experiences where they learned that the previous decision makers

spent little time on exploring the decision space, and therefore the results were “*too immature to be picked up and reused*” and “*missing obvious criteria that you should definitely not leave out*”, and they ended up choosing to ignore those previous decisions and started from scratch to conduct their own research instead. This motivated us to automatically keep track of some of the authors’ actions as they create tables using Unakite, such as the search queries used, the pages visited, the duration of their stay on each page and each query, etc. We then use these data to compute key statistics as well as timelines and visualize them to the consumers to help them better understand the author’s research and exploration process.

P9 also envisioned that having a holistic understanding of the author’s process would give her the ability to parse out the author’s intention and focus (which may shift throughout the process, as discussed earlier), and therefore provide hints about what she needs to focus on next if she were to reuse this table as the basis for her own decision.

6.3.3.2 Alternatives or competitors

In addition to the process and effort, prior research recommends that knowledge and sensemaking results should also make apparent their coverage and scope [74, 191], for example, what alternatives have been considered, since not all options will necessarily appear in a Unakite table (especially when the author thinks one does not fit his or her particular needs and is therefore not worth further investigation). However, this does not necessarily imply that the option is inferior for the consumer. In our study, a few of our participants (6/15) were also interested in knowing what would those alternatives (or competitors) be and how they compare with the existing options before they could know if it is appropriate to reuse a table. For example, “*I heard anecdotally that Svelte gives you much better performance than all these big (JavaScript) frameworks [React, Angular, and Vue]. I should take a look at that before I decide. Or maybe there’s again something else?*” (P14). This motivated us to take advantage of the Google Autocomplete API to automatically obtain commonly searched-for alternatives to the options that are already in the table, and present these alternatives to the consumers.

6.3.3.3 Usable artifacts

Lastly, participants (10/15) stressed the need for code examples and other usable artifacts from a decision, just as prior work reported that developers need help finding and reusing code examples [46, 47, 208, 221]. For example, P2 directly asked for code examples and the author’s chosen option when presented with a decision table on various Java AST parsers: “*[are there] any code snippets that I can immediately plug into mine and test? Or if you can tell me which is the one that the author used, I’ll just try that one first.*” A few (3/15) participants also suggested that quickly trying out code examples to see if they work or not supersedes almost all other information needs. However, we do not claim this is typical, and later follow-up exchanges with these participants revealed that a vast majority of their current work is low-level detailed implementation, where making sure the code works is of paramount importance. Nevertheless, we implemented techniques to automatically extract code blocks from various snippets and present them to consumers. In addition, we also detect authors’ copy events in the browser, and use those as the basis for a heuristic to tell which option the author chose for the decision.

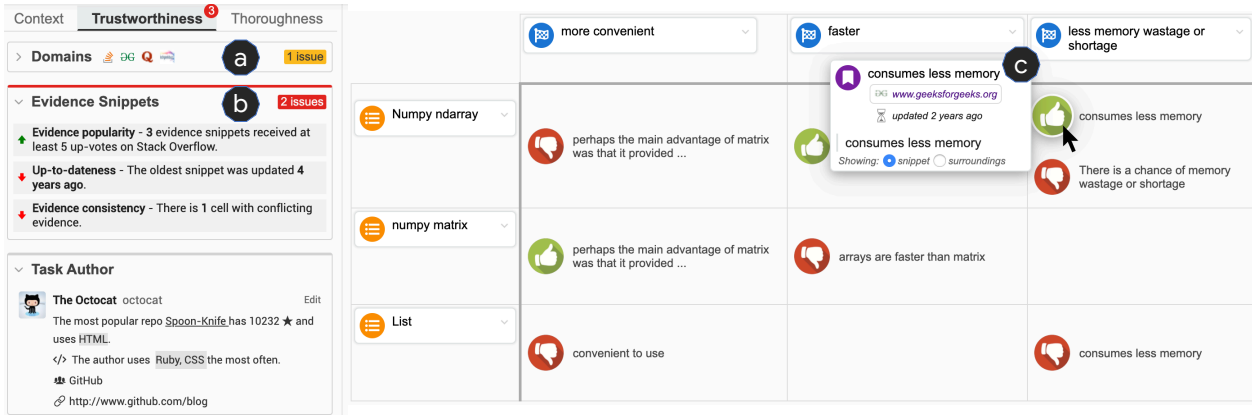


Figure 6.2: On Strata startup, none of the groups are activated to keep the Unakite table on the right clean and concise. Groups can also be collapsed to keep the sidebar interface clean (such as (a)). Mousing over each snippet in the table will only show the exact content that an author captured by default (c), the same as the original Unakite system, rather than the automatically captured *context snapshots*. Only after a user activates some groups in the Strata sidebar (by clicking on their titles) will the corresponding additional metadata appear on the snippets in the table, as shown in Figure 6.1.

6.3.4 Summary

We found that when evaluating the appropriateness to reuse a piece of knowledge, one should not only assess its trustworthiness (as the majority of the prior research has focused on), but also check for its context and thoroughness. However, no previous system has made significant attempts to address developers' specific information needs with regard to all three of these facets, or to extract appropriateness properties from the original content and present them to the consumer of the knowledge to facilitate reuse. In addition, this process should not put much burden on either the author or the consumer [177, 267] by requiring them to manually locate those appropriateness properties, suggesting the need for largely automatic mechanisms.

6.4 Strata Design and Implementation

Based on the findings in our interviews and the framework, we built a prototype system called Strata to visualize properties and signals of the appropriateness to reuse for the consumers of a decision.

6.4.1 Core Design Process and Rationale

We first consulted the interview data and brainstormed the various signals and properties that would theoretically address each of the information need listed in Table 6.1, column 2. Some information needs can be directly addressed by obvious signals, such as surfacing the domain names of the source web pages to consumers so that they know where the information in the table were collected from and if those sources are credible. For information needs that would require explicit effort from the table author to provide, such as the goal of a decision, we also consulted prior literature as well as brainstormed about potential indirect signals that can be used by consumers to infer those needs. For example, search queries are useful for inferring task goals and contexts of an author [39, 198, 215, 247].

In order to obtain these signals, we then built tracking techniques to automatically keep track of the author’s activities in the browser while searching and browsing during the creation of a Unakite table. Many of these tracking and extraction techniques use heuristics that are based on the current design of websites that developers most often use, such as extracting the number of up-votes for an answer on a Stack Overflow page. These are meant as a proof-of-concept, and more elaborate and crowd-sourced extraction techniques could be added in the future.

We then set out to design a visualization that presents the consumers with these signals and properties. During our exploration of the design space, we struggled with a fundamental tension between consumers’ awareness of all the signals and consumers’ limited attention bandwidth. In our initial prototypes, we placed all the signals (approximately 15) in a scrollable vertical list to the left of the original Unakite table. Users would also be able to hide a signal if it was not relevant. We hoped to make the users aware of all the signals that Strata can provide and give them complete freedom to explore them as they wish. Another rationale for this design was that users would be able to use a combination of signals to fulfill a single information need, for example, both the search queries and the pages visited will help indicate the author’s research process and effort, as evidenced by the formative interviews. However, by implementing and testing these design probes with a convenience sample of 8 developers, we realized that having “*everything all at once*” can be overwhelming to the consumers, and they would prefer to just examine one facet at a time and tune out the “noise” (signals that are irrelevant to the facet currently being examined). In addition, we found that there was a disconnect between the signals we showed in the list on the left and the actual content in the table on the right, causing consumers the additional mental burden of trying to match them up. Showing the signals in context along with the various information snippets in the table seemed to be a much better design to address this problem.

These findings guided us towards a hierarchical visualization design of Strata’s consumer-facing user interface: to structure these properties and guide the consumers through their evaluation process, we designed Strata as a sidebar to a Unakite table. Strata’s sidebar contains three tabbed overview panels for the three facets in the aforementioned framework (Figure 6.1-a). Each overview panel provides multiple *groups* (e.g., Figure 6.1-b,c,d) of appropriateness properties to directly address consumers’ information needs as summarized in the framework. In addition, by activating one or more of the groups (by clicking on their titles in the sidebar), consumers will be able to view additional information specific to each snippet in the table. For example, Figure 6.2 shows a state where none of the groups are activated. After activating the Domains group and Evidence Snippets group, consumers will be able to see for each snippet: where it originated (Figure 6.1-g1), how popular it is (Figure 6.1-g2,3), and how old it is (Figure 6.1-g4). This is designed to provide consumers with a high-level overview of each of the facets of reuse as well as the ability to dive into the parts of interest, as recommended by Shneiderman [249]. It is also inspired by the *lens* interaction [41, 60] where the same table content is addressed from three different perspectives.

Like Unakite, Strata consists of an extension to the Chrome Web browser and a web application. Strata’s Chrome extension implements the aforementioned new tracking techniques on top of the Unakite Chrome extension. The Strata web application is implemented in HTML, JavaScript, and CSS, using the React JavaScript library [86] as the primary frontend UI development framework and Google’s Firebase on the Google Cloud for data management and synchronization as well as user authentication.

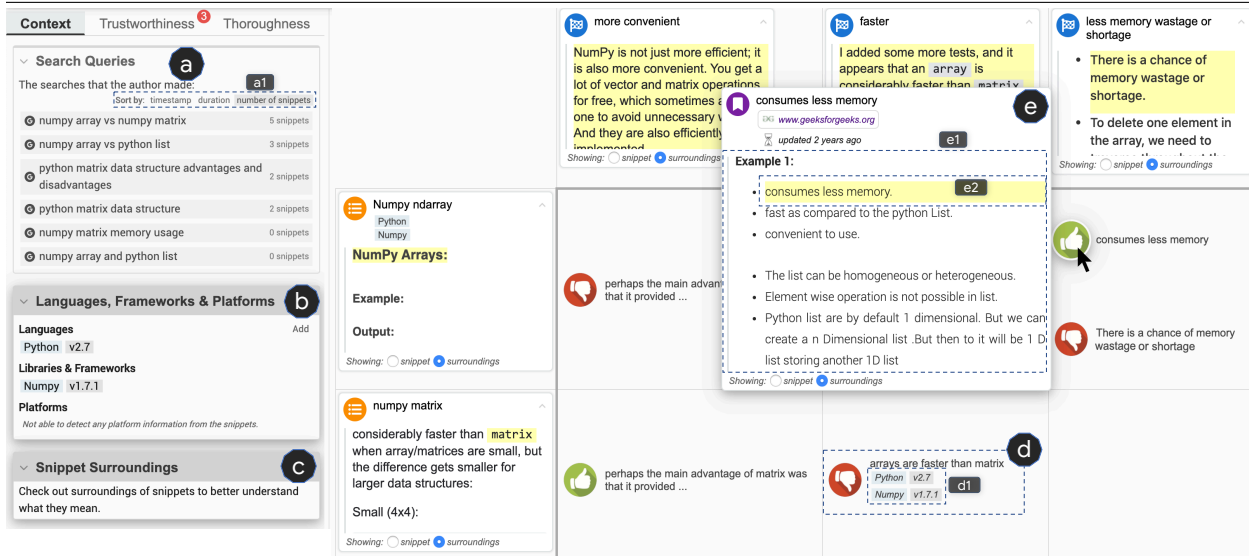


Figure 6.3: Strata’s *Context* panel. Consumers are able to check the search queries (a) that the author used to understand his or her goal, examine the languages, frameworks, platforms, and their versions of the snippets (b, d1), and view the surroundings of a snippet through the automatically captured context snapshots (e1).

We now discuss how the different features in Strata support the three facets listed in the previous framework, and how they are implemented.

6.4.2 Context

6.4.2.1 Capturing goals with search queries

First of all, Strata automatically keeps track of authors’ search queries used in Unakite tasks as well as the duration of time they spent on each and the number of information snippets they collected. The duration information is approximated by comparing the timestamp when the next query is issued to that of the current one. It also automatically leaves out any idle time (i.e., time where there is no activities detected in the browser, by monitoring mouse movements, keyboard input, etc.) that are longer than a certain threshold to make the duration approximation more accurate. The idle threshold was empirically tuned to be 8 seconds based on data obtained through pilot testing, and can be flexibly adjusted in the future. For consumers, Strata visualizes these search queries as a list (Figure 6.3-a) to help consumers understand the goals of the task author. They can use the sorting mechanisms at the top (Figure 6.3-a1) to sort the search queries by chronological order, by duration, or by the number of information snippets yielded from each (which is the default sorting order, where ties are broken by ascending chronological order).

There are several advantages of using search queries as a representation of an author’s goals. First, they are direct translations of what an author thinks and intends to do to satisfy their information need [237] — for example, issuing the query “numpy matrix vs list” implies that the author would like to find out the differences between the two options. Second, unlike the original Unakite where an author sets the single task goal (as the name of a task) at the beginning, keeping track of all of the search queries (in temporal order) captures not only the author’s original goal (which usually is the first query based on pilot study data) but also the evolving nature of the goal (as identified in the formative interviews). Third, the number of snippets yielded from each query serves as an approximation of an author’s effort spent on that particular part of the task, which informs consumers of the author’s focus throughout the decision making process.

6.4.2.2 Contextualizing information with automatic context snapshots

To help consumers contextualize and understand the meanings of options, criteria, and evidence in Unakite (identified as one of participants' frustrations), Strata introduces the idea of automatically keeping a snapshot of the surroundings of a piece of content called *context snapshot* (inspired by [132]) as an author collects information snippets. Strata uses Unakite's *snapshot* feature, where website content can be captured and preserved with its original styling, including the rich, interactive multimedia objects supported by HTML. The bounds of the surroundings are by default defined as the main content (Strata automatically tries to exclude any advertisements and other forms of injected content on a website) in the visible area of a web page in the browser window. In addition, due to the popularity and importance of Stack Overflow in the domain of programming, we specifically optimized this feature to include not only the particular answer block an author collects information from but also the original question block regardless of whether they are within the bounds, which provides consumers with extra context information. Similar optimizations for other popular developer sites, such as the official documentation, could be added in the future. On the consumer side, by clicking on the title of the *Snippet Surroundings* group (Figure 6.3-c) in the Strata sidebar, consumers will be able to view and scroll through the surroundings for each snippet (Figure 6.3-e1), with the content that the author specifically collected highlighted in yellow (Figure 6.3-e2).

This feature offers several benefits to both the authors and the consumers. The surrounding of a snippet is highly likely to include explicit explanations (such as screenshots, code examples, and execution results) that can help consumers understand exactly what a snippet means. For example, the *Python Lists VS Numpy Arrays* article [17] where a criterion snippet “more efficient” was scooped from, also gives examples of how the two data structures allocate memory blocks under the hood, suggesting that the author actually meant “more **memory** efficient” rather than “more **time** efficient”. Unlike in Unakite, where an author needs to specifically include that entire paragraph when creating a snippet and then manually change the title of the snippet into “more memory efficient” (which may disrupt the workflow), Strata will automatically capture that helpful paragraph into the snippet's context snapshot. During the evaluation of context, consumers will be able to directly view a snippet in its surroundings through its context snapshot without frequent switches to the corresponding original web page to find where the content where the snippet was taken from (which is exactly what participants reported doing in the formative study).

6.4.2.3 Detecting languages, frameworks, and their versions

Strata tries to automatically detect the languages, frameworks, platforms, and their versions used in the snippets to directly address consumers' information needs. To ground this feature, we picked the top 10 of each of the most popular languages, frameworks, and platforms from the 2020 Stack Overflow developer survey [18] and built *detectors* for them. The detectors for a language (or a framework, platform, etc.) is implemented as a set of manually devised keywords (e.g., language statements, special variables, file extensions, etc.) that can uniquely identify the usage or presence of that language. For example, “es7”, “console.log”, “setTimeout”, etc. can be used to identify *JavaScript*, and “useState”, “componentDidMount”, “findDOMNode”, etc. and be used to identify the *React* library. Keywords that can cause ambiguities are specifically avoided, such as “\$” (the dollar sign) is simultaneously a way to refer to variables in *PHP* and a shortcut for *jQuery*. Strata then automatically tries to find these detectors through optimized string matching in a snippet upon its collection. If there is no hit within the snippet content, Strata will make a second attempt

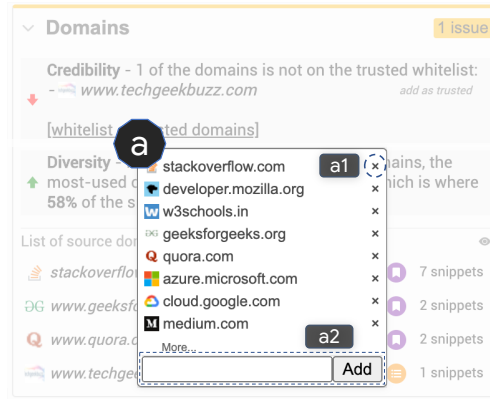


Figure 6.4: The *trusted domains whitelist*. Consumers can remove (a1) or add (a2) a certain domain from the list.

with the content of the snippet’s parent web page. Subsequently, Strata uses regular expressions to find version numbers in the vicinity of detected languages, frameworks, and platforms (e.g., “Angular 9”, “Python 3.5”, “React 16.13.1”, etc.) or in the web page’s URL (e.g., Java SDK version numbers are encoded in the URL of its official documentation website). In an informal evaluation using materials containing only the currently supported languages, this mechanism was able to successfully extract language information 100% of the time and correctly identify the version information 96% of the time. In the future, one might imagine Strata pulling detectors from open-source detector repositories built, verified, and maintained by the community, which can improve their quality, precision, and recall, or at the very least, letting authors add or correct wrongly detected versions. On the consumer side, this detected information is then presented directly on the corresponding snippet cards in the table (Figure 6.3-d) as well as aggregated in the *Languages, Frameworks, and Platforms* group (Figure 6.3-b).

Directly surfacing these version entries to consumers will help them quickly understand the technologies used in the task as well as the specific versions each snippet uses at a glance, to support comparing those with their own situation. For example, one developer would be easily able to figure out that the example code collected by the other developer uses Python 2.7 and therefore does not match with his or her own environment, which uses Python 3.5.

6.4.3 Trustworthiness

To help consumers evaluate the trustworthiness of a table, Strata provides visualizations of various properties that directly address their information needs listed in the framework (e.g., source credibility, information popularity, etc.). Prior work has suggested that surfacing issues or problems that could cause distrust is an effective way to alert and guide users’ attention during credibility evaluations [191]. Therefore, in addition to visualizing the trustworthiness properties, we remind users of potential issues that could negatively impact a table’s trustworthiness by marking them with a red downward arrow (Figure 6.1-b2,c3,c4). The count of the number of issues is shown in a colored badge on the top-right corner of the Trustworthiness panel (Figure 6.1-a1), with one issue having a yellow color, and more than one issue having a red color (these user-adjustable levels were empirically determined). Future development will explore more sophisticated weighting of the issues beyond counting them equally.

6.4.3.1 Visualizing source credibility and diversity

As shown in Figure 6.1-b, Strata visualizes the distribution of the snippets across different domains (websites) (Figure 6.1-b5), giving consumers a high-level overview of the provenance of the information in the table. In addition, each snippet in the table is also marked with its domain (Figure 6.1-g1), giving consumers a detailed understanding of where each snippet originated.

Strata also alerts consumers of potential untrusted domains by checking the presence of each domain on a user-defined *trusted domains whitelist*, and flags the ones that are not on the list. For example, a consumer will be able to immediately notice that one of the websites that the author used to collect evidence, `techgeekbuzz.com`, is not on his or her own trusted domains whitelist (Figure 6.1-b2). Currently, the default whitelist was generated by mining and aggregating the websites that 5 full-stack developers (who work for different technology companies and routinely use a variety of languages and technology stacks) visited from their browsing history. We then had them each annotate the websites as either “credible” or “not credible”, and removed the ones that they did not all agree upon. This resulted in 25 domains that are considered “credible”, including community Q&A sites like `stackoverflow.com`, official documentation sites like `angular.io`, and blog sites like `medium.com`. Domains that sometimes contain non-objective and low-quality information are rejected, such as `reddit.com`. We by no means claim this is complete nor that it applies to everybody — instead, it serves as a starting point and the consumers are able to add and remove items themselves (Figure 6.4-a1,a2). They can also use the “add as trusted” button (Figure 6.1-b3) to add a flagged website to the whitelist so that any future information originating from that website will not be considered as an issue. In the future, one can imagine taking advantage of a larger consumer base and automatically marking websites as trusted if a majority of the consumers have it on their whitelist. We also expect to periodically update the default whitelist over time, as new programming technologies are created and become popular in the future.

To help with the evaluation of source *diversity*, Strata also alerts consumers when there is only limited sources used to construct a table. Currently, Strata considers that there is an issue in terms of source diversity if all of the information comes from one single source (reported by participants in the formative studies as the worst scenario). If that is the case, the green upward arrow for source diversity in Figure 6.1-b4 will become a red downward arrow, reminding consumers that it is an issue. However, this threshold can be set by individual consumers, which would then apply to all future table evaluations they perform. Similar to source credibility issues, this can also be resolved or dismissed by individual consumers if they do not think it is problematic.

6.4.3.2 Examining evidence trustworthiness

Consumers will be able to get information about the popularity, up-to-dateness, and the consistencies of the evidence by activating the *Evidence Snippets* group (Figure 6.1-c).

Each snippet in the table will be marked with signals showing its popularity depending on the websites and pages that it originates from. For example, if a snippet is collected from a Stack Overflow answer post, Strata will automatically extract and show the up-vote number of that post (Figure 6.1-g2) as well as if that answer is the officially accepted answer (Figure 6.1-g3). If a snippet is collected from a Medium.com article, Strata will show the number of claps that article had at the time of collection. We designed this feature to closely fit developers’ current ways of evaluating popularity, as reported in the formative studies. Strata will also display an alert in the Evidence Snippets group if some of the snippets in the table have particularly low popularity,

such as down-votes on Stack Overflow. As with the other kinds of detectors, we envision these being augmented over time based on where developers are mostly getting their information from.

Unlike the original Unakite, which only showed *when* information was collected (reported as “*not exactly helpful*” by participants in the formative interviews), each snippet in the table will be marked by Strata with the timestamp of when its parent webpage (or answer post if it is from Stack Overflow) was last updated (Figure 6.1-g4). Strata uses a combination of techniques to extract the last updated timestamp information, including using regular expressions to look for date strings in website source code and taking advantage of the JavaScript `document.lastModified` variable (only when the website is static). This serves as a direct measurement of the age of information, and gives consumers an idea of how old the information is. Our study participants also mentioned that they often had trouble quickly locating when articles or blogs are updated online as these timestamps are often displayed in less salient font styles or not visible at all. In addition, Strata will flag snippets that are older than 3 years as a potential issue in the Evidence Snippets group (Figure 6.1-c3), which, similar to other issues, can be manually adjusted or dismissed by the consumer.

Finally, Strata provides initial support for information consistency by informing consumers if there are corroborating or conflicting evidence snippets in a table cell (e.g., there are simultaneously both thumbs-up and thumbs-down ratings for “`numpy ndarray`” causing “less memory wastage or shortage”) (Figure 6.1-c4). The culprit table cells with conflicting evidence will be highlighted by mousing over the issue in the Evidence Snippets group, addressing concerns from participants in the formative studies about how such contradictions could be overlooked once a table gets larger with more evidence ratings.

6.4.3.3 Surfacing properties about author credibility

Strata provides consumers with help in evaluating author credibility by allowing authors to manually provide information about themselves. In the current implementation, a table author can input a link to their GitHub profile, and Strata will automatically present the author’s name, numbers of stars on the most popular code repositories he or she owns, most used programming languages, affiliation, and a link to his or her GitHub profile page in the *Task Author* group (Figure 6.1-d). We opted to let authors voluntarily provide this information in order to give them the option to protect their privacy and identity. In the future, we will work on mechanisms to automatically perform author modeling in a privacy-preserving way — one idea is to analyze the topics of Stack Overflow questions and coding forums that an author frequently visits to infer his or her expertise. We will also provide an option for authors to provide certain information to consumers anonymously.

6.4.4 Thoroughness

6.4.4.1 Understanding the research process

In order to provide consumers with a clear understanding of an author’s research and exploration process, Strata automatically keeps track of several of the author’s activities in the background — in addition to the search query tracking discussed earlier, Strata also automatically records the web pages visited, as well as the time spent, progress made (approximated by tracking the percentage of a page that has been scrolled into the visible viewport using JavaScript’s `window.onscroll` event), and the number of information snippets collected on each of the web pages.

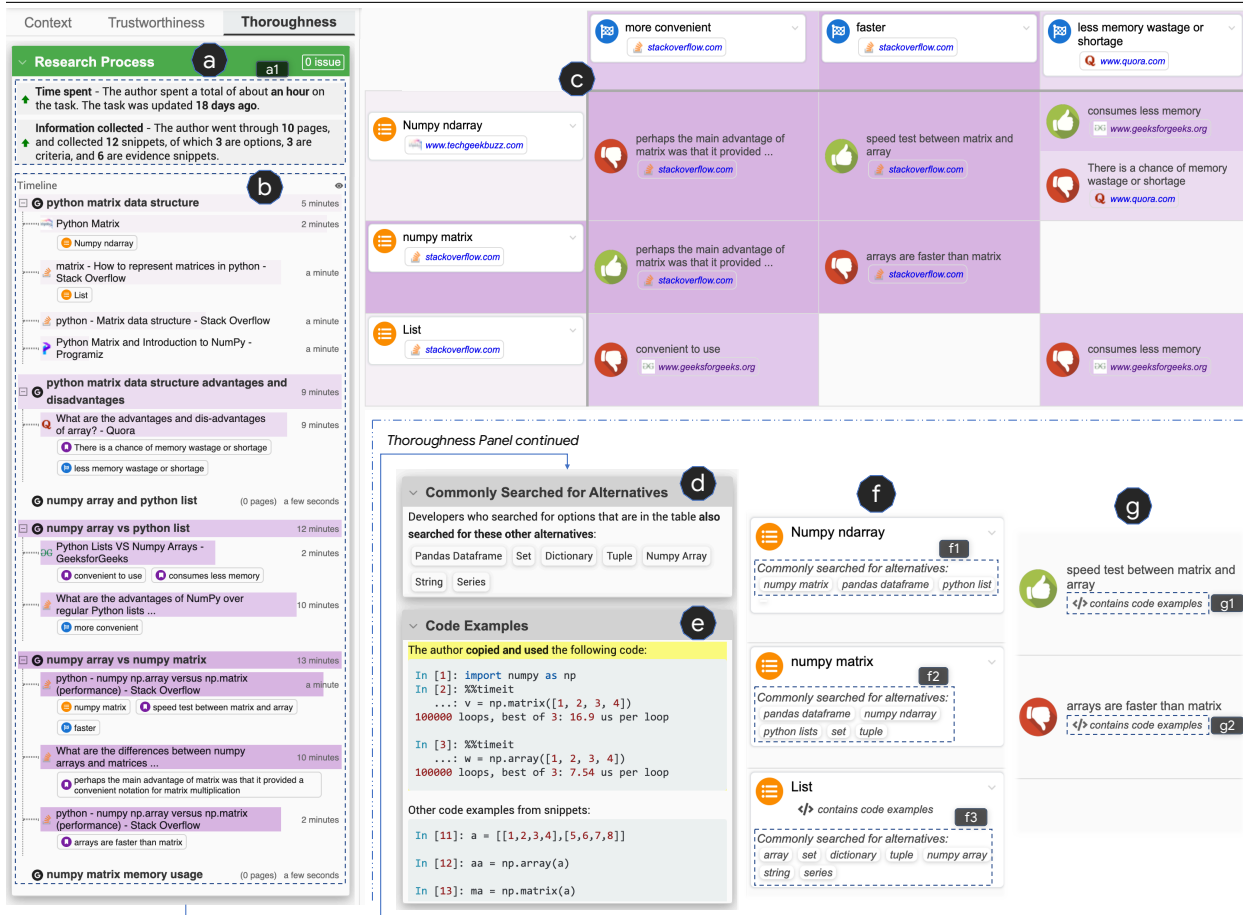


Figure 6.5: Strata's *Thoroughness* panel. Consumers are able to understand the author's research process (a) with the help of the timeline view (b) (a lighter violet means older chronologically), check commonly searched for alternatives to the existing options (d, f1, f2, f3), and check the code examples in the snippets (e).

With these activity data, Strata computes the duration of time the author spent working on a task, the length of time since the task was last updated by the author, and the numbers of options, criteria, and evidence snippets that the author collected (Figure 6.5-a1).

In addition, Strata visualizes the activity information on a timeline view (Figure 6.5-b), which provides an integrated chronological representation of the author's entire research and exploration process during a task. The timeline view is organized with two levels of hierarchies: first by the search queries, and then by the pages that are visited during a particular search. The timeline view is color-coded by different shades of a violet color, with increasing intensity indicating the chronological order (a lighter violet means older). The same color scheme is also applied to the background of the table cells (Figure 6.5-c) when the *Research Process* group is activated. The timeline view is also interactive, mousing over a search query or a page will highlight its corresponding information snippets in the table, together with the colored background, giving consumers an understanding of how the table was constructed chronologically.

6.4.4.2 Suggesting alternatives

Another way for Strata to help with the thoroughness evaluation is to provide consumers with *commonly searched for alternatives* to each option (Figure 6.5-f1,f2,f3). For every option in the table, Strata will automatically obtain the potential alternatives to that option by making Google

search queries in the form of “[option_name] vs” or “[option_name] versus” and obtaining a list of top 10 auto-complete candidates using the Google Autocomplete API. This will then be transformed into the *alternatives list* for the corresponding option by extracting and cleaning the part after “vs” or “versus” for each auto-complete candidate, followed by aggregating and removing duplicates. The results are presented in the *Commonly Searched for Alternatives* group (Figure 6.5-d). These alternative lists are generated on the spot every time a table is being reviewed, making sure that Strata always presents the latest information.

This approach offers several benefits to the consumers of the table. First, it offers insights into the popularity of the existing options in the table — if an option (such as “React”) appears in all other options’ alternatives lists (such as for “Angular” and “Vue”), it suggests that this option has a high popularity. Second, it provides consumers with an understanding of the coverage of the author’s research process as well as guidance on potential new opportunities to explore next — if an item (such as “pandas dataframe” in Figure 6.5-d) frequently appears in the existing options’ alternatives lists (and therefore will rank higher in the aggregated list in the Commonly Searched for Alternatives group), it suggests that this item might have been overlooked by the author initially, or it might not have been available back when the table was made, and the consumers can focus their investigative effort on it next before deciding whether to reuse this table. This feature could help authors as well, offering real-time reminders of the coverage of their research process and possible new options to consider as they are making decisions.

6.4.4.3 Presenting usable artifacts

Finally, Strata automatically detects and extracts any code examples included in the collected snippets and presents them in the *Code Examples* group under the Thoroughness panel (Figure 6.5-e). This provides consumers the opportunity to directly examine and try out any code examples involved first without diving deeper into the table. In addition, when the Code Examples group is activated, a “contains code examples” badge (Figure 6.5-g1,g2) will appear on snippets that contain code examples, helping consumers quickly locate potential code examples for a particular option or criterion in the table.

6.5 Evaluation

We conducted a lab study to evaluate the effectiveness of the framework and the prototype Strata system in helping developers evaluate the appropriateness of reusing decisions.

6.5.1 Experiment Design

6.5.1.1 Participants

We recruited 20 participants (13 male, 7 female) aged 22-37 ($\mu = 26.95$, $\sigma = 3.81$) years old through emails and social media. The participants were required to be 18 or older, fluent in English, and experienced in programming. Participants on average had 8.3 ($\sigma = 3.3$) years of programming experience, with 11 of them currently working or having worked as a professional developer and the rest having programming experience in universities.

6.5.1.2 Procedure

Participants were presented with 3 tasks in random order. The topics of the tasks were: (a) *choosing a python data structure to represent matrix-like data* (referred to as *Python* from here on), (b) *choosing a deep learning framework to build neural networks* (referred to as *Deep* from here on), and (c) *choosing a cloud computing service to build a video-streaming application* (referred to as *Cloud* from here on). For each task, participants were told what to pretend their background and context was, and they needed to read a table and answer questions about: (1) how much do they think the table is relevant to their given background and context; (2) how much do they trust the content of the table; and (3) to what extent do they think the research effort put into making the table is thorough. Participants were required to list out specific reasons to justify their evaluations.

The study was a between-subjects design, where participants were randomly assigned to either the Strata condition or the Unakite (control) condition. In the Strata condition, participants had full access to all the Strata features described above (along with the table produced by Unakite), while in the Unakite condition, these new features were turned off, so the participants saw only the table, and snippets in the table only showed their titles, contents, timestamps of collection, and links to their original web pages. We imposed a 10-minute limit per task to keep participants from getting caught up in one of the tasks. However, participants were instructed to inform the researcher when they thought they had finished the task or felt like they could make no further progress.

We chose Unakite as the control condition as opposed to raw (and textual) comparison tables online to make sure both conditions had a similar user interface to work with. It also makes the comparison between conditions more realistic — since the original Unakite is already keeping track of where snippets are collected, participants in the Unakite condition would have the ability to go back to the source to examine the appropriateness signals (such as up-vote numbers, last-updated timestamp, etc.) if they wanted to.

Each study session started by obtaining the proper consent and having the participant fill out a demographic survey. Participants in the Unakite condition were given a 10-minute tutorial showcasing the various features of the Unakite web application as well as a practice task on the topic of “choosing a JavaScript frontend framework” before starting. Those in the Strata condition were given a same-length tutorial as well as the same practice task but in Strata instead. At the end of the study, the participant was invited to fill out a questionnaire focusing on the experience of using either Strata or Unakite. We asked questions on the usability of the system they used in their respective conditions, the usefulness of such tables generated by the system, their opinions of the different features of the system, their willingness to author tables using the system to keep track of their decisions, their concerns about privacy if they were to author tables, as well as their familiarity with the topic of the three tasks used in the study. Finally, we ended the session with an informal interview on any additional thoughts they had about the system they used. Each study session took about 60 minutes per participant and was done remotely using the Zoom video-conferencing application. All participants were compensated \$15 for their time.

6.5.2 Quantitative Results

All participants were able to complete all of the tasks in both conditions, and none of them went over the pre-imposed time limit.

	Time	n_{Total}	n_{Valid} for Context	n_{Valid} for Trustworthiness	n_{Valid} for Thoroughness	n_{Valid}	$n_{\text{High Quality}}$	Precision	Recall
Unakite	484.2 (37.8)*	5.20 (0.92)*	1.50 (0.53)	1.30 (0.48)*	1.20 (0.42)*	4.00 (0.67)*	2.90 (0.57)*	55.7% (4.9%)*	24.2% (4.7%)*
Strata	328.2 (48.1)*	7.90 (1.91)*	1.50 (0.53)	3.20 (0.79)*	2.70 (0.82)*	7.40 (1.51)*	7.10 (1.45)*	90.1% (6.8%)*	59.2% (12.1%)*
(a) Python ($n_{\text{Ref. High Quality}} = 12$)									
	Time	n_{Total}	n_{Valid} for Context	n_{Valid} for Trustworthiness	n_{Valid} for Thoroughness	n_{Valid}	$n_{\text{High Quality}}$	Precision	Recall
Unakite	393.4 (50.9)*	5.70 (1.06)*	1.70 (0.48)	1.60 (0.70)*	1.40 (0.52)*	4.70 (0.82)*	3.20 (0.92)*	56.1% (12.4%)*	29.1% (8.3%)*
Strata	276.2 (68.3)*	7.80 (1.87)*	1.70 (0.67)	3.00 (1.15)*	2.60 (0.70)*	7.30 (1.83)*	6.90 (1.97)*	88.1% (9.7%)*	64.5% (17.4%)*
(b) Deep ($n_{\text{Ref. High Quality}} = 11$)									
	Time	n_{Total}	n_{Valid} for Context	n_{Valid} for Trustworthiness	n_{Valid} for Thoroughness	n_{Valid}	$n_{\text{High Quality}}$	Precision	Recall
Unakite	420.4 (58.9)*	6.20 (1.03)*	1.40 (0.51)*	1.90 (0.74)*	1.50 (0.53)*	4.80 (1.14)*	3.60 (0.97)*	58.5% (15.2%)*	30.0% (8.1%)*
Strata	271.8 (35.3)*	9.60 (2.37)*	2.60 (0.84)*	3.80 (0.92)*	2.60 (0.70)*	9.00 (2.00)*	7.90 (1.45)*	83.8% (8.5%)*	65.8% (12.1%)*
(c) Cloud ($n_{\text{Ref. High Quality}} = 12$)									

Table 6.2: Lab study results. The numbers of gold standard high quality reasons for each task, $n_{\text{Ref. High Quality}}$, are listed in their respective captions. We report the mean and standard deviation for: (1) the **time** in seconds taken to finish a task; (2) the total number of reasons participants came up with, n_{Total} ; (3) the number of valid reasons, n_{Valid} ; (4) the number of high quality reasons, $n_{\text{High Quality}}$; (5) the precision of high quality reasons, calculated as $n_{\text{High Quality}}/n_{\text{Total}}$; (6) as well as the recall of high quality reasons, calculated as $n_{\text{High Quality}}/n_{\text{Ref. High Quality}}$. Statistically significant differences ($p < 0.05$) through t-tests are marked with an *.

The results show that the participants in the Strata condition took significantly *less time* to finish compared to the Unakite condition for all three tasks, as shown in Table 6.2. Across all three tasks, the average time for completion was reduced by 32.5% when using Strata (Mean = 292.1 seconds, $\sigma = 56.9$ seconds) compared to using Unakite (Mean = 432.7 seconds, $\sigma = 61.8$ seconds), which is also statistically significantly ($p < 0.05$). Thus, using Strata did help participants evaluate the appropriateness for reuse faster.

To assess the *quality* of the reasons that participants came up with, before the study, two professional developers who are not affiliated with the research each generated a list of *high quality* reasons for all three tables independently. After resolving conflicts through discussions between the two developers, we produced a list of high-quality reasons for each table as the “gold standard”. We then calculated and report in Table 6.2 the numbers of high quality reasons participants identified that are on the “gold standard” list, as well as the precision (calculated as $n_{\text{High Quality}}/n_{\text{Total}}$) and recall (calculated as $n_{\text{High Quality}}/n_{\text{Ref. High Quality}}$) of high-quality reasons (where n_{Total} is the total number of reasons they generated, and $n_{\text{Ref. High Quality}}$ is the number of “gold standard” high-quality reasons for each task). By plotting the precisions and recalls in Figure 6.6, we can see that participants in the Strata condition achieved higher precision in all three tasks, that is, they gave a higher percentage of high-quality reasons in their responses compared to the Unakite condition. Participants in the Strata condition also achieved higher recall in all three tasks, that is, they were able to find more high-quality reasons compared to the Unakite condition. Thus, using Strata did help participants improve the quality of their evaluations compared to using Unakite.

In case participants came up with valid answers we had not thought of, after the study, we asked the same two developers as above to rate each reason that participants gave as either *valid* or *not valid* blind to the conditions. Valid reasons are considered as the ones that are specific and correct according to the content of the table. After resolving conflicts through discussions between the two developers, we filtered out the reasons that are considered *invalid*, and presented the resulting numbers of valid reasons in Table 6.2 (the numbers of invalid reasons were negligible

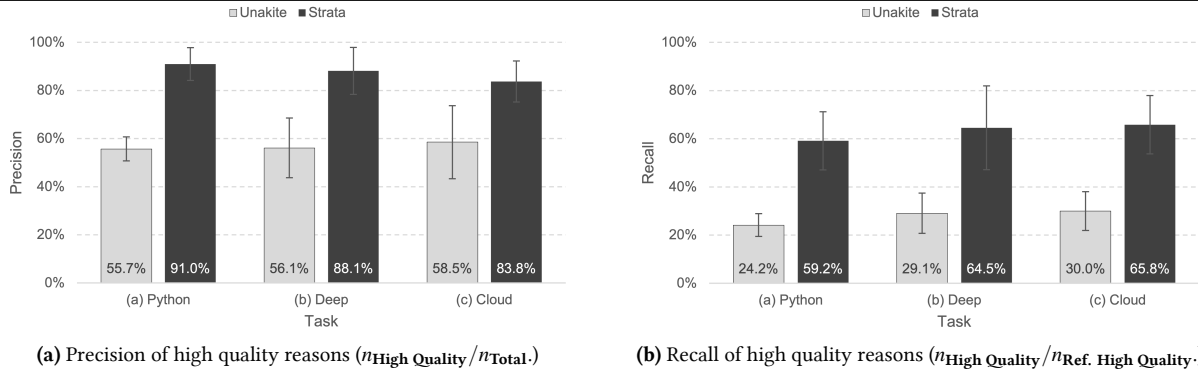


Figure 6.6: Precisions and recalls of high quality answers in all three tasks. All results are statistically significant under t-tests ($p < 0.05$).

and were therefore not included in the table). Across all three tasks, the average total number of valid reasons (n_{Valid}) increased by 75.6% when using Strata (Mean = 7.90, $\sigma = 1.90$) compared to using Unakite (Mean = 4.50, $\sigma = 0.94$), which is also statistically significant ($p < 0.05$). Thus, using Strata appeared to help participants come up with more valid evaluations for appropriateness for reuse compared to Unakite alone.

In the survey, participants reported (in 7-point Likert scales) that they thought the interactions with Strata were understandable and clear (Mean = 6.20, Median = 6.00, 95% CIs = [5.75, 6.46]), they enjoyed Strata’s features (Mean = 6.00, Median = 6.00, 95% CIs = [5.45, 6.72]), and would recommend Strata to friends and colleagues (Mean = 6.10, Median = 6.00, 95% CIs = [5.65, 6.35]).

6.5.3 Qualitative Results

6.5.3.1 Usability and usefulness of Strata’s features

Overall, participants appreciated the increased transparency and efficiency afforded by various Strata features and highlighted the values of the appropriateness properties that we visualize, arguing that “*it helps me understand how a table was made step by step*” (P10), “*lets me know what the author searched for, so if I don’t understand something, I can search again. And more importantly, I can sort of know what the author didn’t look for, and sometimes that’ll become what I can do next*” (P4), “*[the automatic context snapshot feature] saves me lots of time that I would otherwise spend going to the source web pages and making sense of things, which could be a rabbit hole sometimes*” (P15), and “*[allows me to] see on a high-level where stuff comes from and if there’s any source that is potentially questionable*” (P13). In addition, P8 reflected that Strata “*serve(d) as a guidance for things that I should pay attention to,*” which underlines the value of our framework, and reminded some participants of appropriateness properties that they would otherwise overlook, such as “*I never really thought about what the author(s) looked for or not, but now I think it’s actually quite important, especially if they miss obvious things that an expert would never miss,*” (P6) and “*I realize that I’m more of a grab-and-go kinda person and I don’t usually remember to check how many up-votes a Stack Overflow answer gets or when it was last updated*” (P17).

6.5.3.2 Authoring tables

Participants were also excited about authoring tables with Strata running, as it will automatically extract and produce the sidebar on the left and the various signals in the table. They mentioned that such “*honest signals enhanced*” (P10) tables would be particularly useful in situations such

as code reviews (P6: “going through the three main aspects is like going through our usual quality checklist, which makes sure that we’re not missing anything”) and project takeovers (P13: “if my previous browsing sessions are captured by this, then I won’t need to make myself available again and again if somebody else suddenly has a question that only I know the answer to, since I made it in the first place—this table thing will almost be self-explanatory”).

6.5.3.3 Privacy concerns

Some participants shared their privacy concerns from an author’s perspective, mentioning that certain types of metadata that could reveal their personal preferences and idiosyncrasies (e.g., the code that they used, the snippet surroundings, and their search queries) should be kept private until they felt comfortable sharing. Indeed, prior work has pointed out that there may be negative effects of surfacing certain types of information [83]. These findings identified new research opportunities for (1) intelligent mechanisms that can automatically screen for and block out information that should be kept private (e.g., similar to [168] or [140]) and (2) mixed-initiative and interactive mechanisms [129] that collaborate with users to only preserve the information that they are comfortable sharing (e.g., similar to [169]) without compromising the usability and effectiveness of the system.

6.6 Discussion

Prior research on web credibility stressed the importance of trustworthiness measurement during the evaluation of the appropriateness to reuse a previously created knowledge artifact [127]. However, as we found from literature on sensemaking handoff and our formative study, evaluating the appropriateness of reuse is much more than simply verifying the trustworthiness [127], especially since the artifacts are often an author’s collection and synthesis of different individual pieces of information from different sources and reflect the author’s opinion about the trade-offs among multiple valid options [177]. As a result, in addition to understanding whether the content is trustworthy, consumers also need to understand if the original problem context when the author created the artifact matches with the consumer’s [127, 187], and if the author’s research process was thorough [79, 215]. One of the contributions that we make in this work is a framework (Table 6.1) that summarizes the aforementioned three major facets, serving as a checklist that guides consumers through their evaluation processes. Strata, which is an instantiation of the framework, improves consumers’ abilities to evaluate these facets compared to using Unakite alone, as evidenced by both the quantitative (i.e., number of valid reasons given by the participants in terms of each facet) and qualitative results (e.g., participants’ comments on Strata reminding them of double checking appropriateness properties that they would otherwise overlook).

Although prior work on trust and sensemaking handoff offers insights into the various aspects and properties that are important for evaluating the appropriateness of reuse, it remained costly and difficult for not only the author who was creating the knowledge to also keep track of those signals and save them somewhere (since it is extra work without immediate benefit), but also for the consumer who was interpreting the knowledge to deduce and speculate about those signals. Through our research, we learned that a reasonable number of appropriateness signals can automatically be captured at authoring time as well as processed and visualized to the consumers subsequently to help with the reuse evaluation, and thereby reduce the cost for people to build on each other’s knowledge artifacts.

6.7 Limitations and Risks

There are certain types of information that Strata is not able to automatically obtain and visualize. One set of limitations results from Strata working in the browser, so it cannot monitor activities which happen in the authors' code editors or IDEs, command line interfaces, and relevant discussions with friends and colleagues (communicated either verbally or electronically through chat applications like Slack). Further development of extensions in these different environments as well as research into how to coordinate the collection and organization of this information would be needed in order to provide consumers with a more complete picture of an authors' working context beyond the browser. However, even in situations where Strata cannot automatically calculate a signal, we believe that the three major facets still alert consumers that these are important aspects to be considered. Also, to the extent that consumers come up with their own measurements and ways to fulfill their information needs, they are perfectly welcome to do so, such as testing if a piece of sample code returns the desired result by running it in a terminal, which the current Strata does not automatically do.

Some of the features in Strata are currently implemented based on heuristics, such as the bounds of the automatic context snapshots and the threshold beyond which information is considered out-of-date. These heuristics are based on our preliminary piloting through limited iterations, and may not apply universally to every situation. Further development can make these features more universally applicable and more adaptive to different situations so that users will be able to rely more on the judgements that Strata automatically generates.

The current design of Strata is intended for use cases where people collaborate and communicate their knowledge artifacts with each other in good faith; for example, software engineers sharing design rationale within a team. However, for Strata to be used at scale with potentially malicious actors, such as in situations where some authors might try to increase the trustworthiness and thoroughness scores by manipulating the different metrics that it uses and displays, additional signals as well as mitigation techniques might be needed to combat such gaming behaviors. One approach would be to aggregate multiple knowledge artifacts with similar context (options, criteria, and goals in the case of Unakite comparison tables) together and detect and filter out anomalous components, inspired by mechanisms like "down-voting" that community Q&A sites (e.g., Stack Overflow) use to guard against incorrect and malicious answers at scale. Further, some of the information, like the context, seems difficult and pointless to distort.

One of the concerns that repeated during our iterative design process is that each surfaced appropriateness property ultimately competes for user attention and takes time for the reader to process [149], which could result in the overall user interface being overwhelming. The current solution we employed, inspired by prior work in recursive summarization and sensemaking [286, 287], takes a hierarchical approach that presents users with an overview and the ability to dive into specific details, letting them take the initiative of exploring parts relevant to their own interests. Future research is needed to untangle the relative importance of the various factors and how they can be alternatively represented. One idea is to gather large amounts of usage data from a field deployment and develop statistical or machine learning-based models that can predict importance metrics given various input parameters.

Chapter 7

Proposed Work

7.1 Introduction

In our work thus far, we have designed and developed various mechanisms, interfaces, and techniques to better support users in collecting and structuring information while searching and browsing with little added cognitive or physical effort beyond what they would normally engage in. The results were promising – not only the individual techniques were shown to be useful and effective through a series of user studies, but the amassed information and knowledge in the tabular structure afforded by Unakite also proved to be helpful for subsequent people who may need to consume and reuse it.

Building on the foundation laid out by my existing work, I further recognize that the dynamic and evolving nature of sensemaking – particularly in the early stages – means that users often would avoid committing to a particular structure or doing any type of structuring at all. For example, both the Unakite participants as well as those from prior work (such as [204]) have expressed that, to some extent, organizing everything into a single type of structure (such as a table or decision tree) felt too rigid and constraining for the iterative and incremental process that they naturally use for sensemaking when investigating what decision to make.

Indeed, prior research [148] suggested that the asking users to structure information too early might lead to a more poorly structured information space. In addition, the knowledge structures that people created often become obsolete and new structures often emerge as their mental representations evolve over the course of their investigation (such as realizing a particular criterion should be prioritized, which prompts an entirely different investigation of several new options, etc.), with no single type of information structure likely to remain the most appropriate throughout the whole sensemaking process [90, 119, 148]. As a result, people often would just try to keep everything in their working memory, which, unfortunately, is not unlimited [43, 185, 229]. Continuing to do so may bring adverse effects, such as information overload [43] and loss of focus [25, 151].

In my proposed work, I attempt to address this issue by exploring **fluid tool scaffolding that would incentivize users to freely externalize their thoughts, interests, and emergent mental models at any time during sensemaking**. Guided by prior research as well as the findings and limitations of my existing work, I hypothesize that such an effective system should support the following:

1. **fluid collection and organization techniques** that would capture not only the information itself, but also potential signals of users' evolving mental models while foraging. Examples of such signals include users' perceived priority or valence of information that were captured in Crystalline and Wigglyte, but the proposed system should also explore implicit behavioral and process-level patterns, such as cross-referencing sources or initiating new branches/threads of investigation.
2. **flexible organizational structures** beyond tables (e.g., topical threads, check lists, mind maps, affinity clusters, etc.) that users can leverage to organize and transform the amassed information to reflect their evolving mental models during different stages of sensemaking. The system should attempt to bootstrap these structures, for example, by taking advantage of the signals from the foraging phase, to lower the entry barrier and provide a scaffold for users to iterate and improve on.

Similar to my previous work, I plan to evaluate the new systems through lab or field studies with people solving their real-world problems. I elaborate my current state of thoughts and planning in the following sections.

7.2 Proposed System Design

7.2.1 Fluid Information Collecting and Organizing

My existing work Crystalline and Wigglyte has opened up two paths towards enabling fluid information collection and organization: 1) implicit foraging through automatically inferring user interest from their behaviors and 2) explicit foraging through lightweight interaction techniques. In my proposed system, I plan to further extend these approaches as they were proven useful and effective in our evaluations.

7.2.1.1 Capturing Behavioral Signals

As reviewed in chapter 2, prior work has introduced many theories and models that try to characterize the common themes and processes for sensemaking. However, a key challenge with existing theories and models is that they tend to be too high level for our goals of identifying and taking advantage of low-cost signals that are useful for foraging and later structuring [71, 75, 99, 150, 195, 219, 234, 288]. Through the Crystalline system, I explored a small portion of the design space for taking advantage of natural behavioral signals that people exhibit when searching and browsing, which can be used to approximate the amount of attention or interest users had towards different pieces of information.

Building on the direction of leveraging people's natural behaviors while browsing, I plan to explore in my proposed work signals from higher order behavioral patterns and sequences. We have noticed in interviews with developers choosing APIs or consumers making product purchase decisions that they often, for example, *cross-reference* sources that mention multiple options or criteria (e.g., StackOverflow answers or Best X in 2021), *short-list* a small set of options from them and *put aside* the other seemingly less competitive ones, *deep-dive* into the most promising to learn about the contexts it is used in and how well they match their own goals and background, *switch* to a new branch of alternatives when they believe that they have sufficiently reduced the

estimated uncertainty and potential value of the current branch, etc.. These are process-level thoughts and behaviors that are currently overlooked by foraging support tools, but could be the kinds of useful meta-information about a user’s sensemaking process that is helpful downstream (for both the later structuring and the adaption and reuse of that structure by subsequent users).

My goal is to first develop ways to intelligently and automatically detect and capture these signals through observing and understanding higher order patterns and sequences in users’ sensemaking behavior, such as closing a series of tabs in a row when they have decided to discard an entire branch of alternatives, backtracking or creating new branches when they encounter particularly promising or deal-breaking information, and even minute signals of their judgments as they browse like micro-scrolling or mouse movement patterns when they encounter new or unexpected information that prompts additional cognitive processing [236]. The system can then act accordingly by intelligently keeping track of, prioritizing, or archiving information on behalf of the user. And like Unakite and Crystalline, users can view and edit these changes and updates in an always-available sidebar at any given point of time during their sensemaking process. The edits should be further leveraged to recalibrate system behaviors.

7.2.1.2 Leveraging Lightweight Interactions

I will also explore novel lightweight explicit interactions in addition to taking advantage of the signals from people’s browsing behaviors. The intuition here is that there is an relatively under-explored design space for interactions that are not yet part of a user’s natural browsing process but could become so with very little added physical or cognitive demand, and could, in the meantime, provide rich signals of a user’s current attention, interests, and mental models.

My existing work on Wigglite has specifically looked at the “wiggling” interaction technique that combines the selection, collection, and optional triaging of interested content in a single coherent gesture. In my proposed system, I would like to explore another low-cost interaction technique for quickly consuming and triaging large amounts of content – users can enter a “grabber” mode in which they would use normal clicking (or right-click, double-click, press) on desired content and save them into an information repository (similar to what Unakite supports, see section 3.3.2.2). The key idea here is that users do not have to learn and get into the habit of executing a new type of interaction (which prevents adoption [146]), but can use interactions that they already perform frequently and are familiar with, which lowers the entry barrier and improves speed and efficiency. In addition, as reported by prior research [134], it is often the case that users’ mouse cursor follow their eye gaze when they read and process content on the web, suggesting that little cross-screen cursor traversal is required for them to point and click on the desired content. Furthermore, users can specify how the information should be annotated, classified, or organized by optionally interacting with an always-available sidebar after capturing, which I elaborate in the next section.

7.2.2 Flexible Structuring

The key goal for the system at this stage is to provide representations and lightweight interactions for users to bootstrap and evolve the structures of their foraged information. As mentioned in the introduction, I would like to explore alternative knowledge organizational structures beyond tables to offer users a more flexible structuring experience. To achieve this, the system can

leverage the rich signals of users' evolving mental models during the foraging phase that was discussed above and those introduced by my existing work. For example, a starting point would be a sorted lists of important criteria, where each can be marked as to whether it is a *deal-breaker* (if it does not have the appropriate value, then the option does not need to be further considered), *tradeoff* (values in this criteria trade off with values in another, and the user must balance which is more important), or *informational* (all the options are pretty much the same for this criteria, so it turns out to not be a useful discriminator). Then, a table might be automatically created just for the trade-offs.

I also propose to integrate other views, such as 1) a branch view that represents the major branches/threads of research that users investigated and the key information that they learned for each, 2) a cluster or kanban-board view that can be automatically bootstrapped and ordered based on similarity, amount of attention given, or estimated level of user interest, and 3) a infinite workspace view where information clips are by default clustered via content similarity [223] and users can also freely position, regroup, annotate the individual clips and clusters. In the meantime, the system should try to adapt the structures and views to the current sensemaking context (such as prioritizing the branch and information related to that branch that users are currently on), and provide flexible, interactive transitions among them.

Given the iterative nature of sensemaking, as users discover and extract new information, I plan to research automatic ways to identify where in the structure the collected information should go, such as identifying whether it is a new option, new criteria, evidence for an existing option or criteria, or something else entirely (like product picture, code snippet, or tutorial useful if this is chosen in the end). This will also alleviate the need to decide on the structure and do all the setup up-front – users can begin with a simple default representation, such as a list, and incrementally evolve into more structured views as needed.

Another key aspect of flexibility is to be able to easily discard, archive, or modify information and structures if they are no longer considered relevant, useful, or accurate. This can be achieved by letting users initiate via lightweight interactions similar to what was described above and letting the system do the rest of the heavy-lifting. For example, users may decide that a criteria is ultimately a deal-breaker, then the system can intelligently filter out the victim options based on this new insight.

7.3 System Implementation

I plan to primarily support sensemaking activities on desktop, specifically in a web browser. Like my previous systems, I envision the new system as a browser extension. I also plan to leverage the Skeema platform that was discussed in section 5.3.1 – Skeema provides mechanisms for users to collect their tabs into projects, extract the pieces of pages that they find useful, and organize them into simple thread-based structures, thus providing a basic scaffold and also a control condition for new features and interventions. In addition, Skeema already has a strong user base of more than 2000 public users (as of November 2022), especially after the recent launch on Product Hunt [255]. Based on informal survey results, large segments of the users are engaged in programming and consumer decision making, the two domains that I focus on in this thesis. Therefore, I consider Skeema an idea platform for me to iteratively design and build my proposed work on and recruit future study participants to perform tasks in a more organic fashion.

One notable addition I would like to add to Skeema is an always-available sidebar. The general design of the sidebar will be similar to that of the Unakite and Crystalline system (see Figure 3.1 and 4.1), which serves both as a visualization and a canvas for people to quickly scan and organize the knowledge they have gained so far. However, it should differ from Unakite and Crystalline in that it provides a lot more ways for users to flexibly organize their collected information clips. I expect to iterate on the specific design of this sidebar in the coming months.

7.4 Evaluation Plan

While I am still at an early stage of exploring the design space for this new sensemaking tool, I plan to conduct a controlled lab study to evaluate its usability, usefulness, and effectiveness. I would like to compare the tool to both using the original Skeema platform (which already boasts significant improvements in terms of the ease of use and effectiveness when sensemaking) and a more common baseline of using Google Doc to take notes and structure thoughts while sensemaking (the appropriateness of which has been discussed in detail in section 3.4.1.1).

I plan to obtain both quantitative and qualitative data from the study. Quantitative metrics include but not limited to the *overhead cost* of using the tool (see section 3.4.1.2 and 4.5.1), the *time* it takes for participants to finish tasks, the *number of operations* (such as collecting, organizing, prioritizing, archiving, etc.) performed, the *number of low-level actions* (such as clicks, cross-screen cursor movements, drags, scrollings, etc.) performed/saved, the *number of iterations* went through to reach the final organizational structure, etc. Qualitative evidence can be gathered through administering NASA TLX surveys, think-aloud transcripts (if applicable based on the actual study design), and post-study semi-structured interviews.

I am particularly interested in the following research questions:

- Can people use the new system to collect and organize information and externalize their thought processes when sensemaking?
- Does the system offer value over what people would normally do when reading through and making sense of web content for decision making?
- How much effort do people perceive that they have to put into to keep the external structure up-to-date and reflective of their state of thinking at any given point in time?
- How can the design of the system be improved?
- What are some potential common characteristics of the structures that people externalize depending on the nature of the tasks?

7.5 Timeline of Completion

My goal is to complete the dissertation by July 2023. My proposed schedule is shown below:

- December 12, 2022: Thesis Proposal
- December 2022 - April 2023: Design and build proposed system
- March 2023 - June 2023: Run lab studies of the proposed system
- January 2023 - June 2023: Job search
- June 2023 - Aug 2023: Thesis writing & defense

Appendix A

Related Work for the Strata Framework and System

A.1 Information and Knowledge Reuse

As formulated by Davenport et al. in 1996 [73] and Markus in 2001 [187], knowledge processes are often categorized by whether they involve *knowledge creation* (e.g., research and development of new products and services, or writing books or articles) or *knowledge reuse* (e.g., reapplying existing components and best practices to solve common problems). While there is much research into the significance and difficulties of knowledge creation and innovation [73, 113, 115, 147, 154, 205], the effective reuse of knowledge has been shown to be a more frequent strategy and concern to individuals and organizations [73, 77, 187, 207, 209, 286, 287].

Many systems have been developed to support the multiple stages of information and knowledge reuse as mapped out by Markus [187]: *capturing and documenting knowledge*, *packaging and distributing knowledge*, and *reusing knowledge*. Among them, some systems support capturing, organizing, and keeping track of information in the first place (e.g., [39, 114, 170, 171, 177, 269]), some aim to deliver and surface existing knowledge directly to a user without the need of complex matching and frequent context switches (e.g., [46, 60, 221]), and others facilitate the digesting and understanding of knowledge (e.g., [175, 177, 258]). However, having a literal understanding of a knowledge artifact does not by itself imply reuse — a major barrier to that knowledge actually being useful is the consumer does not know whether it is *appropriate* to use it or not [187, 274].

Prior research provides insights into various properties that people look for in order to evaluate the appropriateness for reuse, such as source credibility [74, 85, 92, 191, 244, 264], information currency (or up-to-dateness) [24, 45, 191], information popularity [191, 244], goals and purposes (what the author wanted to achieve) [216, 247], etc. However, much research such as the above focuses on specific issues about the general credibility of web content, while knowledge artifacts previously collected and synthesized by an author require many more types of judgements beyond credibility in order for a consumer to decide its appropriateness for reuse. To the best of our knowledge, there remains no systematic models or frameworks for understanding the factors that affect the judgements of the reuse of previously created knowledge artifacts. Such a framework could be helpful for driving research studying and augmenting reuse across a variety of domains and forms. In this thesis, we take a step towards such a framework, starting with knowledge

artifacts in the form of comparison tables, which are widely used, and in the domain of programming, where knowledge reuse happens frequently [46, 112, 121, 131, 153, 159, 177, 221, 254, 254]. In the following sections, we discuss three of the most relevant threads of research as they relate to judgements of knowledge reuse.

A.2 Evaluating Online Information Credibility

A.2.1 Models and Heuristics for Evaluating Online Information Credibility

One of the most researched facets of knowledge reuse is evaluating online information credibility [93, 191, 244, 273] (or “trustworthiness” [264]), which focuses on facets of authenticity, reliability, and trustworthiness of a given piece of content online, ranging from e-commerce transactions to online discussions and collaborations [149, 258, 263]. Prior work has employed bottom-up approaches like surveys and contextual inquiries and reported various factors that influence credibility assessment, including but not limited to: domain name and URL, presence of date stamp showing information is current, author identification and indication of his or her expertise, citations to scientific data or references, and user ratings and reviews [24, 45, 85, 92, 98, 190, 191, 193, 250, 264, 273].

In addition, models and heuristics for credibility assessment have also been proposed, for example, the *checklist model*, which guides users through a checklist of critical factors during assessment [191], and the *contextual model*, which emphasizes the use of external information to establish credibility [190], such as promoting peer-reviewed resources and seeking corroborating or conflicting evidence. A summary by Metzger et al. [193] suggests that users routinely invoke *cognitive heuristics* to evaluate the credibility of information and sources online, such as the *reputation heuristic* (checking if the source of the information has good reputation and credentials), and the *expectancy violation heuristic* (checking if a website or its content conforms to their original expectations).

However, in reality, it has repeatedly been shown that people are often underprepared and have trouble determining how to evaluate the credibility of online information [29, 190, 192, 240], which is often deemed to be too much work [190, 245], having a high possibility of missing important details [191, 193], and eventually leading to abandonment, mistrust or misuse [174, 175, 191] of the information. This reflects a significant gap between research and reality: while prior work provides insights into the various factors affecting online information credibility and ways people reason about them, people need tool support that systematically helps with credibility assessment and information reuse. We address this gap by providing a prototype system (the Strata system) that (1) automatically extracts appropriateness signals (including those related to credibility) from the original knowledge content when possible; and (2) processes and presents them to the consumer of the knowledge in a hierarchical visualization that directly addresses their information needs during the evaluation of the appropriateness to reuse.

A.2.2 Support for Evaluating Collaboratively-built Knowledge Content

Collaborative knowledge building, exemplified by the Wikipedia project [7] and Stack Overflow [6], has become highly popular in many domains, and its mutable nature that virtually *anyone can edit anything* has invited considerable research into helping users evaluate the trustworthiness of its content. For example, the revision histories [258, 271, 284, 285], review processes [272], and the external references [93, 95] of an article can be modeled and visualized to help improve transparency and the evaluation of its trustworthiness. In addition, an author’s past performance, such as their editing history on Wikipedia or previously answered questions on Stack Overflow, can be mined [23, 250] and surfaced [258] to help knowledge consumers determine the author’s reputation, expertise, and other accountability metrics. Encouragingly, Kittur et al. [149] showed that surfacing trust-relevant information from Wikipedia articles had a dramatic impact on users’ perceived trustworthiness of those articles, holding constant the content itself.

However, despite the overwhelming importance and increasing research effort, being considered trustworthy is often not the sufficient condition for reuse, nor is trustworthiness always the first facet that users evaluate — research has shown that people often have trouble understanding a piece of information when it is taken out of its original context [177, 187] and figuring out if it is indeed relevant to their own situation [44, 238, 245] before they start to think about trustworthiness and credibility. In addition, they also wonder about how much effort has been put into creating a piece of knowledge and does it cover everything that they are interested in [187, 215, 245, 247, 289] before they can give a final verdict on reusing it or not. Therefore, we draw from and build upon these prior works, where we iterated to identify, extract, and surface not only the important elements of trustworthiness but also context and thoroughness to help consumers make a more comprehensive assessment of the appropriateness of reusing knowledge, exemplified by decisions and their rationale in programming.

A.3 Sensemaking Handoff

Much research has explored the activity of *sensemaking handoff*, during which one individual must continue the sensemaking work where another has left off. It frequently happens in asynchronous collaborations [90, 215, 216, 289], shift changes [214], etc., during which the current sensemaker (consumer) needs to make sense of and evaluate the appropriateness of reusing the results generated by a previous sensemaker (author) [187, 245]. Various metadata and properties parallel to the main artifacts of sensemaking have been proposed that would help the people with this process, such as the awareness of the previous sensemaking process [79, 215] (e.g., search queries and visited web pages), the level of expertise of the author [187, 247], and the context of the original sensemaking problem [187].

However, it is both time and effort intensive for an author to keep track of their rationale and processes with little immediate payoff, which is also often for the benefit of others rather than themselves [177]. Even in situations where authors have the explicit wish to help, they are often uncertain of what metadata and properties to provide and how those can be instantiated using concrete signals that would be valuable to the consumers in evaluating the reusability of their sensemaking results [245]. We address these barriers in the context of reusing decisions in programming by iteratively developing a framework that summarizes the major facets that

consumers care about during the evaluation of appropriateness to reuse along with the corresponding detailed information signals, and a set of technical approaches that can automatically extract, compute, and visualize them when possible. We integrated these into our Unakite system [177] that helps authors organize and record their decisions for reuse, saving them the burden of coming up with the appropriate signals to keep track of as well as potential extra effort needed to accurately obtain them.

A.4 Knowledge Reuse in Programming

The practice of knowledge reuse has been particularly relevant in the software industry [112]. Code reuse, in particular, has become a hugely successful paradigm in the development of new software products and services in both the commercial and open source sector. Developers frequently use well-maintained functional code modules from code-sharing platforms such as GitHub [2] and npm [4], enjoying the benefits of significantly reduced workload, improved productivity, enhanced software performance, stability and security, and more time for innovation [96, 97, 112, 139, 187, 196, 202, 254].

Despite the fact that software code is the most obvious target for reuse [112, 196, 254], knowledge reuse in programming may go well beyond code, as stated by Barns and Bollinger [33]: “The defining characteristic of good reuse is not the reuse of software *per se*, but the reuse of human problem-solving.” Indeed, developers on community Q&A websites like Stack Overflow [6] share not only code examples [46, 221] but also decision making strategies, design rationale such as alternative options, criteria or constraints that should be met, and the resulting trade-offs [131, 177]. Furthermore, questions about design rationale are widely cited by developers as some of the hardest to answer [159, 160, 252]. Tools like Unakite [177] can greatly reduce the costs to keep track of and later understand such rationale knowledge, with the hope that such knowledge can ultimately be better reused rather than be obtained from scratch requiring duplicated research effort [112, 176]. In Strata, we further advance this research thread by developing features and affordances enabling developers to evaluate the context, trustworthiness, and thoroughness of previously-made decisions, which is arguably one of the missing links between understanding and reuse.

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