

User Interfaces for Fine-grained Integration of Information

Dissertation Proposal • Monday, August 4, 2025

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Alyssa Hwang

New AI capabilities enable opportunities to enhance information-heavy sources.



The image displays four examples of AI-enhanced information sources:

- Search Interface (Left):** A screenshot of a search results page for "what is user-centered design?". It shows a brief definition, a "Follow Up" section with links to "Consensus Meter" and "User-centered design principles", and a "Results" section with a paper titled "User-Centered Design for Psychosocial Intervention Development and Implementation". A green arrow points from this interface to the Google search result.
- Google Search (Top Right):** A screenshot of a Google search for "what is a large language model". The top result is an AI-generated overview: "A large language model (LLM) is an advanced artificial intelligence model, trained on massive amounts of text data, that can understand, generate, and interact with human language. It's a type of artificial intelligence that excels at natural language processing, allowing it to perform tasks like translating languages, answering questions, and even generating creative text formats." A green arrow points from the search bar to this definition.
- Clinical Report (Bottom Left):** A screenshot of the PORTER – Patient-Oriented Radio Reporter tool. It shows a clinical report for a 24-year-old patient with tonsillitis. A green arrow points from the report title to the glossary entry for "iopamidol".
- Code Editor (Bottom Right):** A screenshot of a code editor showing a function setup for "Ask Copilot". The code uses jQuery to get data from "/get-data", parses it as JSON, and then loads it into a ribbon or passage. A green arrow points from the "Ask Copilot" input field to the code snippet.

Recent AI advancements support unprecedented levels of work in fine-grained augmentations.

Penn Medicine

PORTER – Patient-Oriented Radiology Reporter

PORTER makes it easier to read your report. Move your mouse over the underlined words to see what they mean.

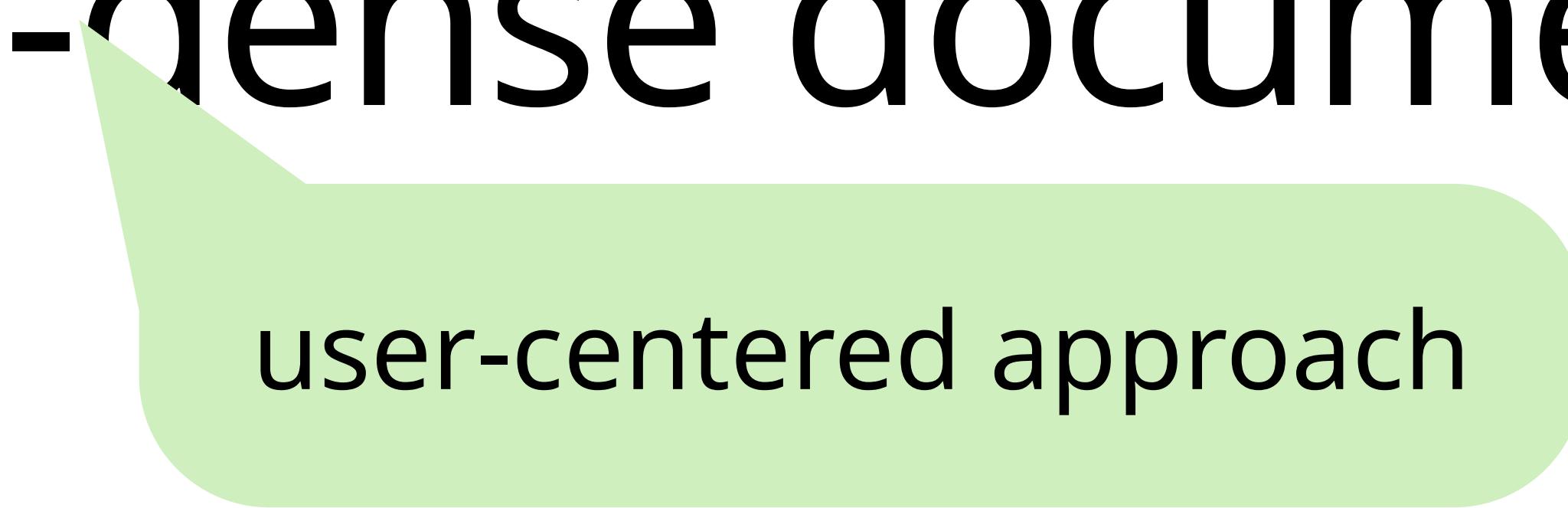
CLINICAL INFORMATION: 24 years old. Tonsillitis

 **iopamidol**
A contrast agent used in x-ray and CT.

neck was performed with images obtained from the skull base to mid thorax. Images were reviewed for soft tissue and bone detail.

Contrast: 90 mL IOPAMIDOL 76 % IV SOLN intraVENOUS.

In this thesis, I aim to show that fine-grained augmentations can help **users** understand information-dense documents.



user-centered approach

Presentation Structure

1. Needs-finding study
2. Case study of prototype
3. Behavioral analysis
4. Proposed work + timeline

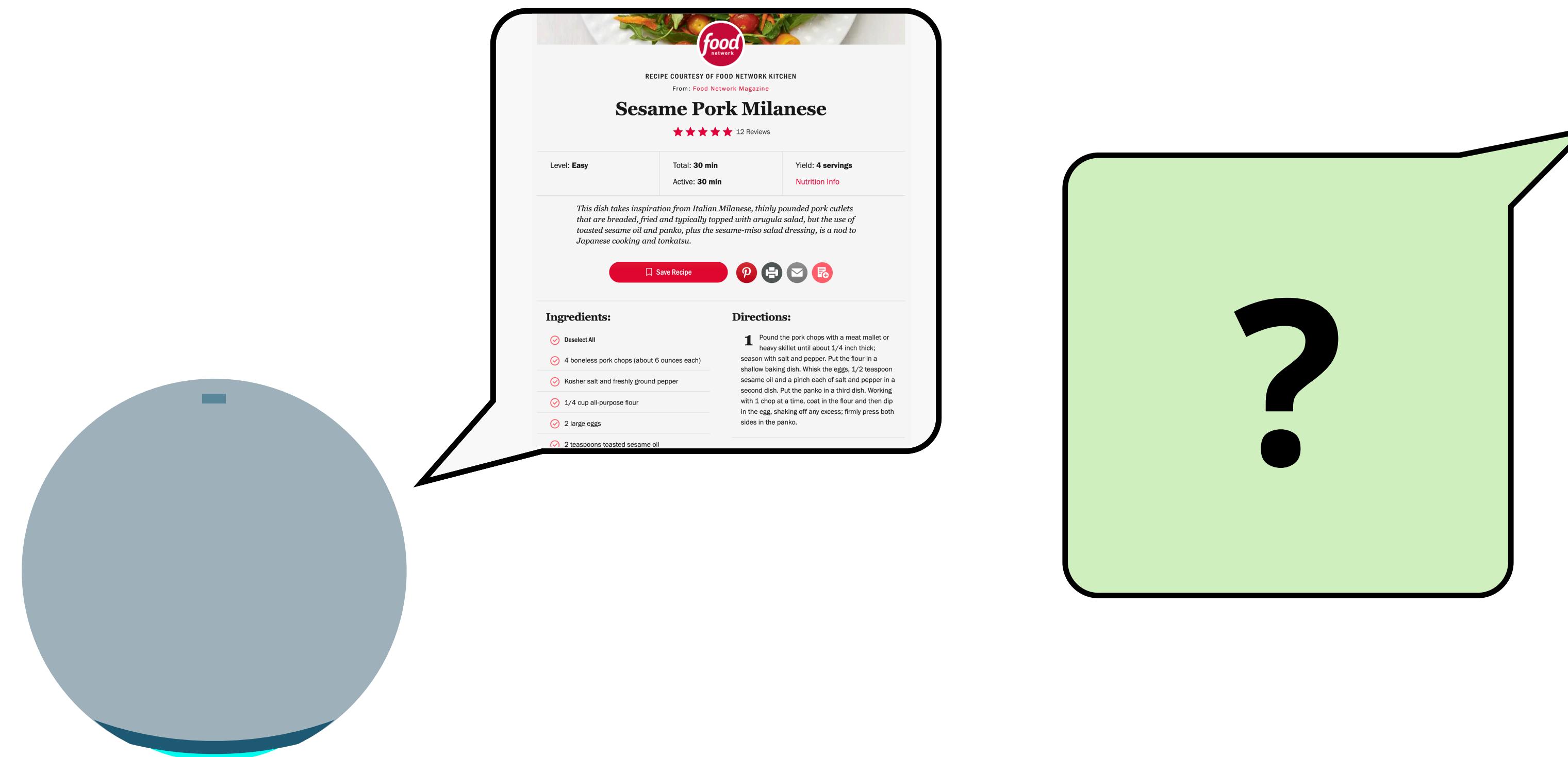
Questions are welcome after each section

1. Needs-finding study

Motivation: understand user needs for fine-grained augmentations

Method: observe users cooking at home with voice assistant

Outcome: definition of user challenges and potential augmentations



We recruited 12 participants to cook with an Alexa Echo Dot.



Participants cooked and annotated recipes of their choice in their homes.



Herb-Roasted Salmon with Tomato-Avocado Salsa



Recipe courtesy of Valerie Bertinelli

Show: Valerie's Home Cooking Episode: A Heart-y Valentine's Day



Level: Easy

Total: 45 min

Active: 20 min

Yield: 6 servings

Ingredients:

2 tablespoons olive oil, plus more for the baking sheet and salmon
1/3 cup finely chopped fresh dill
1/3 cup finely chopped fresh flat-leaf parsley
3 tablespoons finely chopped fresh chives
3 tablespoons finely chopped fresh basil
2 1/4 pounds center-cut salmon fillet, skin and bones removed
Kosher salt and freshly ground black pepper
2 large avocados
12 ounces mixed-colored cherry or grape tomatoes, halved or quartered if large
2 tablespoons fresh lemon juice
1 small shallot, minced

Directions:

- 1 Preheat the oven to 350 degrees F. Line a large rimmed baking sheet with parchment paper and brush it lightly with oil.
+ Q: do you remember the quantities or do you want me to repeat them? maybe mention "let me know when you're ready to continue with the toppings"
- 2 Mix together the dill, parsley, chives and basil in a small bowl. Reserve 2 tablespoons of the mixture for the salsa and set aside.
+ Q: do you want me to repeat this? (it takes time to do this!)
- 3 Put the salmon on the prepared baking sheet and sprinkle all over with salt and pepper. Drizzle the top lightly with oil, then top evenly with the herb mix. Bake until just cooked through, 20 to 25 minutes.
+ Do you want me to start a timer?
- 4 Meanwhile, halve and peel the avocados and cut them into 1/2-inch pieces. Put the avocados in a large bowl and gently toss with the tomatoes, lemon juice, shallots, 2 tablespoons oil, 1/2 teaspoon salt and the reserved herbs. Transfer to a serving bowl.
*+ Shall we go step by step?
1. Start with the avocados...
2. Now time for the tomatoes...
3. ...*
- 5 Serve the salmon with the salsa on the side.



We observed 9 types of challenges during the user study sessions.

- Missing the big picture
- Information overload
- Fragmentation
- Time insensitivity
- Missing details
- Discarded context
- Failure to listen
- Uncommunicated affordances
- Limitations of audio

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Directions:

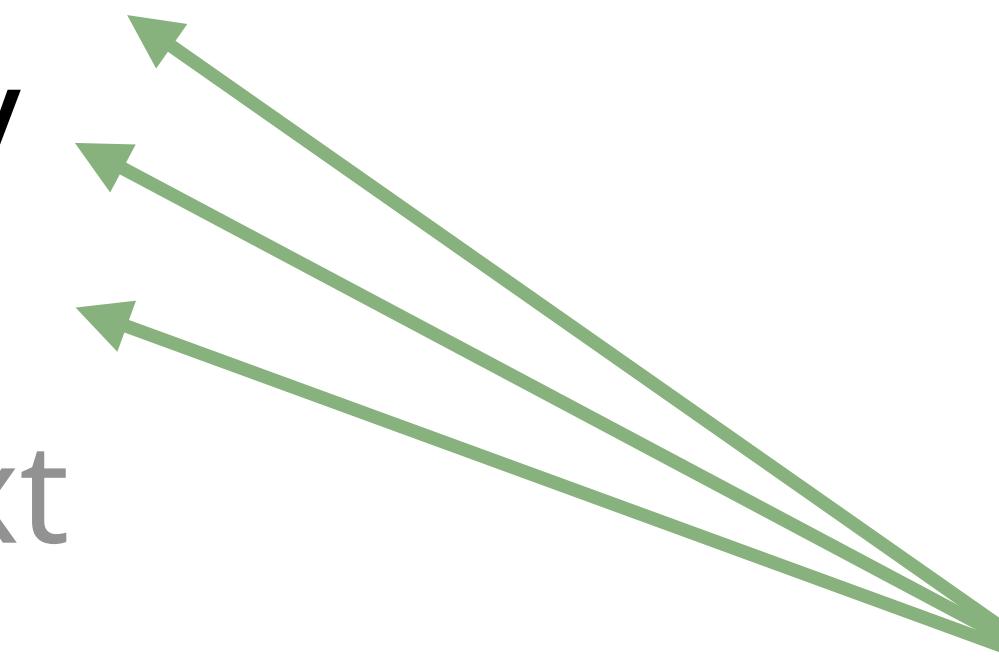
- 1** Preheat the oven to 350 degrees F. Line a large rimmed baking sheet with parchment paper and brush it lightly with oil.
- 2** Mix together the dill, parsley, chives and basil in a small bowl. Reserve 2 tablespoons of the mixture for the salsa and set aside.
- 3** Put the salmon on the prepared baking sheet and sprinkle all over with salt and pepper. Drizzle the top lightly with oil, then top evenly with the herb mix. Bake until just cooked through, 20 to 25 minutes.
- 4** Meanwhile, halve and peel the avocados and cut them into 1/2-inch pieces. Put the avocados in a large bowl and gently toss with the tomatoes, lemon juice, shallots, 2 tablespoons oil, 1/2 teaspoon salt and the reserved herbs. Transfer to a serving bowl.
- 5** Serve the salmon with the salsa on the side.

We propose 8 augmentations to enhance the source material.

- Missing the big picture
- Information overload
- Fragmentation
- Time insensitivity
- Missing details
- Discarded context
- Failure to listen
- Uncommunicated affordances
- Limitations of audio
- Summarize
- Signpost
- Split
- Elaborate
- Volunteer
- Reorder
- Redistribute
- Visualize

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- Failure to list ingredients
- Uncommunicated affordances
- Limitations of audio

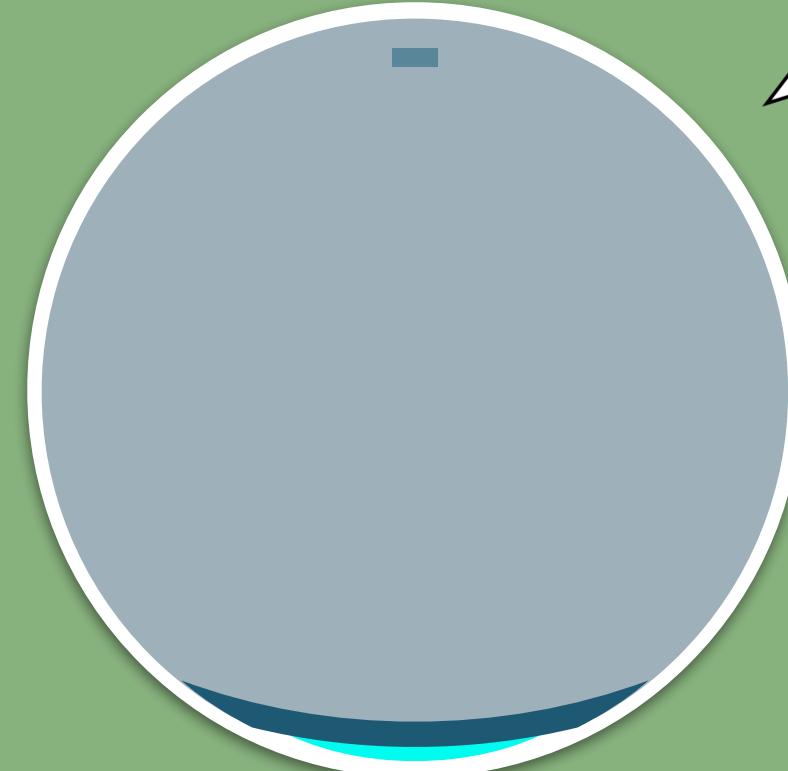
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- Limitations of audio

Put the avocados in a large bowl and gently toss with the 12 ounces of halved tomatoes, 2 tablespoons lemon juice, 1 small diced shallots, 2 tablespoons oil, 1/2 teaspoon salt and the reserved herbs. Transfer to a serving bowl.

Needs-finding study outcome



User challenges grounded
in realistic study scenario

Potential fine-grained
augmentations

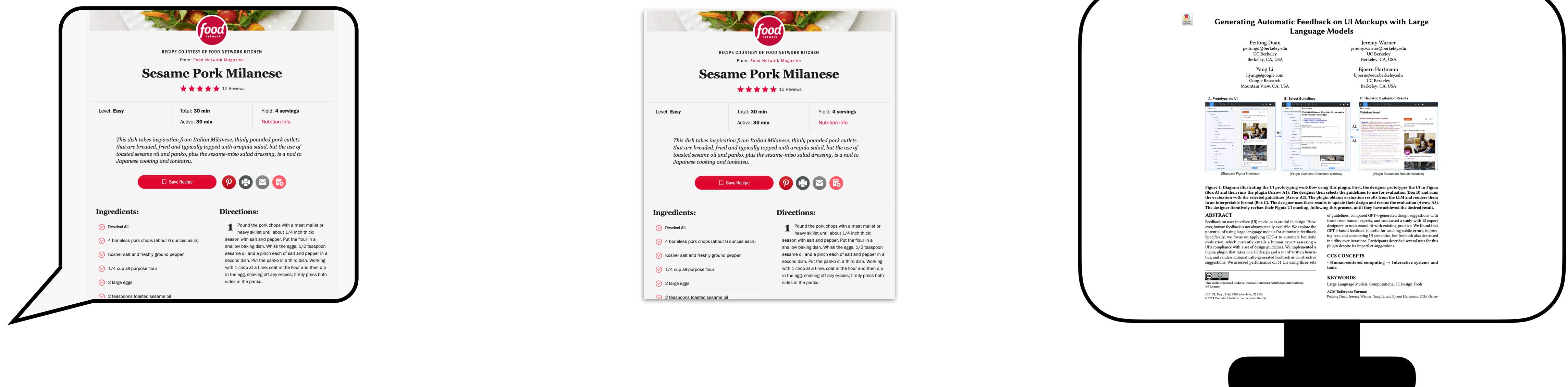
“Rewriting the Script:
Adapting Text Instructions for
Voice Interaction” (DIS 2023)

2. Case study of prototype

Motivation: observe fine-grained augmentations for real task

Method: implement prototype to support reading info-dense docs

Outcome: augmented reading interface for research papers



Generating Automatic Feedback on UI Mockups with Large Language Models

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DOI: <https://doi-org.proxy.library.upenn.edu/10.1145/3613904.3642782>

CHI '24: Proceedings of the CHI Conference on Human Factors in Computing Systems, Honolulu, HI, USA, May 2024

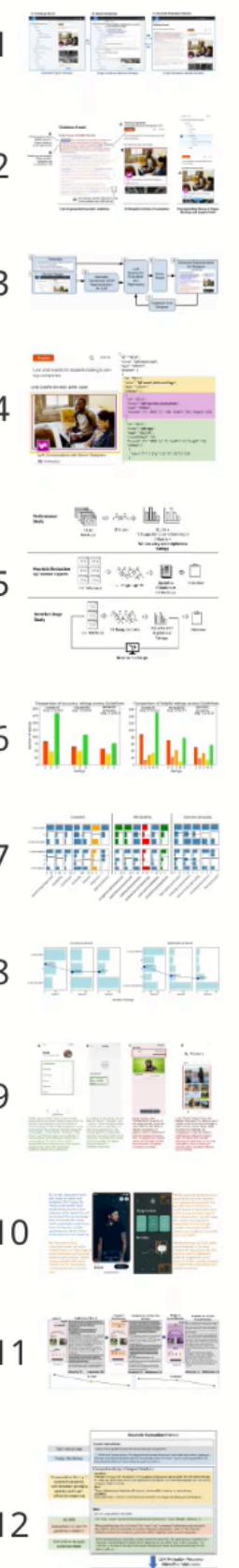
Feedback on user interface (UI) mockups is crucial in design. However, human feedback is not always readily available. We explore the potential of using large language models for automatic feedback. Specifically, we focus on applying GPT-4 to automate heuristic evaluation, which currently entails a human expert assessing a UI's compliance with a set of design guidelines. We implemented a Figma plugin that takes in a UI design and a set of written heuristics, and renders automatically-generated feedback as constructive suggestions. We assessed performance on 51 UIs using three sets of guidelines, compared GPT-4-generated design suggestions with those from human experts, and conducted a study with 12 expert designers to understand fit with existing practice. We found that GPT-4-based feedback is useful for catching subtle errors, improving text, and considering UI semantics, but feedback also decreased in utility over iterations. Participants described several uses for this plugin despite its imperfect suggestions.

CCS Concepts: • Human-centered computing → Interactive systems and tools;

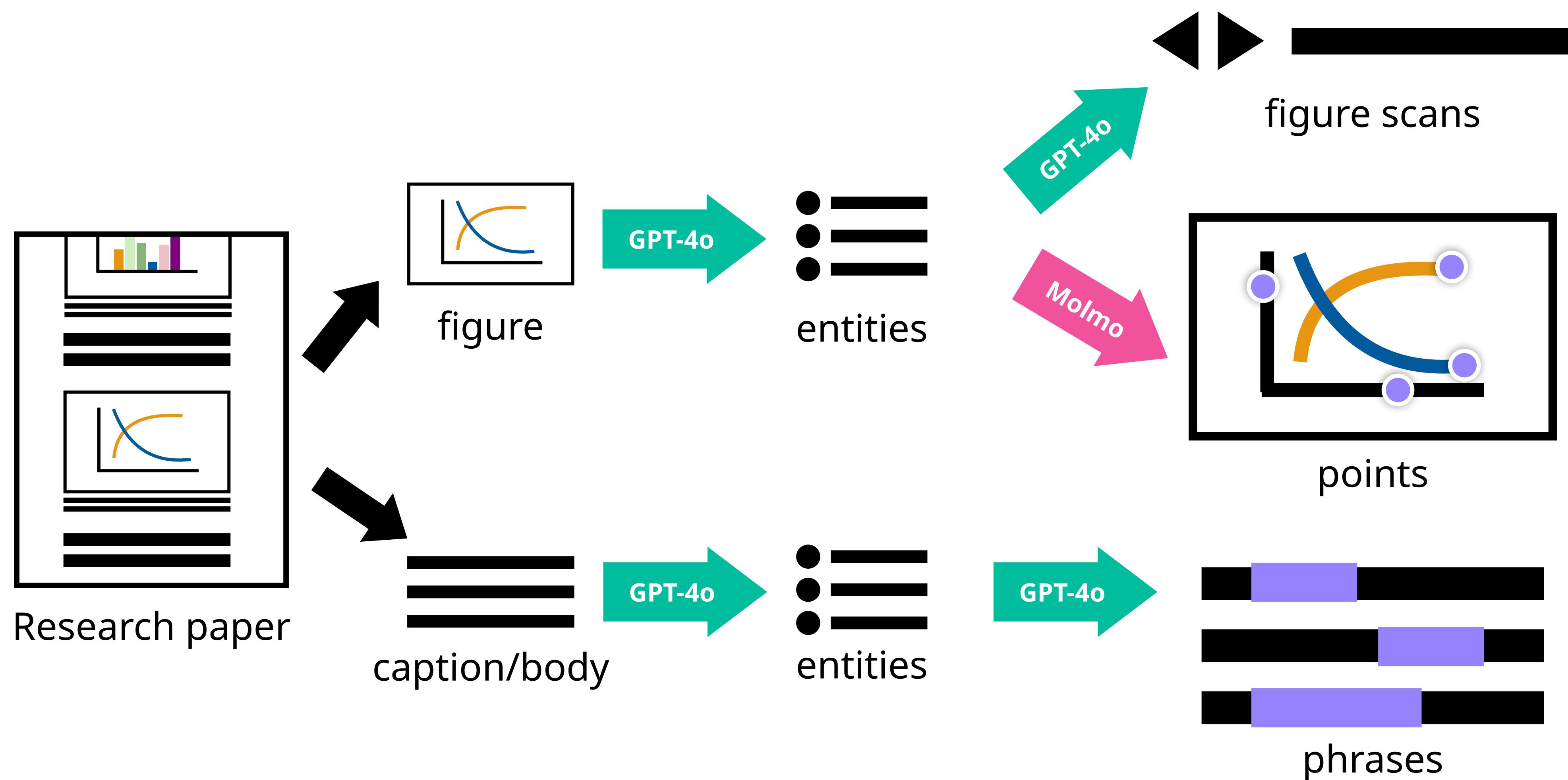
Keywords: Large Language Models, Computational UI Design Tools

ACM Reference Format:

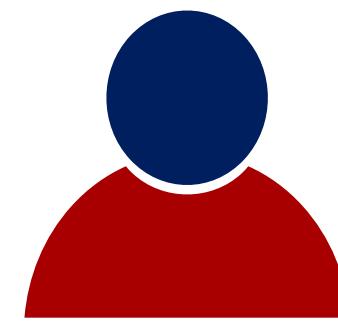
Peitong Duan, Jeremy Warner, Yang Li, and Bjoern Hartmann. 2024. Generating Automatic Feedback on UI Mockups with Large Language Models. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24), May 11--16, 2024, Honolulu, HI, USA*. ACM, New York, NY, USA 20 Pages. <https://doi-org.proxy.library.upenn.edu/10.1145/3613904.3642782>



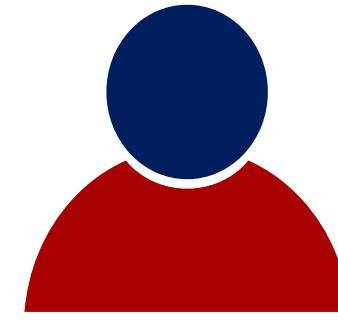
The features in our prototype were generated with a backend AI pipeline.



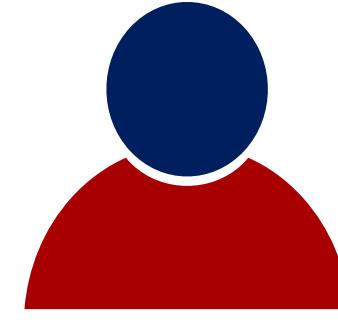
For the formative study, we recruited 10 participants representing a range of fields and reading preferences.



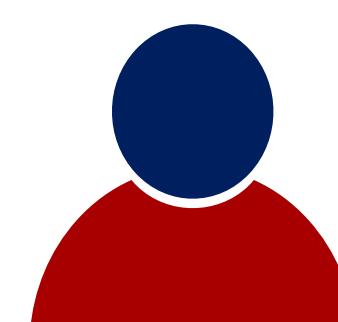
PhD, physics, laptop + tablet



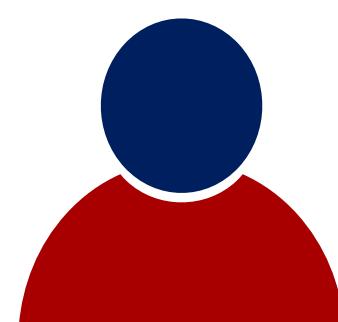
PhD, history of science
& technology, laptop



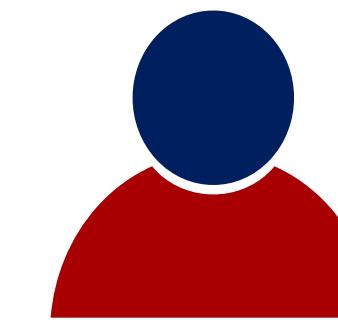
PhD, operations, printed



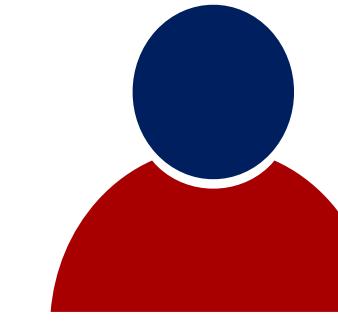
PhD, operations,
laptop + notepad



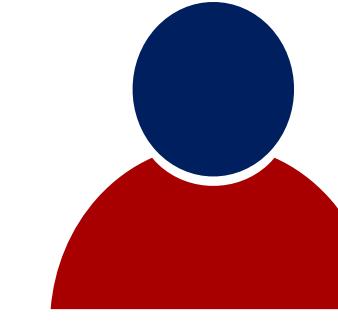
PhD, CS, tablet



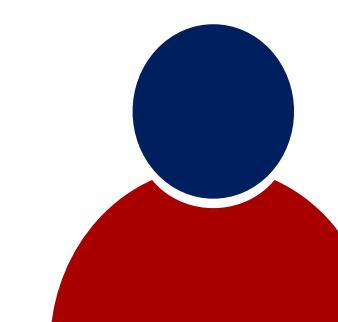
PhD, CS, laptop + notepad



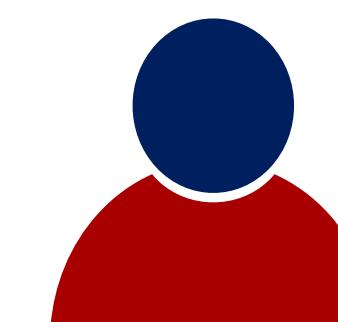
PhD, CS, laptop



PhD, CS, laptop

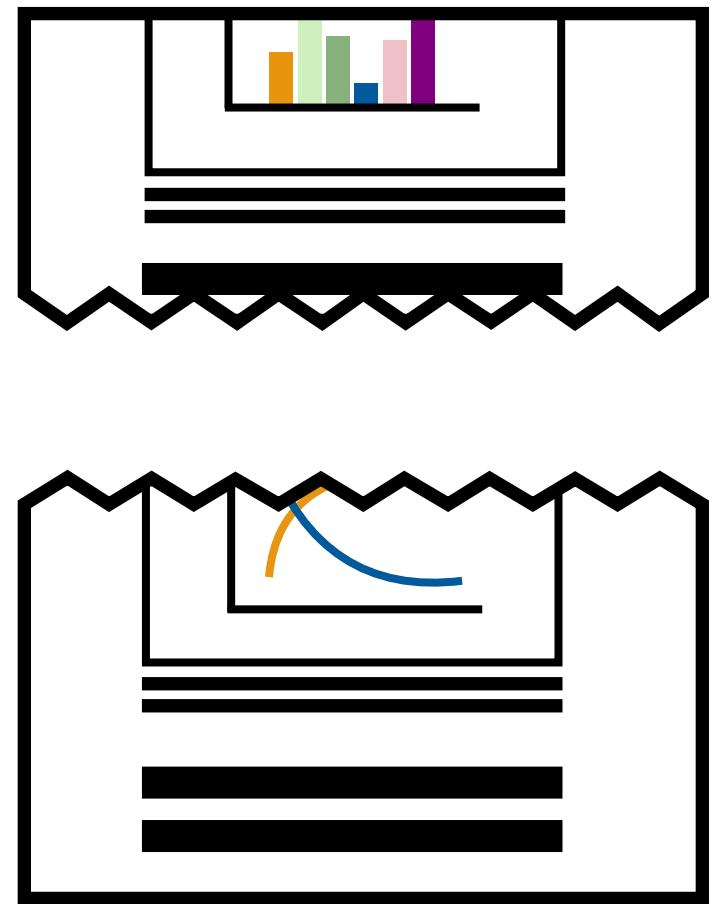


PhD, CS, printed

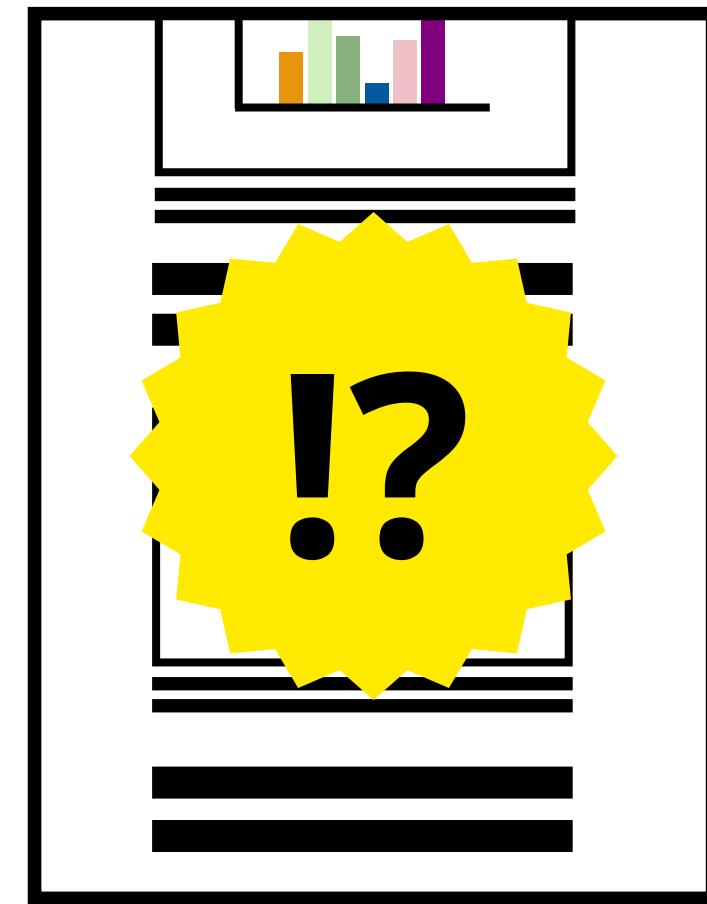


Postdoc, anthropology, printed

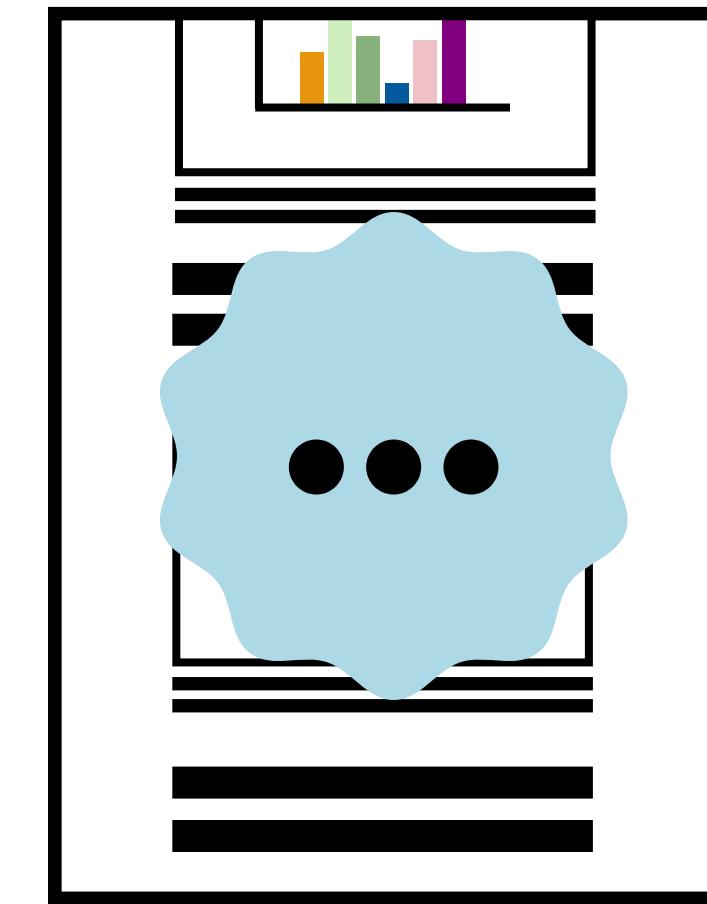
We discovered several reading challenges.



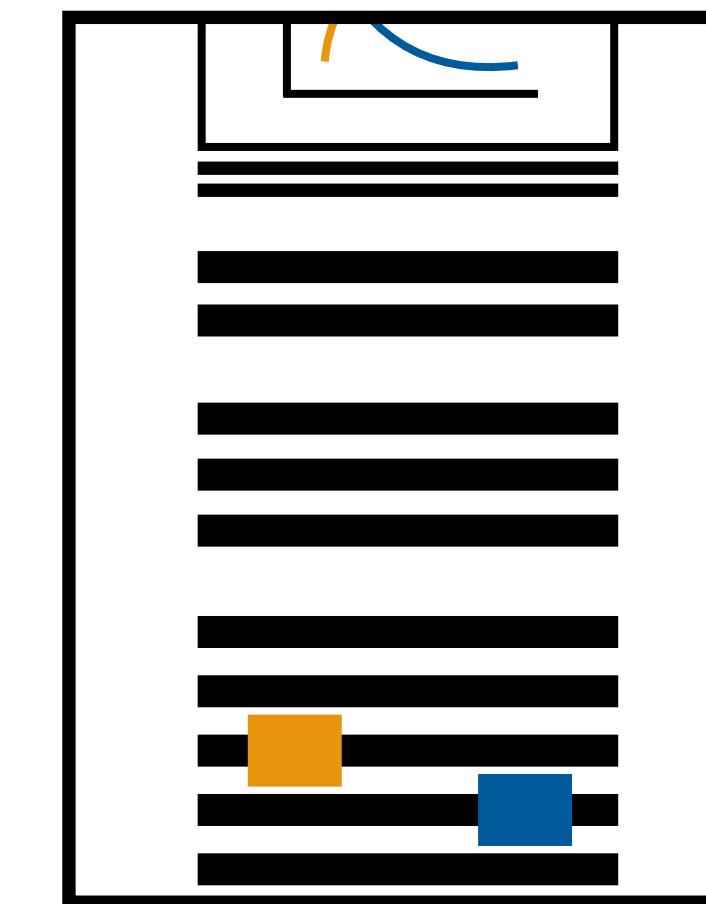
Fragmentation



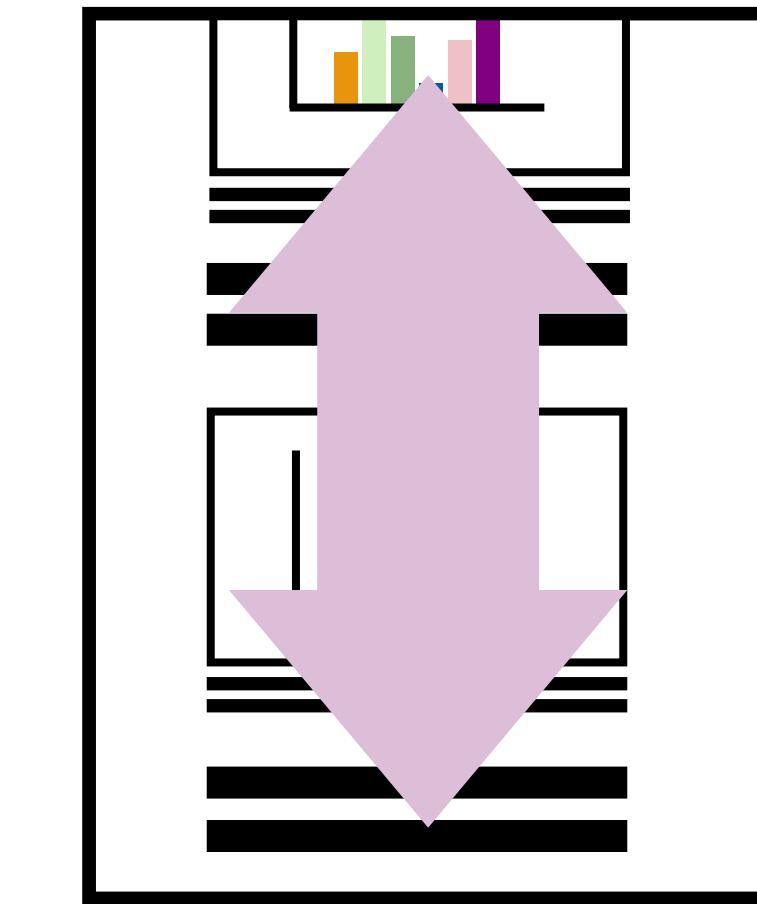
Complexity



Interpretation



Visibility



Searching

We discovered several reading challenges.

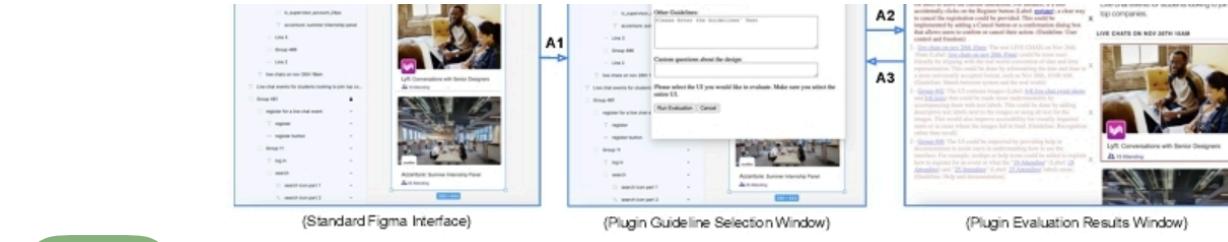
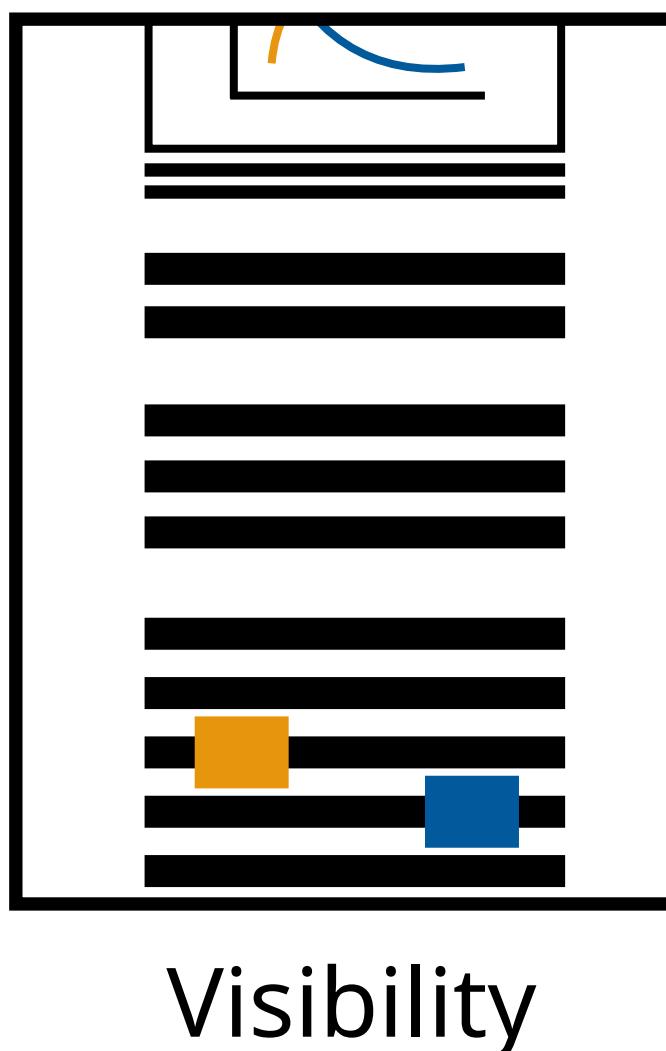


Figure 1: Diagram illustrating the UI prototyping workflow using this plugin. First, the designer prototypes the UI in Figma (Box A) and then runs the plugin (Arrow A1). The designer then selects the guidelines to use for evaluation (Box B) and runs the evaluation with the selected guidelines (Arrow A2). The plugin obtains evaluation results from the LLM and renders them in an interpretable format (Box C). The designer uses these results to update their design and reruns the evaluation (Arrow A3). The designer iteratively revises their Figma UI mockup, following this process, until they have achieved the desired result.

1 INTRODUCTION

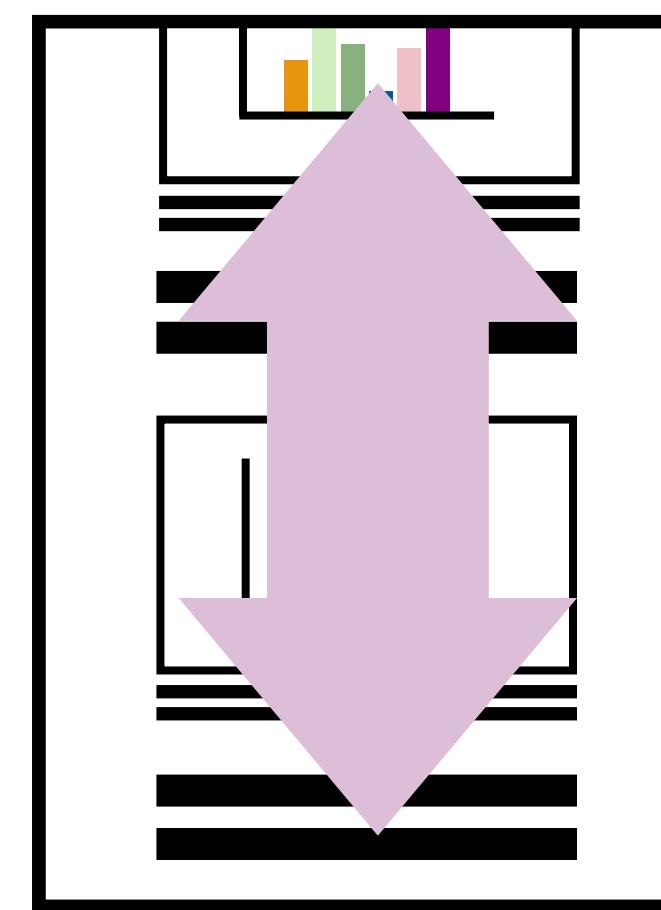
User interface (UI) design is an essential domain that shapes how humans interact with technology and digital information. Designing user interfaces commonly involves iterative rounds of feedback and revision. Feedback is often qualitative and descriptive, guiding designers towards improving their UIs. While this feedback traditionally comes from humans (via user studies and expert evaluations), recent advances in computational UI design enable automated feedback. However, automated feedback is often limited in scope (e.g., the metric could only evaluate layout complexity) and challenging to interpret [50]. While human feedback is more informative, it is not readily available and requires time and resources for recruiting and compensating participants.

One common method of evaluation that still relies on human participants today is *heuristic evaluation*, where an evaluator checks an interface against a list of usability heuristics (rules of thumb) developed over time [39]. One of the most well-known sets of heuristics is Nielsen's 10 Usability Heuristics [39]. Despite appearing straightforward, heuristic evaluation is often subjective [40], dependent on the evaluator's previous training and personality-related factors [41]. These limitations further suggest an opportunity for AI-assisted evaluation.

This paper explores the potential of LLMs for heuristic evaluation. There are several reasons why LLMs could be suitable for automating heuristic evaluation. The evaluation process of heuristic evaluation involves rule-based reasoning, which LLMs have shown capacity for [42]. Moreover, design guidelines are often communicated minimately in text form, making them amenable for LLMs, and the language model could also return its reasoning as text-based explanations that designers prefer [23]. Finally, LLMs have demonstrated the ability to understand and reason with mobile UIs [56], as well as generalize to new tasks and data [28, 49]. However, there are also reasons that suggest caution for using LLMs for this task. For one, LLMs only accept text as input, while user interface designs are complex artifacts that combine text, images, and UI components into hierarchical layouts. In addition, LLMs have been shown to hallucinate [24] (i.e., generate false information) and may potentially identify guideline violations that do not actually exist. This paper explores the potential of using LLMs to carry out heuristic evaluation automatically. In particular, we aim to determine their performance, strengths and limitations, and how an LLM-based tool can fit into existing design practices.

To explore the potential of LLMs in conducting heuristic evaluation, we built a tool that enables designers to run automated evaluations of their UI mockups and receive text-based feedback. We package this system as a plugin for Figma, a widely used UI design tool. Figure 1 illustrates the iterative usage of this plugin. The designer prototypes

We discovered several reading challenges.



Searching

4 STUDY METHOD

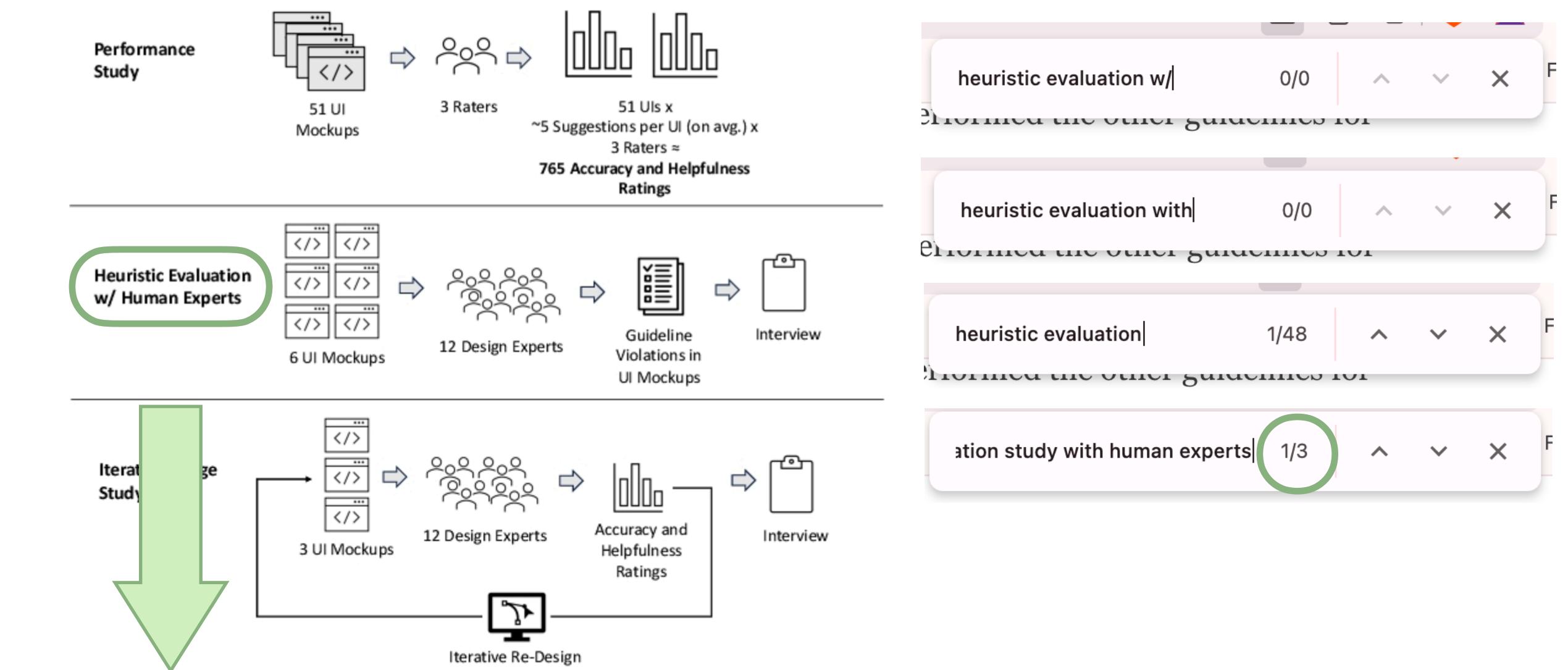
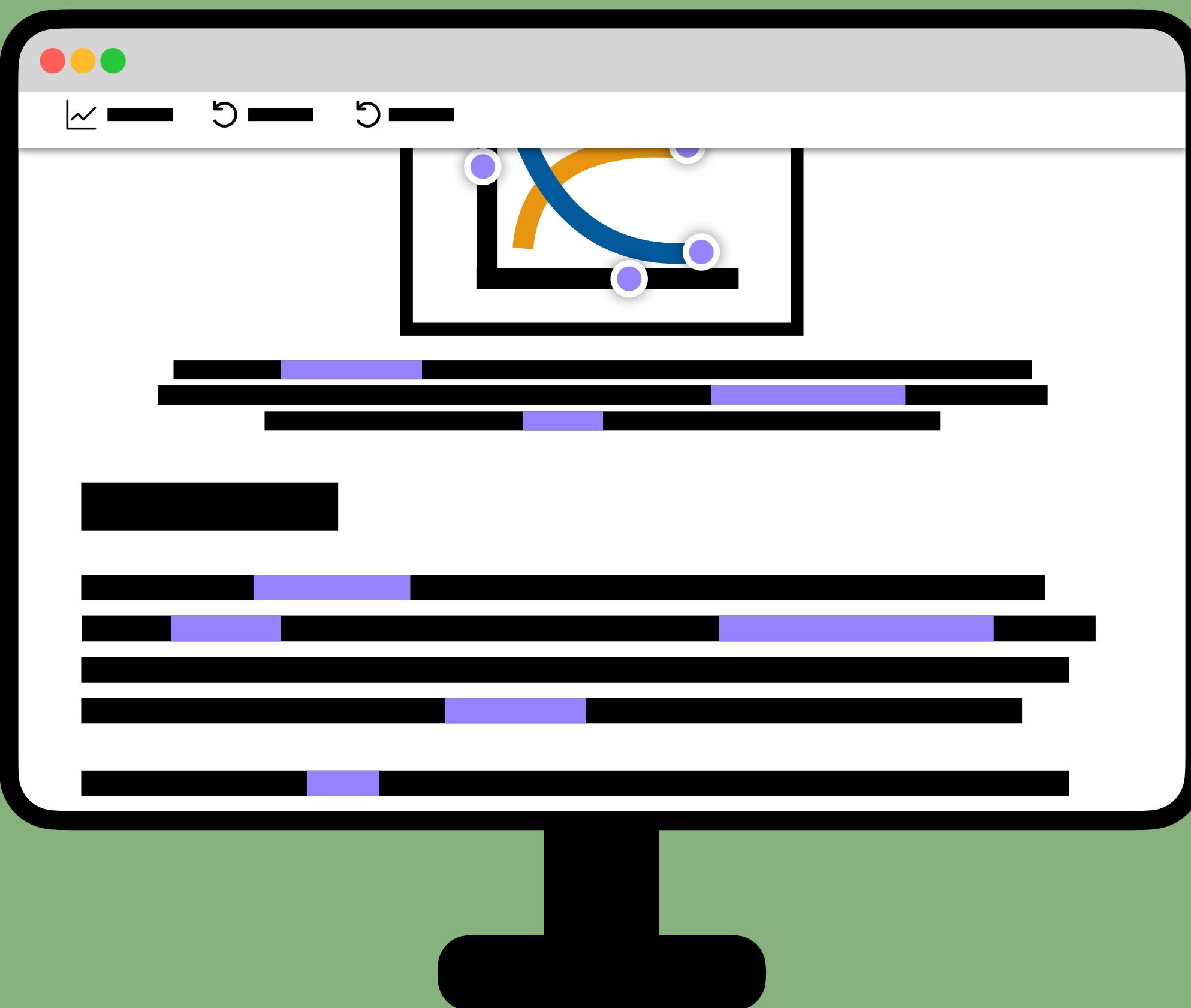


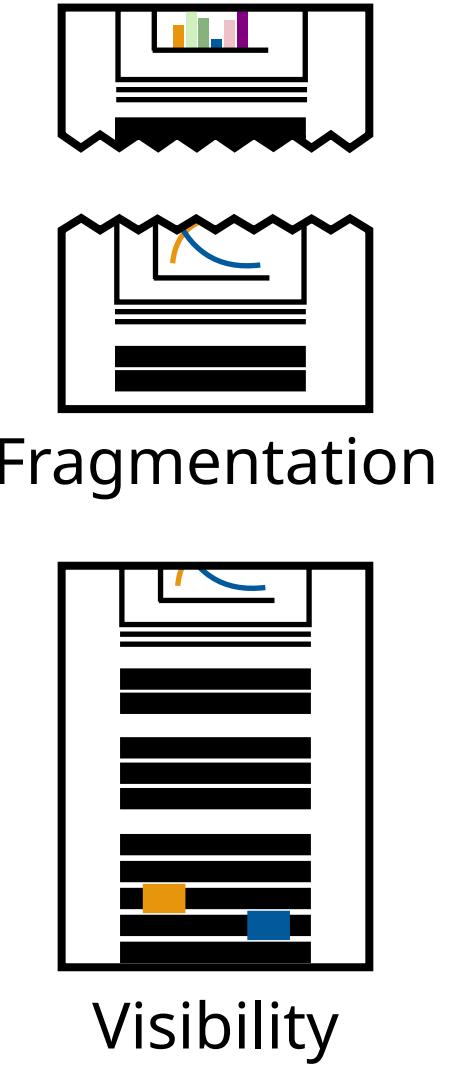
Figure 5: An illustration of the formats of the three studies. The Performance Study consists of 3 raters evaluating the accuracy and helpfulness of GPT-4-generated suggestions for 51 UI mockups. The Heuristic Evaluation Study with Human Experts consists of 12 design experts, who each looked for guideline violations in 6 UIs, and finishes with an interview asking them to compare their violations with those found by the LLM. Finally, the Iterative Usage study comprises of another group of 12 design experts, each working with 3 UI mockups. For each mockup, the expert iteratively revises the design based on the LLM's valid suggestions and rates the LLM's feedback, going through 2-3 rounds of this per UI. The Usage study concludes with an interview about the expert's experience with the tool.

To explore the potential of GPT-4 in automating heuristic evaluation, we carried out three studies (see Figure 5).

We developed a prototype of fine-grained augmentations to address these challenges.



Summon more info by clicking on points or phrases.



Hide Links
Clear Selection
Reset Zoom

3.2 Design Walkthrough

Violations Found

Nielsen Norman: 10 Usability Heuristics

- 3. **Group 406**: The UI could benefit from providing an emergency exit for users to leave the current interaction. For instance, if a user accidentally clicks on the Register button (Label: **register**), a clear way to cancel the registration could be provided. This could be implemented by adding a Cancel button or a confirmation dialog box that allows users to confirm or cancel their action. (Guideline: User control and freedom)
- 2. **live chats on nov 26th 10am**: The text **LIVE CHAT's** on Nov 26th 10am (Label: **live chats on nov 26th 10am**) could be more user-friendly by aligning with the real world convention of date and time representation. This could be done by reformatting the date and time to a more universally accepted format, such as Nov 26th, 10:00 AM. (Guideline: Match between system and the real world)
- 2. **Group 402**: The UI contains images (Label: **lyft live chat event photo** and **lyft logo**) that could be made more understandable by accompanying them with text labels. This could be done by adding descriptive text labels next to the images or using alt text for the images. This would also improve accessibility for visually impaired users or in cases where the images fail to load. (Guideline: Recognition rather than recall)
- 2. **Group 406**: The UI could be improved by providing help or documentation to assist users in understanding how to use the interface. For example, tooltips or help icons could be added to explain how to register for an event or what the "19 Attending" (Label: **19 Attending**) and "25 Attending" (Label: **25 Attending**) labels mean. (Guideline: Help and documentation)

D Dismissing incorrect feedback hides it and updates next LLM prompt

List of generated heuristic violations

C Hovering highlights corresponding element/group in UI

Live chats events for students looking to join top companies.

LIVE CHATS ON NOV 26TH 10AM

Lyft: Conversations with Senior Designers

19 Attending

Lyft: Conversations with Senior Designers

25 Attending

353 x 304

UI Snapshot at time of evaluation

Group in Figma Layers Panel

A
B

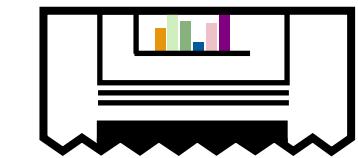
C
D

UI Snapshot at time of evaluation
Group in Figma Layers Panel

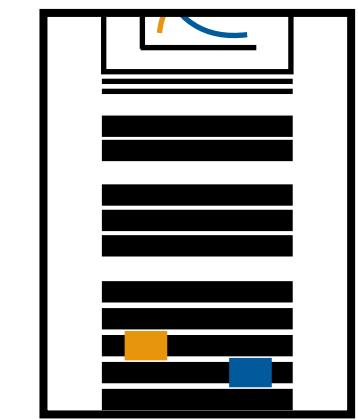
Figure 2: Illustration of plugin interactions that contextualize text feedback with the UI. "A" shows that clicking on a link in the violation text selects the corresponding group or element in the Figma mockup and Layers panel. "B" shows the "click to focus" feature, where clicking on a violation fades the other violations and draws a box around the corresponding group in the UI screenshot. "C" illustrates that hovering over a group or element link draws a blue box around the corresponding element in the screenshot. "D" points out that clicking on the 'X' icon of a violation hides it and adds this feedback to the LLM prompt for the next round of evaluation.

We built our tool as a plugin for Figma, enabling designers to evaluate any Figma mockup (Goal 1). Figure 1 illustrates this plugin's step-by-step usage with interface screenshots. The designer first prototypes their UI in Figma and runs the plugin (Figure 1 Box A). Due to context window limitations, the plugin only evaluates a single UI component at a time. Furthermore, it only accommodates static mocking up evaluation of interactions involving no more than one input or one output. UI

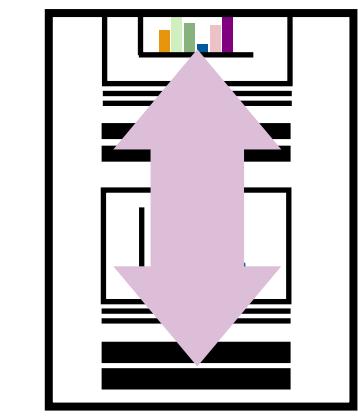
Consolidate scattered details in the reference panel.



Fragmentation



Visibility



Searching

Hide Links

Clear Selection

Reset Zoom

Sections 5.5.1 and 5.4.4, human experts found considerably more. Eight violations, found only by human experts, required advanced visual understanding of the UI. The right screenshot in Figure 10 illustrates two such violations. The tooltip (Figure 10 H3) displayed a monetary amount that not only exceeded the axes of the graph but also mismatched the graph's content about sleep duration. Violation H2 highlighted redundant links to the user profile with via both a profile image and a profile icon. Finally, a few participants stated that parts of the UI shown in Figure 11 (Round 1) had clashing visual design and an overly complicated background.

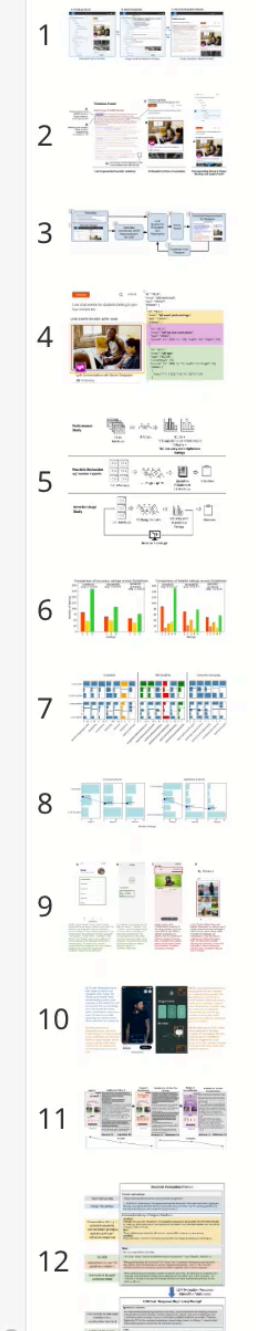
Ten of the violations recorded by the participants involved combinations of several distinct issues for a single group or element. For instance, a violation for the UI in Figure 11 (Round 1) stated that “The title has incorrect spelling and grammar, is not aligned on the page/has awkward margins, has inconsistent text styles for the same sentence, and includes clashing visual elements”. Finally, participants found 22 issues that were similar to the types of issues caught by GPT-4, such as misalignment, unclear labels, and redundancy. This implies that GPT-4 is less comprehensive than a group of 6 human experts, as each UI was evaluated by 6 study participants.

5.5.4 Interview Findings. Participants were generally impressed by the convenience of this plugin, which could find helpful guideline violations at a much faster speed than manual evaluation. H6 said that it “can cut about 50 percent of your work, and is at the level of a good junior designer”, and H3 said they “wish it was already out for use”. Compared to the violations they found manually, several participants said GPT-4 was more thorough and detailed (H3, H4, H5, H6, H10). H1 “appreciated how the LLM could find subtle violations that were missed”, and P5 said they were “overwhelmed by the number of issues in some UIs” and appreciated how the LLM can catch violations that were “tedious to find”. H6 said GPT-4 “goes into a much lower level of resolution than is commercially feasible to do, since it takes a long time”. H1, H3, and H9 valued how GPT-4 could sometimes better articulate the violation. H9 stated that they were “pleasantly surprised at how it picked the right way to describe the problem”, regarding an issue they struggled with describing. Finally, H1, H2, H4, H7, and H8 all appreciated how GPT-4 found violations that were missed during their manual evaluation. H7 said “it was useful, as it captured more cases than I found”.

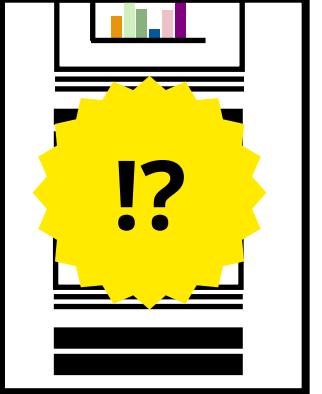
Participants brought up weaknesses of GPT-4’s feedback, which mostly aligned with the findings in Sections 5.4 and 5.5.3. These limitations include missing the majority of the “global” violations (H1, H5, H9), limited visual understanding of the UI (H2, H8, H11), and poor knowledge of popular design conventions (H2, H7, H8, H10, H11). Finally, like the participants in the Usage study, those in this study also did not consider the LLM’s mistakes to be a significant issue. H10 said “if the feedback is correct, then is it very helpful, and if not, it is not a big deal as you can just dismiss it”, and H6 said “the 60 percent success rate is not a problem, as it saves a lot of time in the end”.

5.6 Qualitative Results: Integration into Existing Design Practices

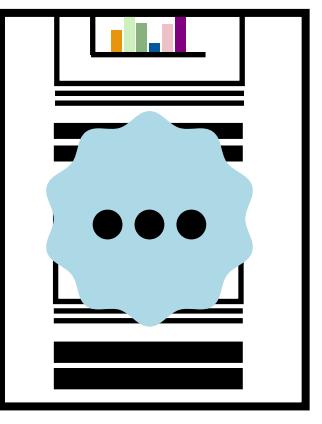
We analyzed the interview responses from the Usage study with grounded theory coding and thematic analysis to determine this tool’s fit into existing design practice. The emerging themes centered around how and when designers would integrate it in their practice, potential broader use cases, and possible dangers of an imperfect tool.



Read figures one step at a time with figure scans.



Complexity



Interpretation

Show Links
Clear Selection
Reset Zoom

Violations Found

Nielsen Norman: 10 Usability Heuristics

A Clicking group name selects group in Figma mockup and Layers panel

B Selecting one violation hides all other violations and annotations in UI

C Hovering highlights corresponding element/group in UI

D Dismissing incorrect feedback hides it and updates next LLM prompt

List of generated heuristic violations

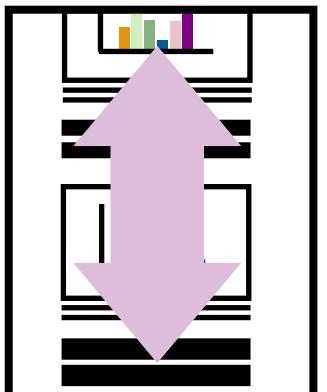
UI Snapshot at time of evaluation

Corresponding Group in Figma Mockup and Layers Panel

Figure 2: Illustration of plugin interactions that contextualize text feedback with the UI. “A” shows that clicking on a link in the violation text selects the corresponding group or element in the Figma mockup and Layers panel. “B” shows the “click to focus” feature, where clicking on a violation fades the other violations and draws a box around the corresponding group in the UI screenshot. “C” illustrates that hovering over a group or element link draws a blue box around the corresponding element in the screenshot. “D” points out that clicking on the ‘X’ icon of a violation hides it and adds this feedback to the LLM prompt for the next round of evaluation.  **Figure Scan**

We built our tool as a plugin for Figma, enabling designers to evaluate any Figma mockup (Goal 1). Figure 1 illustrates this plugin's step-by-step usage with interface screenshots. The designer first prototypes their UI in Figma and runs the plugin (Figure 1 Box A). Due to context window limitations, the plugin only evaluates a single UI screen at a time. Furthermore, it only assesses static mockups, as evaluation of interactive mockups may require multiple screens as input or more complex UI representations, which could exceed the LLM's context limit. After starting the plugin, it opens up a page to select guidelines to use for heuristic evaluation (Box B). Designers can select from a set of well-known guidelines, like Nielsen's 10 Usability Heuristics, or enter any list of heuristics they would like to use (Goal 2). They can also select more

Jump directly to specific figures with the visual index.



Searching

Hide Links Clear Selection Reset Zoom

Generating Automatic Feedback on UI Mockups with Large Language Models

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DOI: <https://doi-org.proxy.library.upenn.edu/10.1145/3613904.3642782>
CHI '24: Proceedings of the CHI Conference on Human Factors in Computing Systems, Honolulu, HI, USA, May 2024

Feedback on user interface (UI) mockups is crucial in design. However, human feedback is not always readily available. We explore the potential of using large language models for automatic feedback. Specifically, we focus on applying GPT-4 to automate heuristic evaluation, which currently entails a human expert assessing a UI's compliance with a set of design guidelines. We implemented a Figma plugin that takes in a UI design and a set of written heuristics, and renders automatically-generated feedback as constructive suggestions. We assessed performance on 51 UIs using three sets of guidelines, compared GPT-4-generated design suggestions with those from human experts, and conducted a study with 12 expert designers to understand fit with existing practice. We found that GPT-4-based feedback is useful for catching subtle errors, improving text, and considering UI semantics, but feedback also decreased in utility over iterations. Participants described several uses for this plugin despite its imperfect suggestions.

CCS Concepts: • Human-centered computing → Interactive systems and tools;

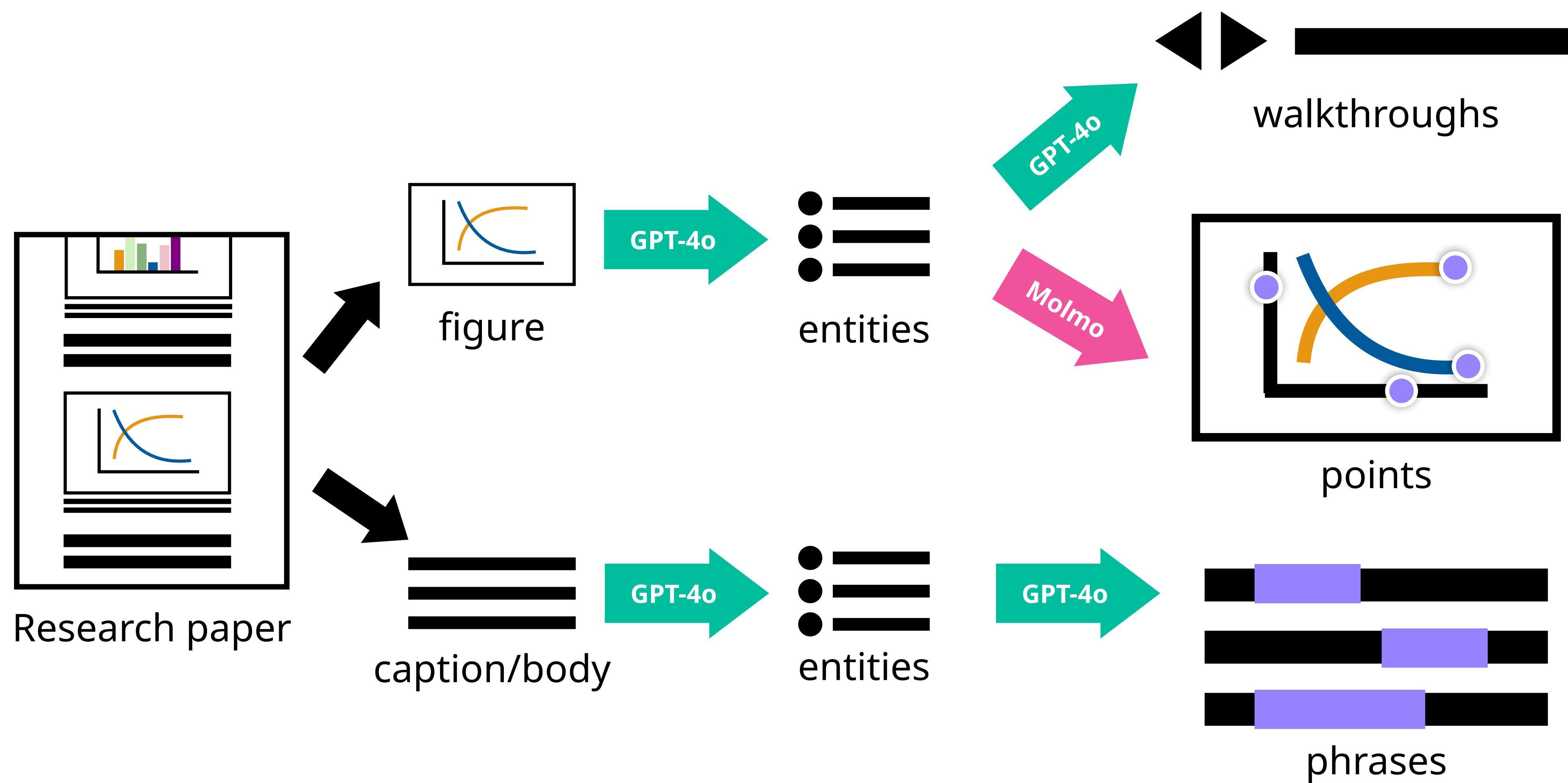
Keywords: Large Language Models, Computational UI Design Tools

ACM Reference Format:

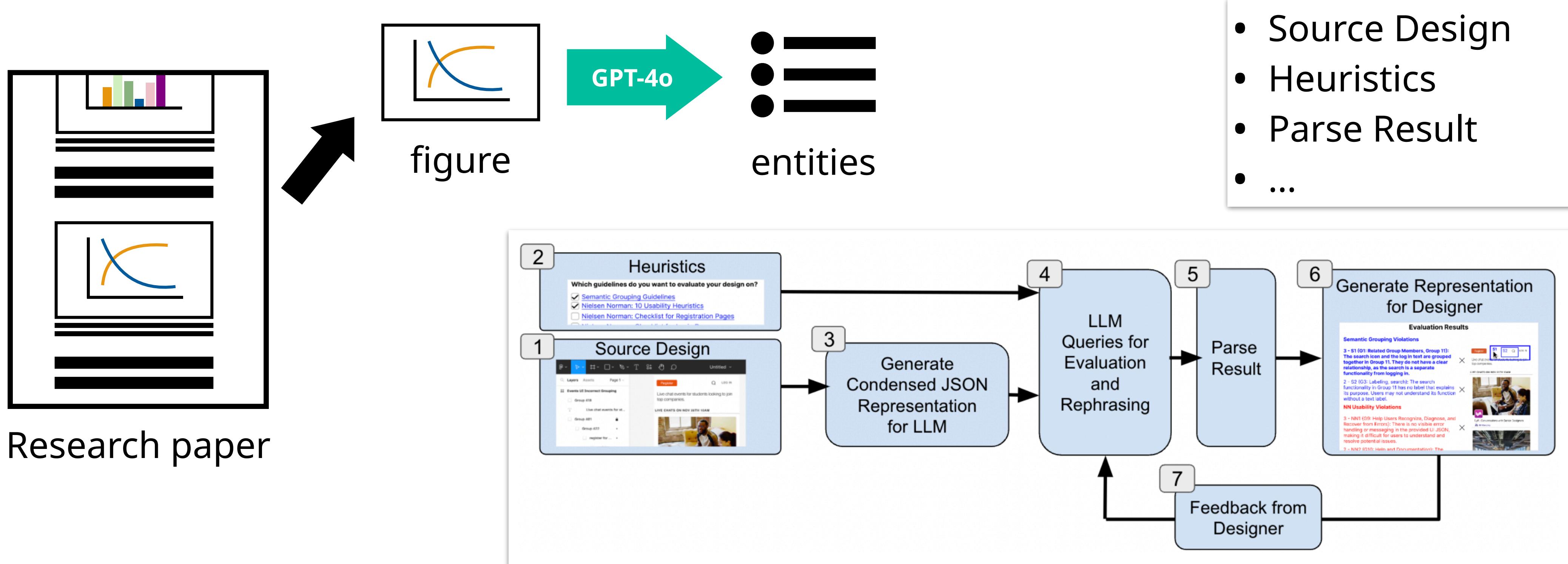
Peitong Duan, Jeremy Warner, Yang Li, and Bjoern Hartmann. 2024. Generating Automatic Feedback on UI Mockups with Large Language Models. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24), May 11--16, 2024, Honolulu, HI, USA*. ACM, New York, NY, USA 20 Pages. <https://doi-org.proxy.library.upenn.edu/10.1145/3613904.3642782>

A screenshot of a Figma plugin interface. It shows three main steps: A: Prototype the UI, B: Select Guidelines, and C: Heuristic Evaluation Results. Step C displays a list of violations found. On the far right, there is a vertical column labeled 1 through 12, each with a thumbnail preview of a UI design. A large purple arrow points upwards from the bottom of the interface towards the 'Search' icon in the top-left corner.

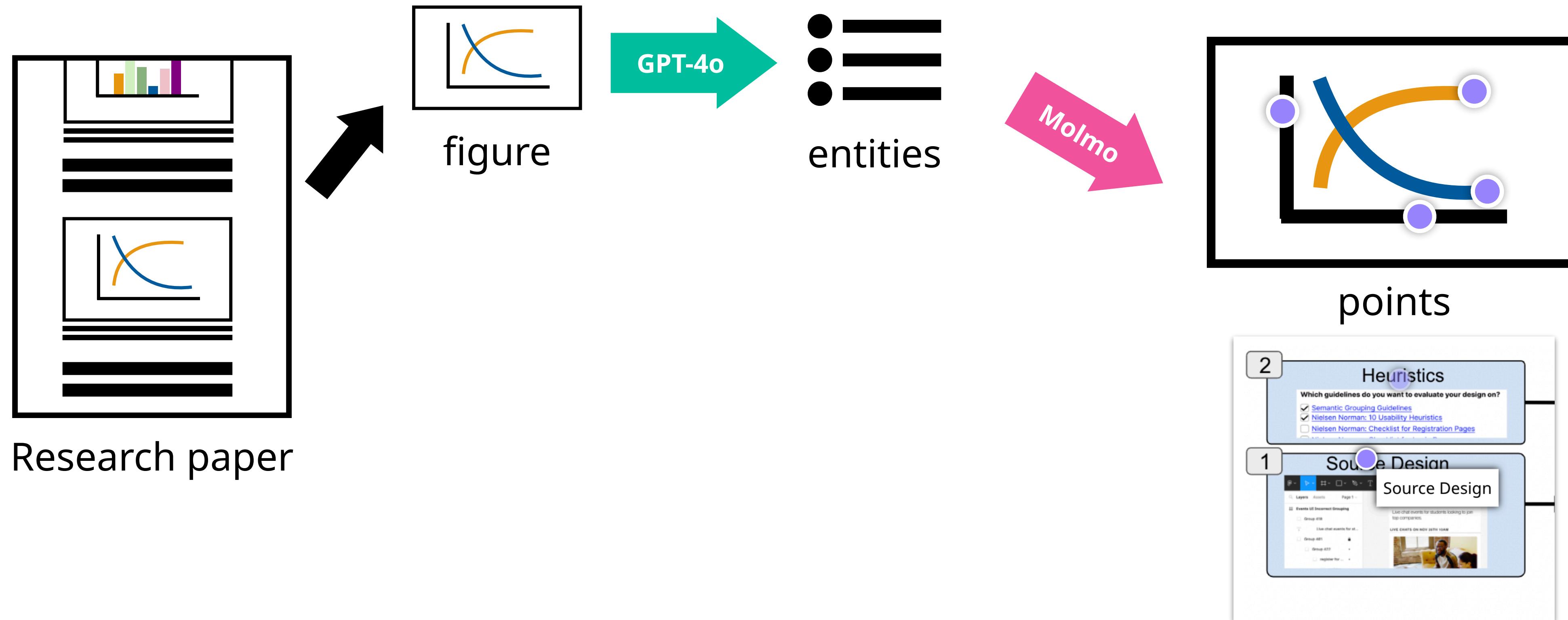
The features in our prototype were generated with a backend AI pipeline.



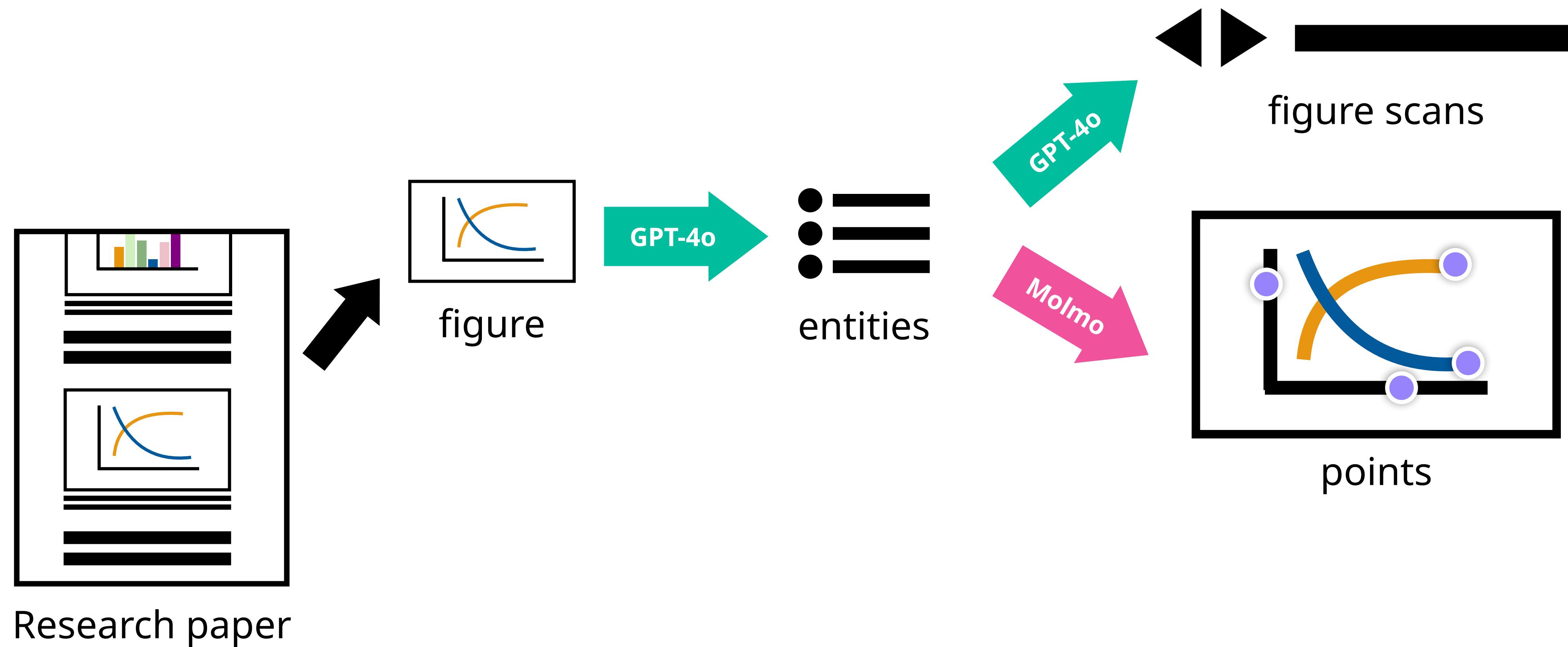
We identified figure entities with GPT-4o.



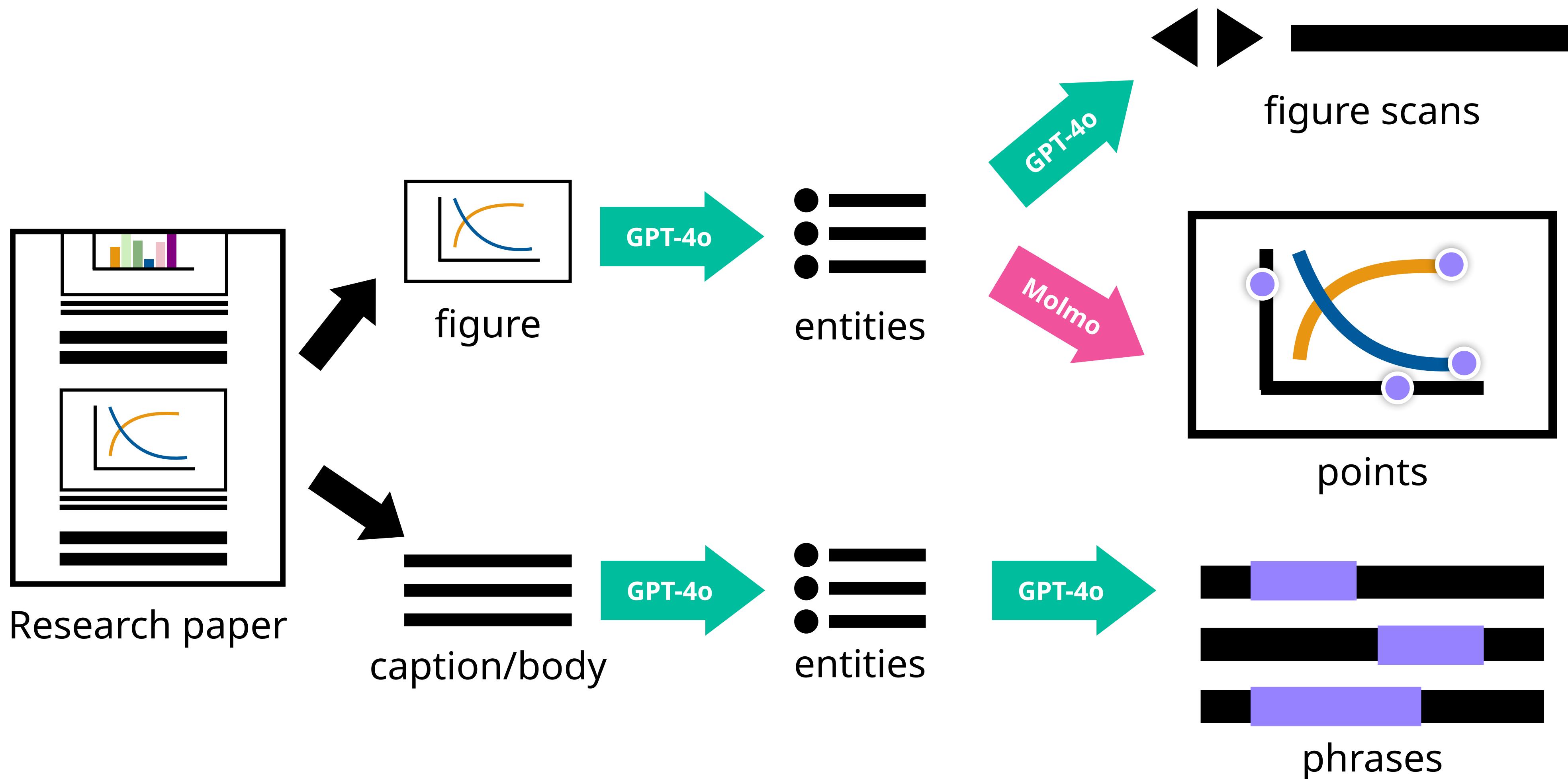
We then had Molmo mark the entities on the figures.



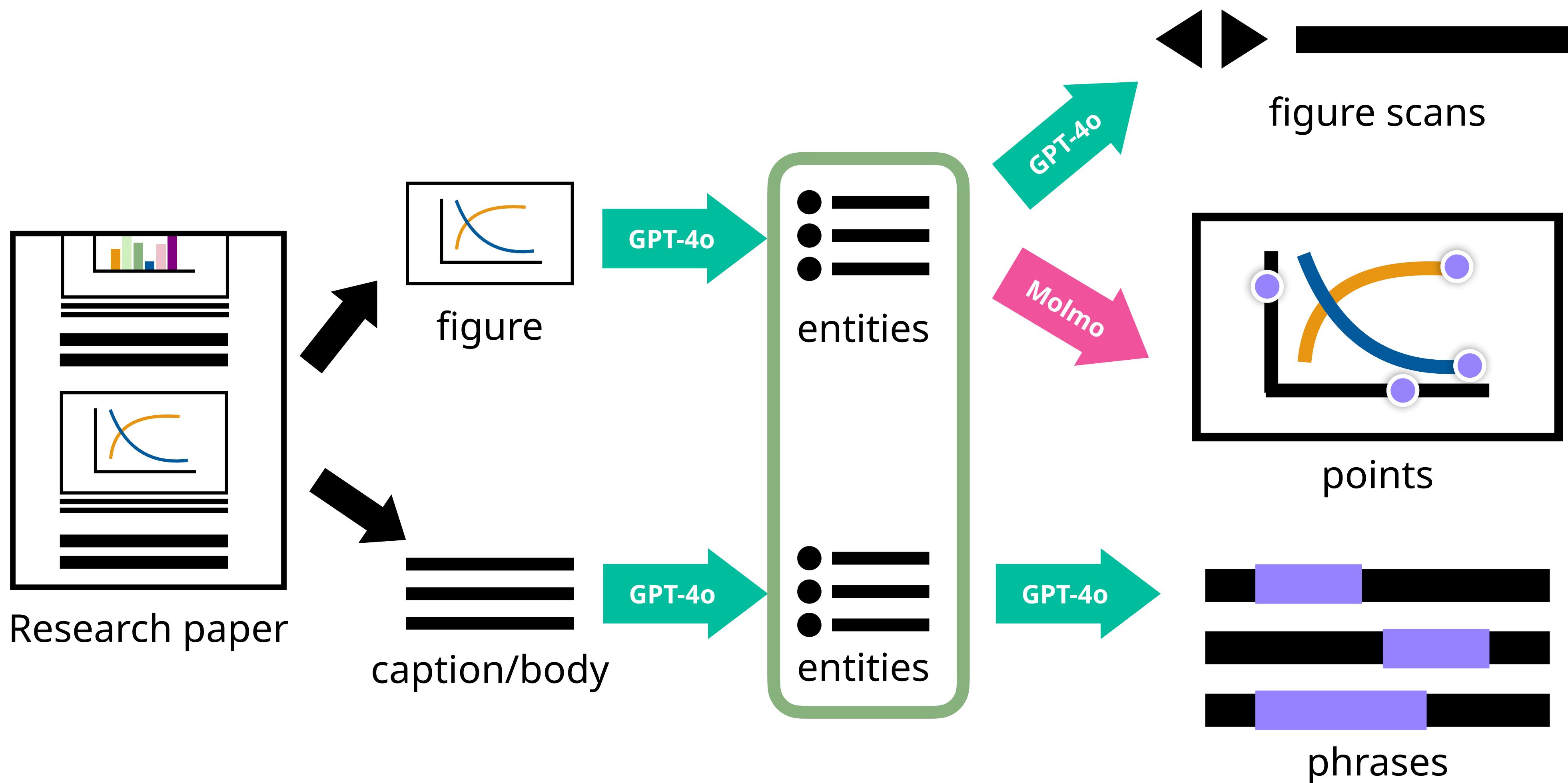
We generated descriptions of each entity with GPT-4o.



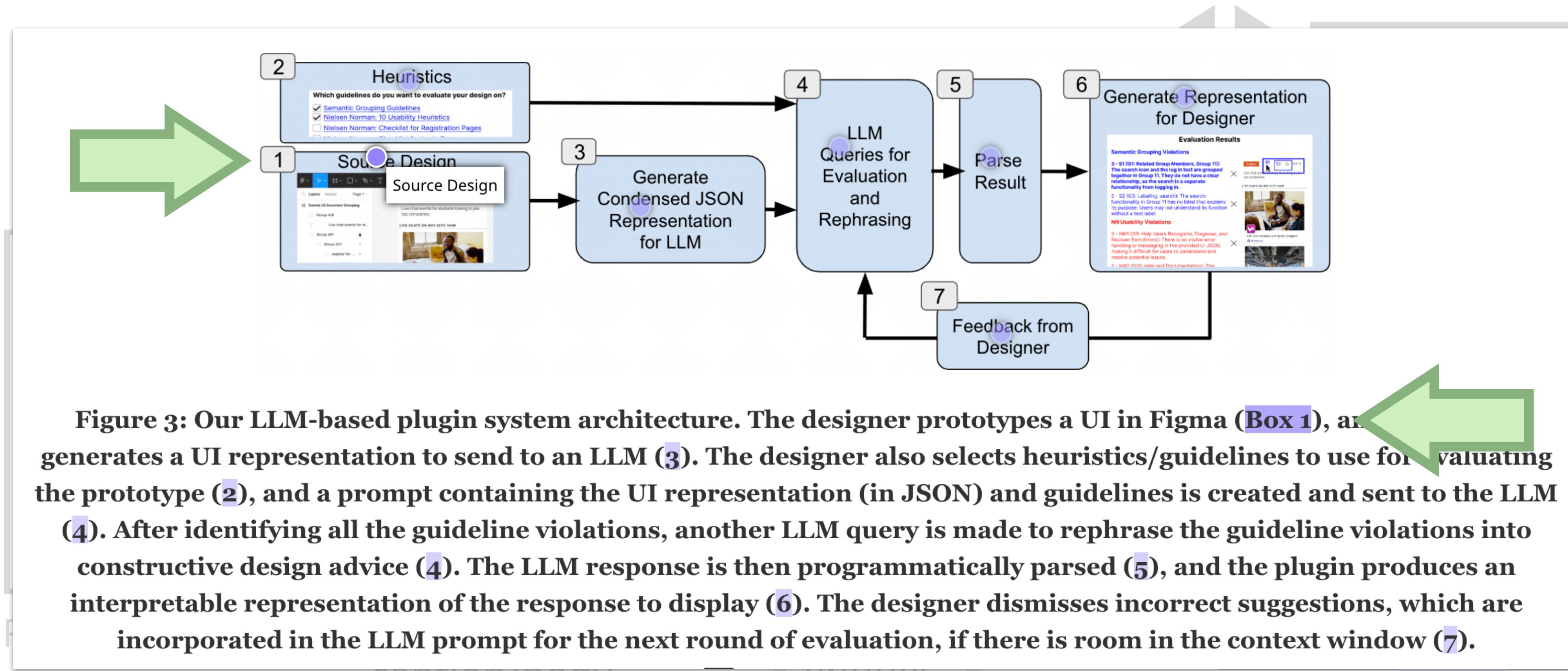
We identified important phrases with GPT-4o.



We connected points and phrases through matching entities.



We connected points and phrases through matching entities.



caption/body

entities

phrases

Case study of prototype outcome

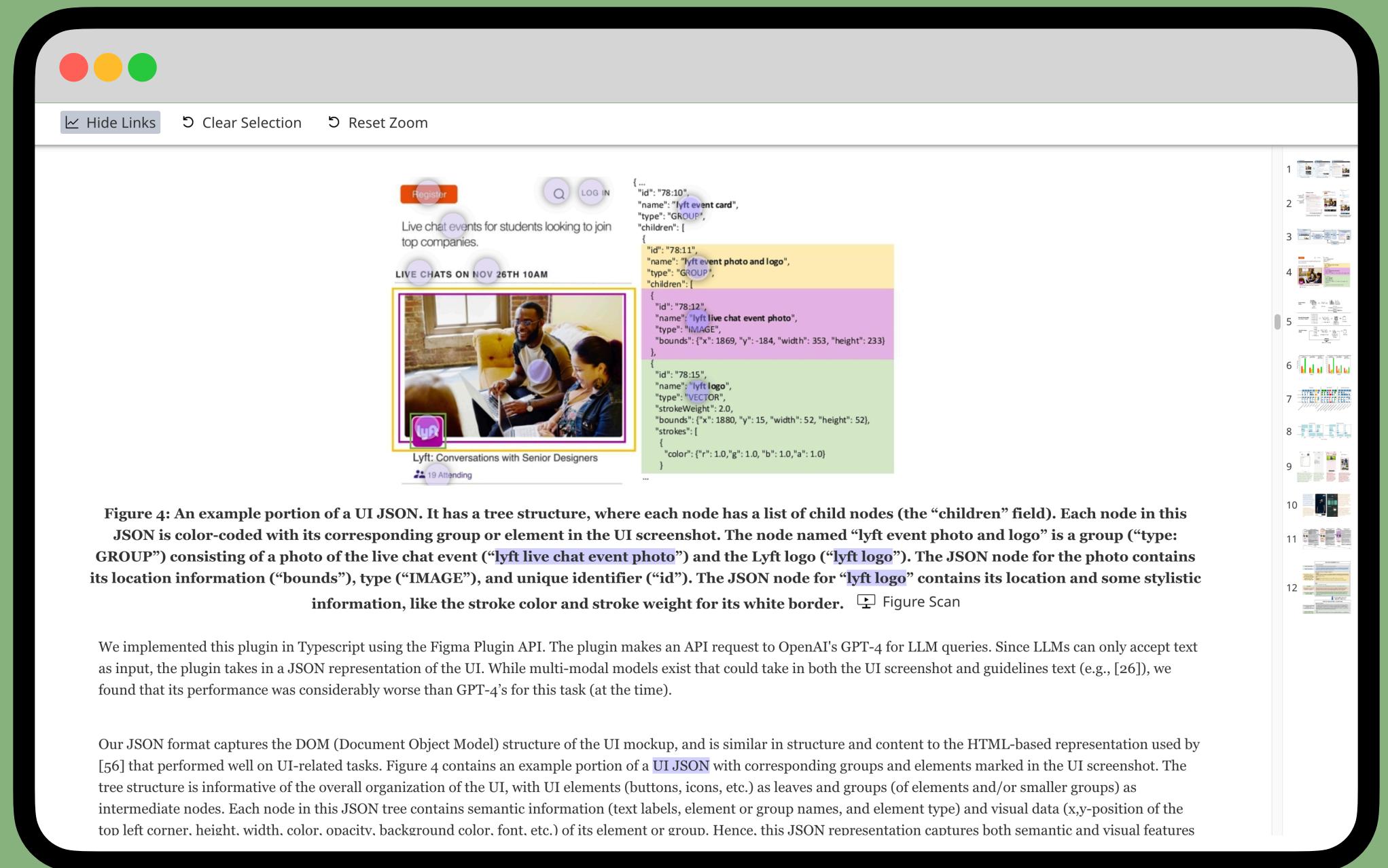


Figure 4: An example portion of a UI JSON. It has a tree structure, where each node has a list of child nodes (the “children” field). Each node in this JSON is color-coded with its corresponding group or element in the UI screenshot. The node named “lyft event photo and logo” is a group (“type: GROUP”) consisting of a photo of the live chat event (“lyft live chat event photo”) and the Lyft logo (“lyft logo”). The JSON node for the photo contains its location information (“bounds”), type (“IMAGE”), and unique identifier (“id”). The JSON node for “lyft logo” contains its location and some stylistic information, like the stroke color and stroke weight for its white border. [Figure Scan](#)

We implemented this plugin in Typescript using the Figma Plugin API. The plugin makes an API request to OpenAI’s GPT-4 for LLM queries. Since LLMs can only accept text as input, the plugin takes in a JSON representation of the UI. While multi-modal models exist that could take in both the UI screenshot and guidelines text (e.g., [26]), we found that its performance was considerably worse than GPT-4’s for this task (at the time).

Our JSON format captures the DOM (Document Object Model) structure of the UI mockup, and is similar in structure and content to the HTML-based representation used by [56] that performed well on UI-related tasks. Figure 4 contains an example portion of a UI JSON with corresponding groups and elements marked in the UI screenshot. The tree structure is informative of the overall organization of the UI, with UI elements (buttons, icons, etc.) as leaves and groups (of elements and/or smaller groups) as intermediate nodes. Each node in this JSON tree contains semantic information (text labels, element or group names, and element type) and visual data (x,y-position of the top left corner, height, width, color, opacity, background color, font, etc.) of its element or group. Hence, this JSON representation captures both semantic and visual features

Fine-grained augmented reading interface based on formative study

AI pipeline for generating entities, points, phrases, and descriptions

In preparation

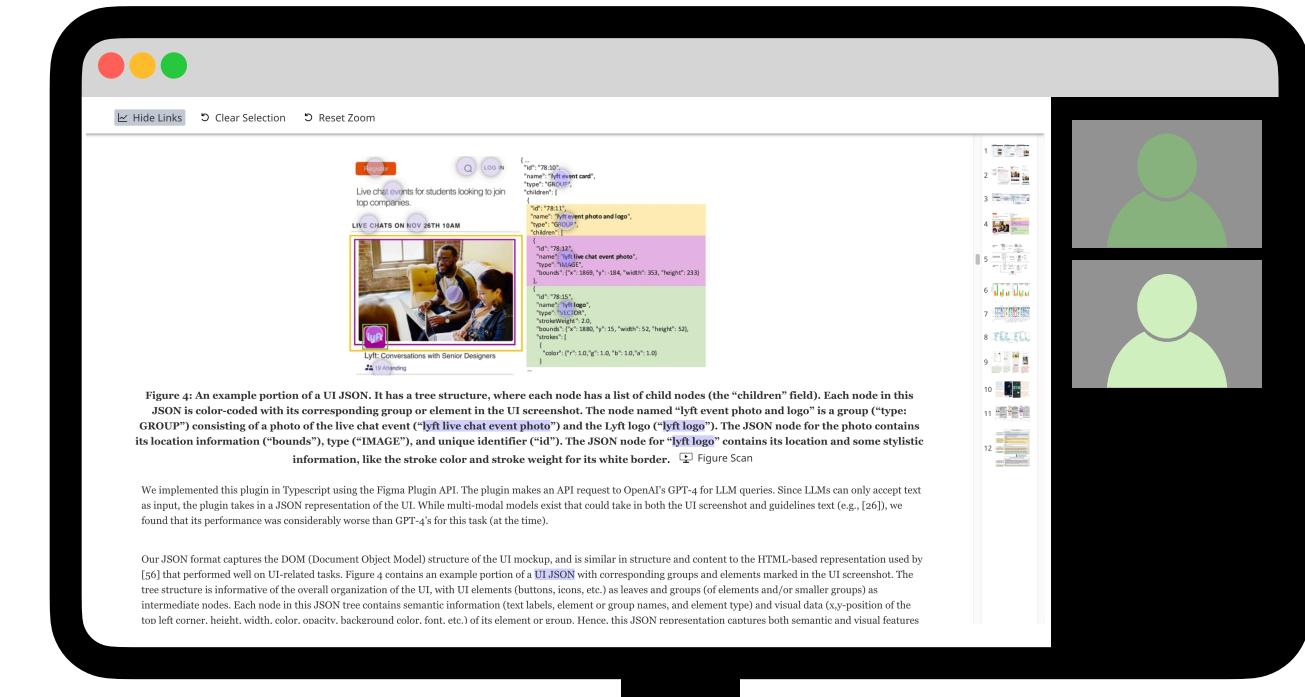
3. Behavioral analysis

Motivation: understand effect of fine-grained augmentations

Method: observe reading with previously developed prototype

Outcome: analysis of strengths and weaknesses of augmentations

We recruited 14 HCI researchers to read a research paper with our prototype on Zoom.



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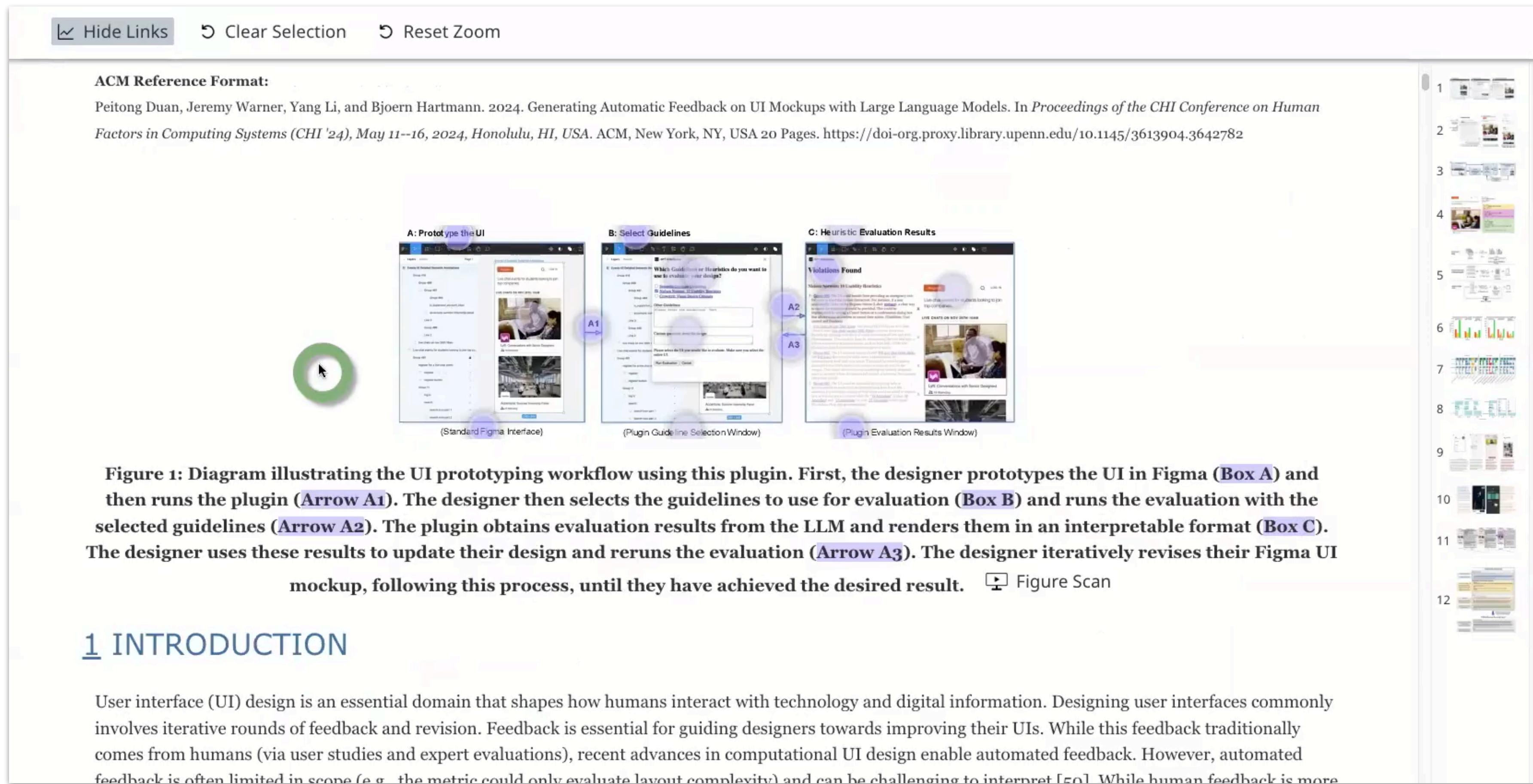


Participants used augmentations in several ways.

- Open exploration through bidirectional links
- Structured guidance through figure scans
- Reduction of search effort through reference panel

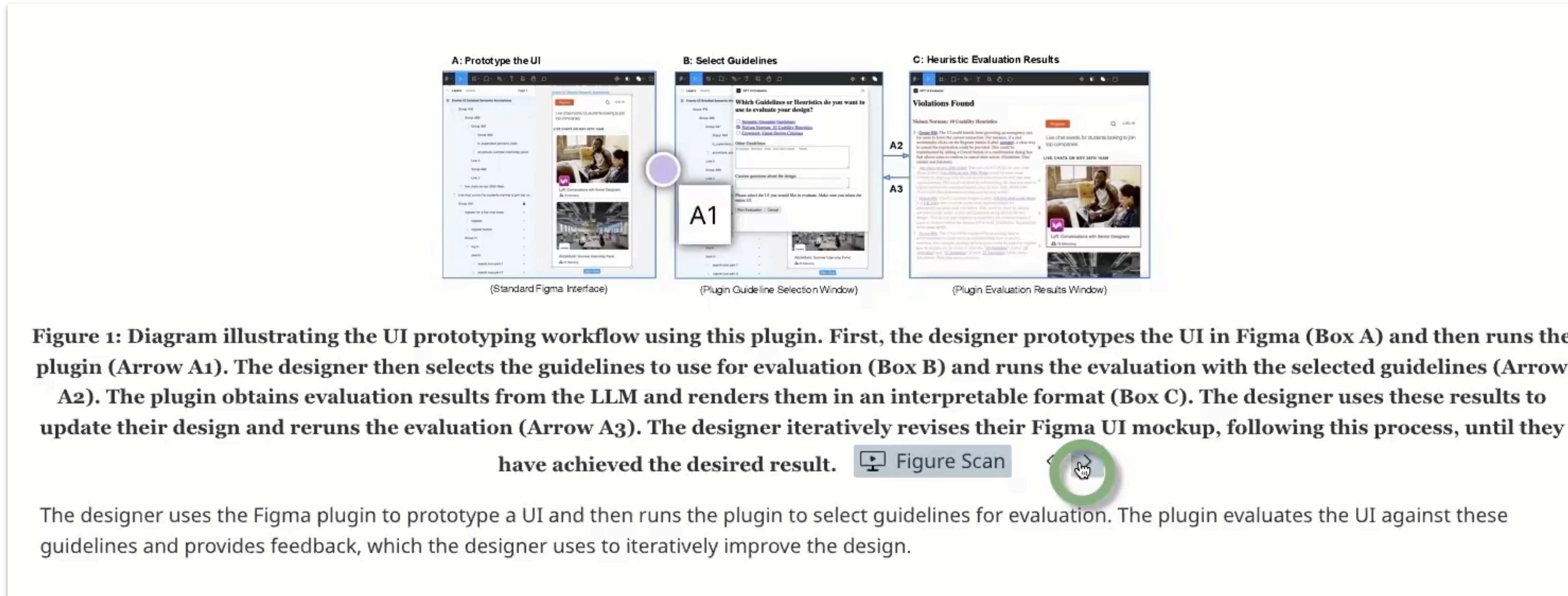
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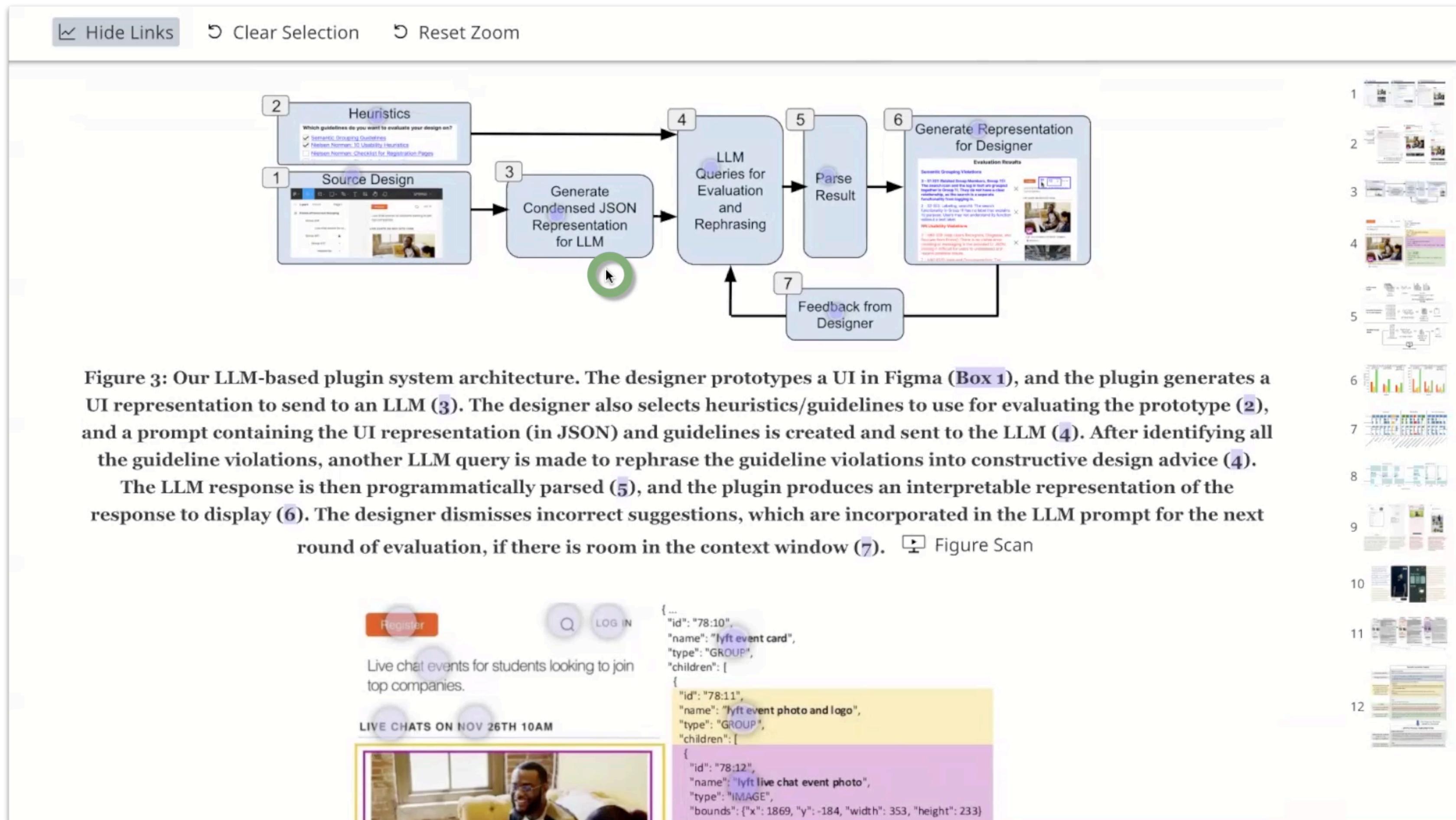
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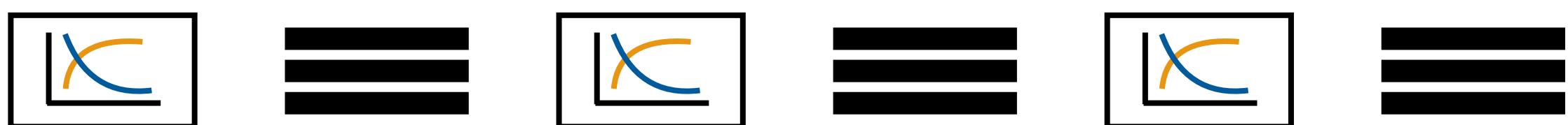
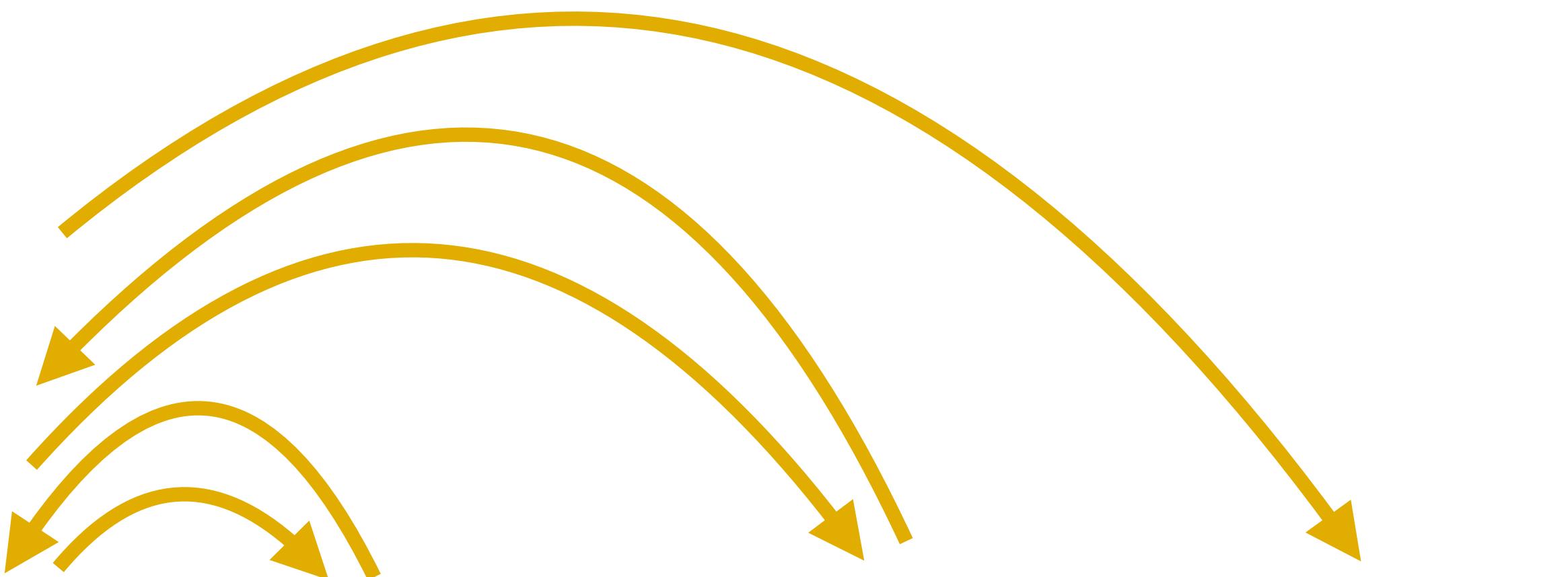


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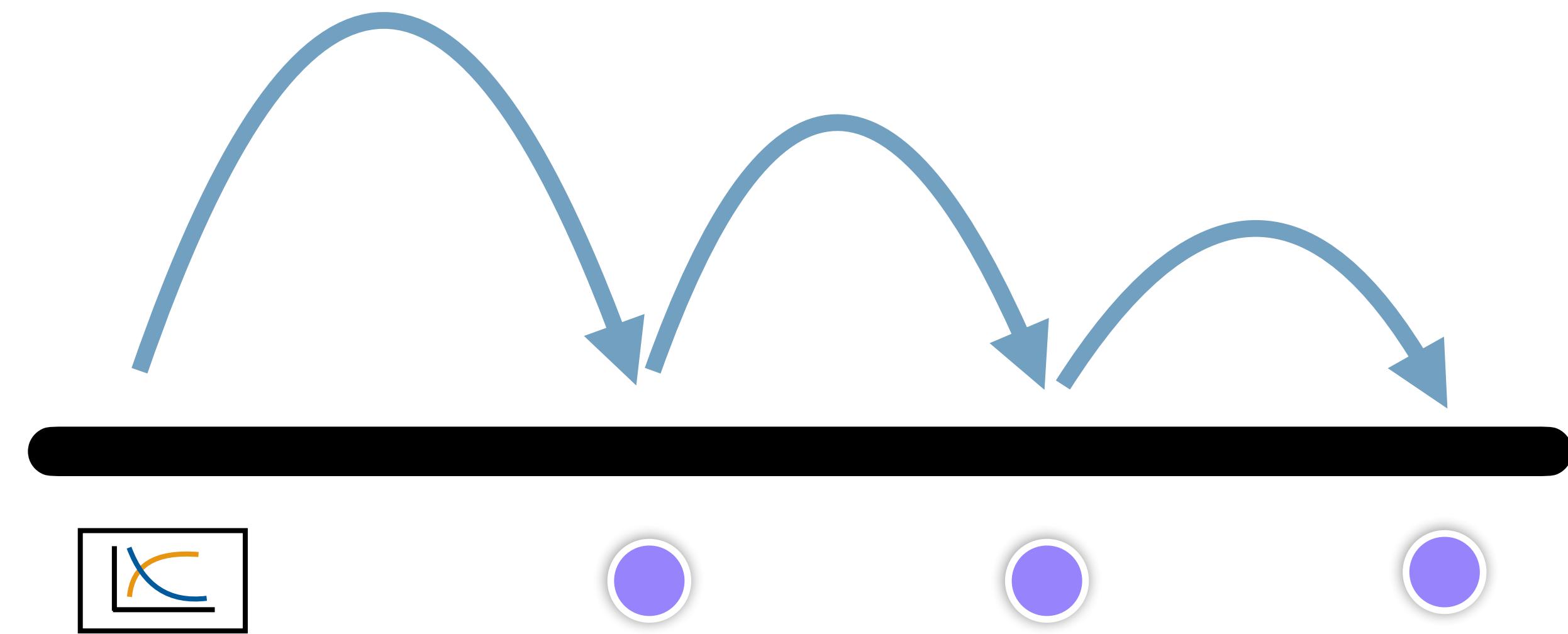
- Reduction of search effort through reference panel



The use of augmentations presented figure-centric reading patterns.



“honeybee path”: exploring
multiple points at a time for
the same figure



“slow dive”: inspecting many parts
of a figure before moving on

3. Behavioral analysis outcome

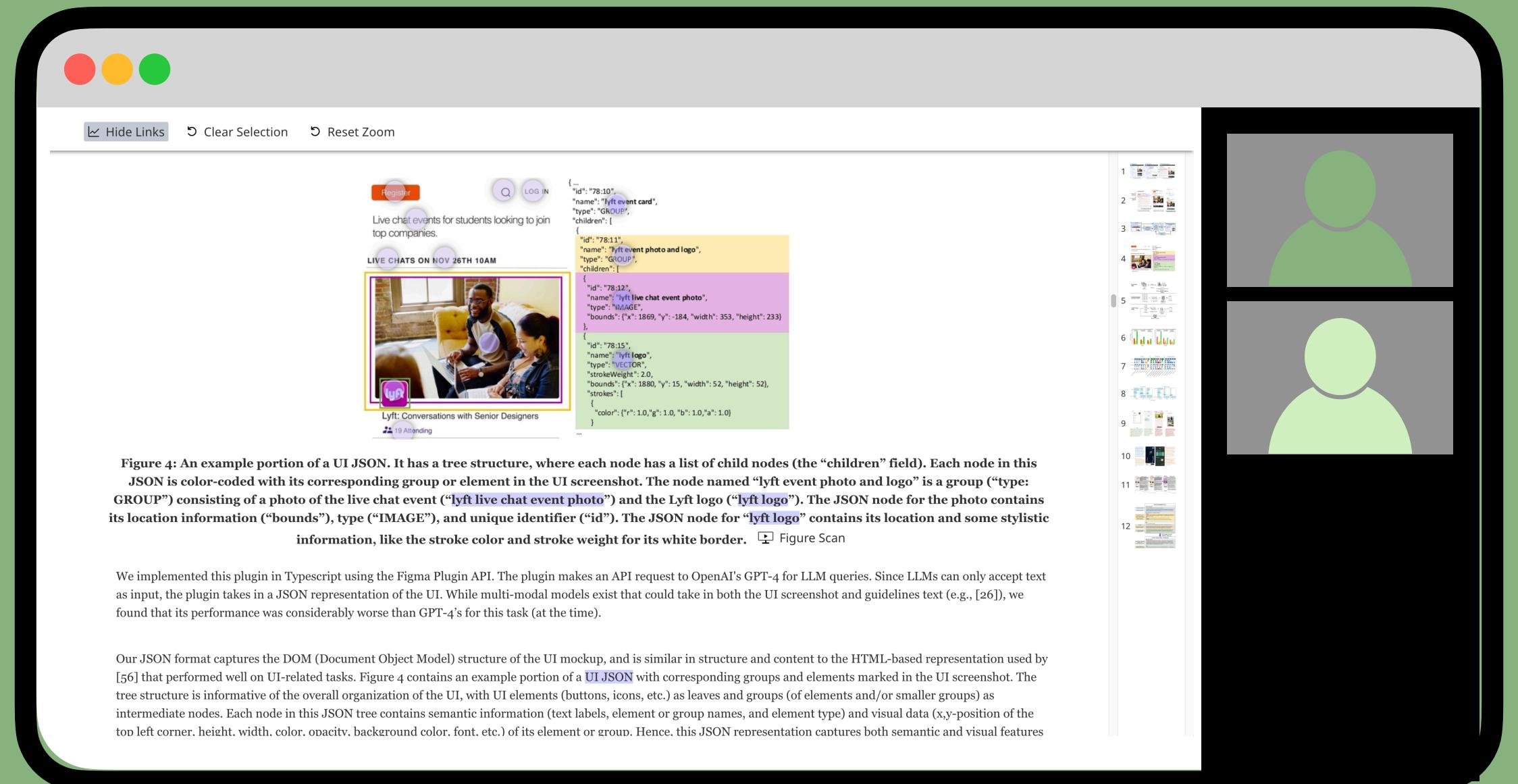


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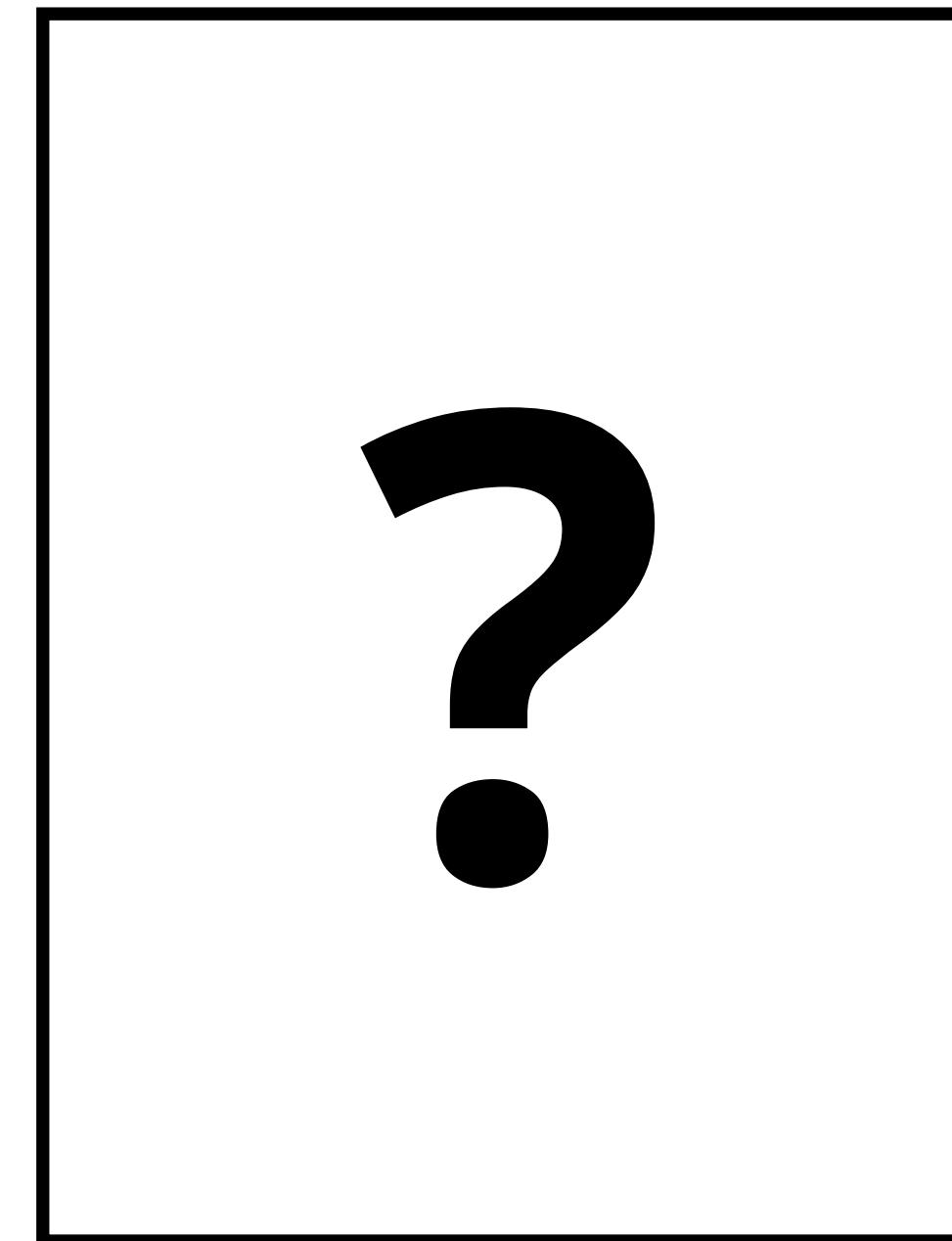
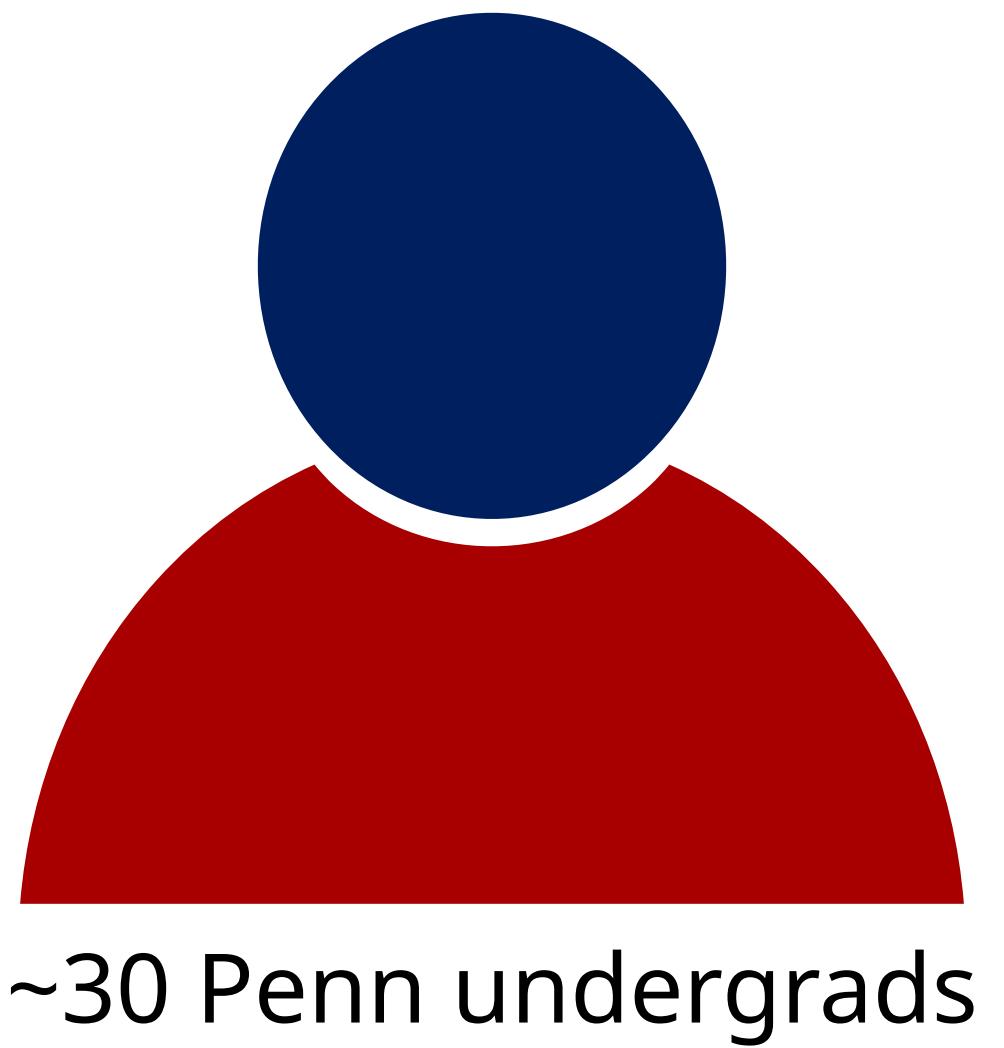
Fine-grained augmentations supported open exploration, structured guidance, faster searching

Figure-centric reading patterns with augmentations

In preparation

4. Proposed work + timeline

We propose extending the previous study to include a comparison to a baseline.



Tasks include...

- Revise + resubmit recent paper
- Update prototype
 - Fix errors
 - Regenerate walkthroughs
 - Possibly replace current paper with shorter one
- Write quiz questions
- Run pilot studies (informal practice + feedback sessions)
- Run ~30 user studies (possibly in groups)
- Write and defend dissertation

- **August 4:** proposal presentation
- **September:** begin job search, resubmit paper, prepare prototype
 - Sept. 11: resubmission deadline
- **October:** run user studies
- **November:** address committee feedback, prepare for defense
 - Nov. 24-26: defense (before Thanksgiving)
- **December:** finish dissertation revisions, graduate
 - Dec. 11: last day to deposit dissertation

Thank you! Questions?

- **August 4:** proposal presentation
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