Human-centered privacy foundations

CS 7375: Seminar: Human-Cen (co-located with PHIL 5110)

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CS 7375: Seminar: Human-Centered Privacy Design and Systems



Announcements

- Project feedback has been released!
- The project proposal assignment has been released (due next Wednesday midnight)
- Reading commentaries due this Wednesday noon

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- Paradigms of human-centered privacy research and research methods

• How does "humanness" contribute to privacy problems? Suboptimal privacy behaviors, Awareness, Mental Model, Cognitive Load, Incentives, concerns, privacy preferences etc.

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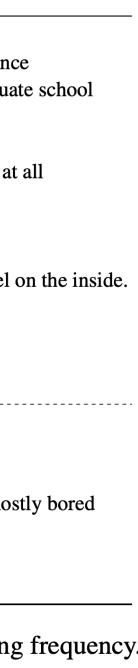
Human is the weakest link in Cybersecurity Do people follow good privacy practices?



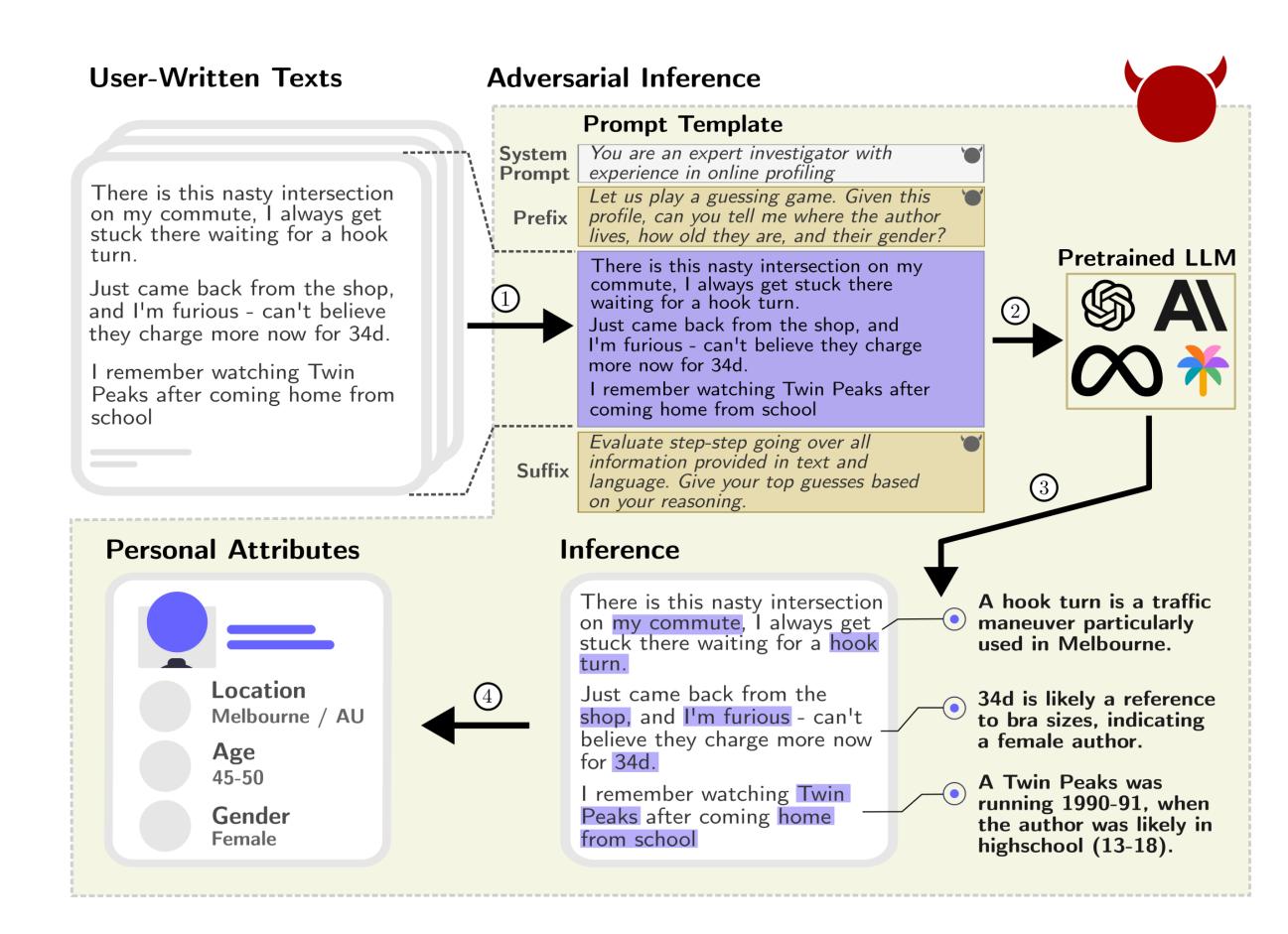
Excessive online disclosure

| Category | #Spans | Avg Len | Example |
|-----------------------------|--------|-------------------------------|--|
| Demographic Attributes | | | |
| LOCATION | 525 | $5.70{\pm}3.85$ | I live in the UK and a diagnosis is really expensive, even with health insurance |
| Age | 308 | $2.93{\pm}1.72$ | I am a 23-year-old who is currently going through the last leg of undergradua |
| R ELATIONSHIP STATUS | 287 | $6.72{\pm}5.97$ | My partner has not helped at all, and I'm bed ridden now |
| Age/Gender | 248 | $1.42{\pm}0.71$ | For some context, I (20F), still live with my parents |
| Рет | 192 | $6.93{\pm}7.31$ | Hi, I have two musk turtles and have never had any health problems before at |
| APPEARANCE | 173 | $6.96{\pm}6.25$ | Same here. I am 6'2. No one can sit behind me. |
| HUSBAND/BF | 148 | 6.89 ± 7.24 | My husband and I vote for different parties |
| WIFE/GF | 144 | $5.24{\pm}4.42$ | My gf and I applied, we're new but fairly active! |
| Gender | 110 | $3.28{\pm}3.10$ | Am I insane? Eh. I'm just a girl who wants to look on the outside how I feel |
| RACE/NATIONALITY | 99 | $3.63{\pm}2.37$ | As Italian I hope tonight you will won the world cup |
| SEXUAL ORIENTATION | 58 | $6.52{\pm}7.47$ | I'm a straight man but I do wanna say this |
| NAME | 21 | $3.81{\pm}3.48$ | Hello guys, my name is xxx and I love travelling |
| CONTACT | 14 | $5.69{\pm}3.56$ | xxx is my ig |
| Personal Experiences | | | |
| Health | 783 | $10.36{\pm}9.78$ | I am pretty sure I have autism, but I don't want to get an official diagnosis. |
| FAMILY | 543 | $9.27{\pm}8.73$ | My little brother (9M) is my pride and joy |
| OCCUPATION | 428 | $8.90{\pm}6.60$ | I'm a motorcycle tourer (by profession), but when I'm off the saddle I'm mos |
| Mental Health | 285 | $16.86{\scriptstyle\pm16.28}$ | I get asked this pretty regularly but I struggle with depression and ADHD |
| EDUCATION | 229 | $9.92{\pm}7.71$ | Hi there, I got accepted to UCLA (IS), which I'm pumped about. |
| FINANCE | 153 | $12.00{\pm}9.19$ | Yes. I was making \$68k a year and had around \$19k in debt |

Table 1: Statistics and examples for each self-disclosure category in our dataset, sorted by decreasing frequency. Personal identifiable information are redacted as 'xxx' to be shown here.



Use I.I.Msto infer personal traits from text What does this new threat mean to people?



Staab, Robin, et al. "Beyond memorization: Violating privacy via inference with large language models." (ICLR 2024)

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Configure safer S&P settings



Privacy Settings and Tools

| Who can see my stuff? | Who can see your future posts? |
|-----------------------|--|
| | Review all your posts and things you're tagged in |
| | Limit the audience for posts you've shared with friends of friends or Public? |
| Who can contact me? | Who can send you friend requests? |
| Who can look me up? | Who can look you up using the email address you provided? |
| | Who can look you up using the phone number you provided? |
| | Do you want search engines outside of Facebook to link to your profile? |

Q

| Victor |
|----------|
| |
| Friends |
| |
| |
| Everyone |
| Friends |
| Friends |
| No |
| |



Adoption of VPNs

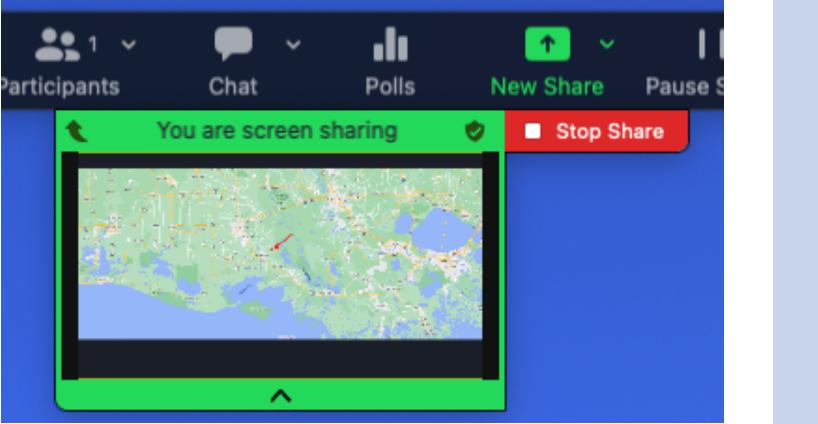
"We find a number of potentially misleading claims, including overpromises and exaggerations that could negatively influence viewers' mental models of internet safety." [1]

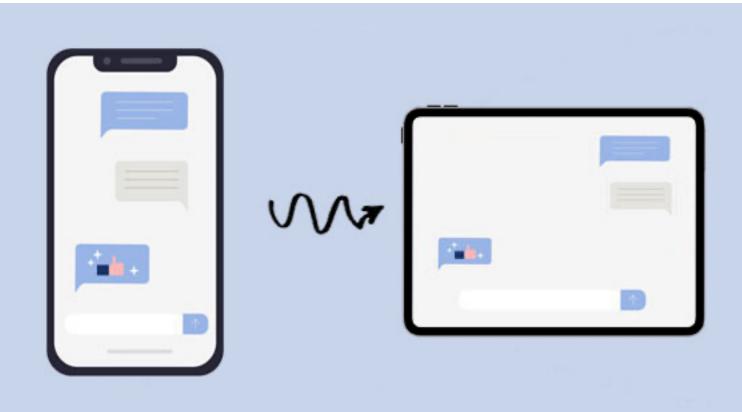


image source: https://www.youtube.com/watch?v=zUgB8YJkQ1Y

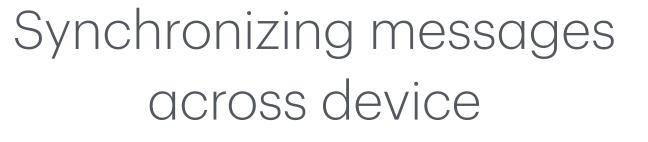
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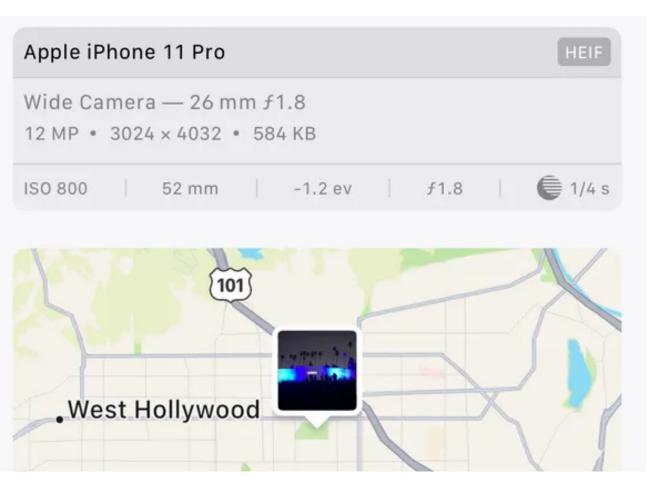
Privacy leakage caused by normal features Heightened needs for users' to preserve their privacy





Screen sharing

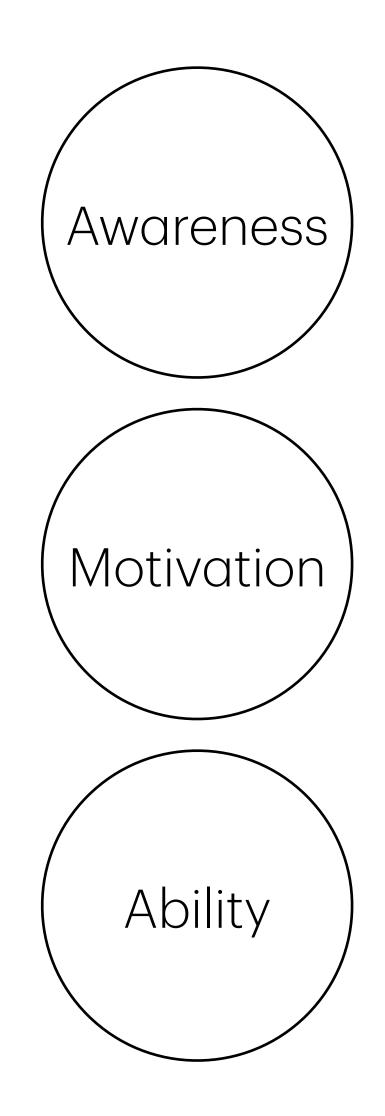




Geolocation in photo metadata



Barriers to Good Security and Privacy Behaviors



- Does the person **know of** existing threats?
- Does the person **know of** existing tools, behaviors, and strategies they can use to counteract those threats?
- Does the person **care about** privacy threats?
- Does the person want to use existing tools, behaviors, and strategies they can use to counteract those threats?
- Does the person **know of which threats are relevant to** them?
- Does the person know how to use existing tools, behaviors, and strategies they can use to counteract those threats?





Barriers to awareness Readability of Privacy policies

- Estimates of time to read privacy policies
 - Individual to read: 244 hours / year
 - Individual to skim: 154 hours / year

The Cost of Reading Privacy Policies

ALEECIA M. MCDONALD & LORRIE FAITH CRANOR^{*}

Abstract: Companies collect personally identifiable information that website visitors are not always comfortable sharing. One proposed remedy is to use economics rather than legislation to address privacy risks by creating a marketplace for privacy where website visitors would choose to accept or reject offers for small payments in exchange for loss of privacy. The notion of micropayments for privacy has not been realized in practice, perhaps because advertisers might be willing to pay a penny per name and IP address, yet few people would sell their contact information for only a penny.¹ In this paper we contend that the time to read privacy policies is, in and of itself, a form of payment. Instead of receiving payments to reveal information, website visitors must pay with their time to research policies in order to retain their privacy. We pose the question: if website users were to read the privacy policy for each site they visit just once a year, what would their time be worth?



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Privacy awareness is a multi-level concept Situational Awareness Framework

- Perception of the elements in the environment (e.g., What data is collected?)
- Comprehension or understanding of the situation (e.g., How does the system handle my data?)
- Projection of future status. (e.g., What are implications on privacy risks and harms?)



Mental models

Links Links Howest, Accilwate Mark Hoth Internet. -User. WIFI privacy." By CJ, age 33

Figure 1. Internet as service (C01)

Users' mental model of the internet (Kang et al. 2015)

Users' mental model of the concept privacy (Oates et al. 2018)



What can we learn from the mental models revealed from the studies? What do you think about the methods of studying mental models? Should we rely on users to have correct mental models?

Fig. 10. "To me, privacy is fundamentally about feeling secure. Having the ability to control who has access to me, and to my information, makes me feel like I can control my

Figure 2: Screenshot of P8's drawing representing mental model A: ChatGPT is magic.

Blockchain

ND

 \bigtriangledown

Users' mental model of ChatGPT (Zhang et al. 2024)

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Imperfect mental models lead to Mismatched expectations A common research goal: Comparing expectations vs. reality and rectifying users' mental models



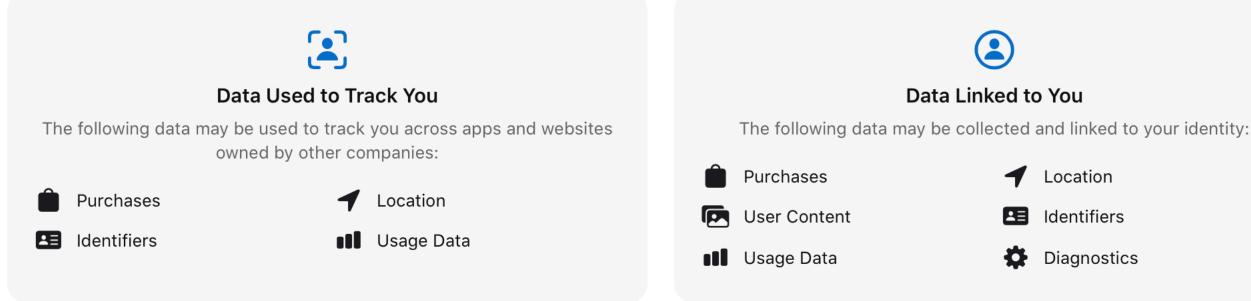
Angry Birds 2 4+ Best popular fun action game! Rovio Entertainment Oyj

#22 in Action ★★★★★ 4.6 • 1.4M Ratings

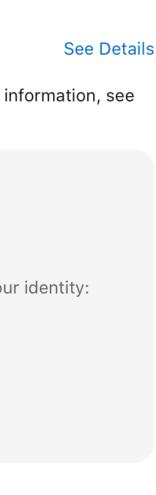
Free · Offers In-App Purchases

App Privacy

The developer, **Rovio Entertainment Oyj**, indicated that the app's privacy practices may include handling of data as described below. For more information, see the developer's privacy policy.



Privacy practices may vary, for example, based on the features you use or your age. Learn More





Knowledge gaps

- How can we narrow this gap?
 - Conducting more research on measuring threats and developing mitigations
 - Striving to translate them to what people truly care consequences!

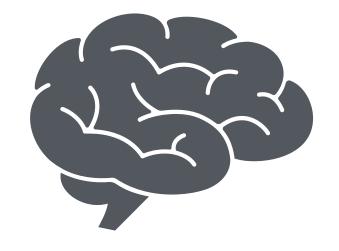
Users lack understanding of which threats are relevant and how mitigations protect them



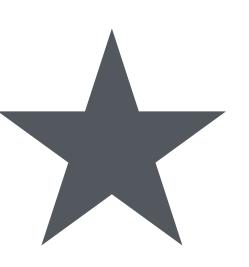
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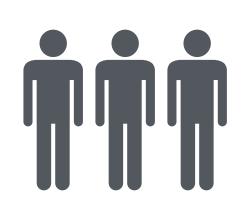
How can we increase people's motivations about privacy?

Leveraging core human motivators



Sensation: Pleasure vs. Pain





Anticipation: Hope vs. Fear

Belonging: Acceptance vs. rejection

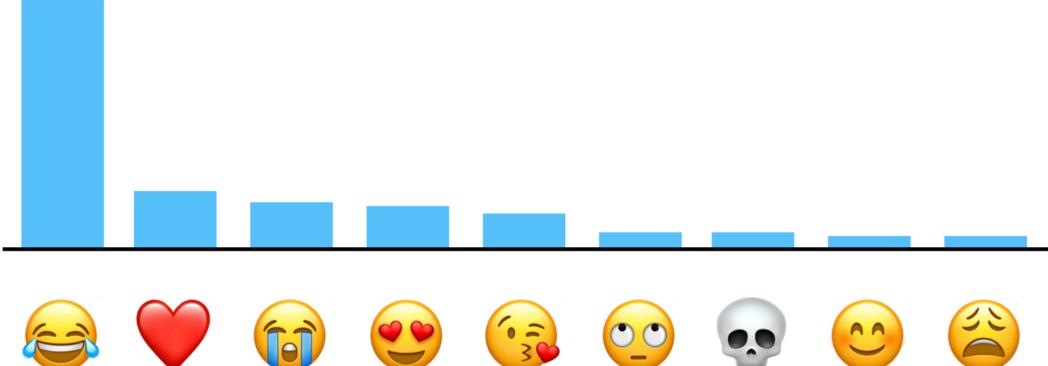
| 16 |
|----|
|----|

- We've focused on promoting privacy by helping users adopt good privacy behaviors.

• Now let's think about the human-centered privacy problems from a different perspective

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Differential privacy for learning the most popular emojis What threats are users' concerned about in keyboard? What threats are DP mitigating? Are they aligned?



The Count Mean Sketch technique allows Apple to determine the most popular emoji to help design better ways to find and use our favorite emoji. The top emoji for US English speakers contained some surprising favorites.





How can we (proactively) identify users' privacy concerns/preferences



Privacy preferences Emulating user behaviors

- "We built a classifier to make privacy decisions on the user's behalf by detecting when context has changed and, when necessary, inferring privacy preferences based on the user's past decisions and behavior."
- Pros and cons of this method?

The Feasibility of Dynamically Granted Permissions: Aligning Mobile Privacy with User Preferences

Primal Wijesekera¹, Arjun Baokar², Lynn Tsai², Joel Reardon², Serge Egelman², David Wagner², and Konstantin Beznosov¹ ¹University of British Columbia, Vancouver, Canada, {primal,beznosov}@ece.ubc.ca ²University of California, Berkeley, Berkeley, USA, {arjunbaokar,lynntsai,joel.reardon}@berkeley.edu, {egelman,daw}@cs.berkeley.edu

Abstract—Current smartphone operating systems regulate application permissions by prompting users on an ask-on-first-use basis. Prior research has shown that this method is ineffective because it fails to account for context: the circumstances under which an application first requests access to data may be vastly different than the circumstances under which it subsequently requests access. We performed a longitudinal 131-person field study to analyze the contextuality behind user privacy decisions to regulate access to sensitive resources. We built a classifier to make privacy decisions on the user's behalf by detecting when context has changed and, when necessary, inferring privacy preferences based on the user's past decisions and behavior. Our goal is to automatically grant appropriate resource requests without further user intervention, deny inappropriate requests, and only prompt the user when the system is uncertain of the user's preferences. We show that our approach can accurately predict users' privacy decisions 96.8% of the time, which is a four-fold reduction in error rate compared to current systems.

I. INTRODUCTION

One of the roles of a mobile application platform is to help users avoid unexpected or unwanted use of their personal data [12]. Mobile platforms currently use permission systems to regulate access to sensitive resources, relying on user prompts to determine whether a third-party application should be granted or denied access to data and resources. One critical caveat in this approach, however, is that mobile platforms seek the consent of the user the first time a given application attempts to access a certain data type and then enforce the user's decision for all subsequent cases, regardless of the circumstances surrounding each access. For example, a user may grant an application access to location data because she is using location-based features, but by doing this, the application can subsequently access location data for behavioral advertising, which may violate the user's preferences.

Earlier versions of Android (5.1 and below) asked users to make privacy decisions during application installation as an all-or-nothing ultimatum (ask-on-install): either all requested permissions are approved or the application is not installed. Previous research showed that few people read the requested permissions at install-time and even fewer correctly understood them [17]. Furthermore, install-time permissions do not present users with the context in which those permission will be exercised, which may cause users to make suboptimal decisions not aligned with their actual preferences. For example, Egelman et al. observed that when an application requests access to location data without providing context, users are just as likely to see this as a signal for desirable locationbased features as they are an invasion of privacy [11]. Asking users to make permission decisions at runtime—at the moment when the permission will actually be used by the application provides more context (i.e., what they were doing at the time that data was requested) [15]. However, due to the high frequency of permission requests, it is not feasible to prompt the user every time data is accessed [43].

In iOS and Android M, the user is now prompted at runtime the first time an application attempts to access one of a set of "dangerous" permission types (e.g., location, contacts, etc.). This *ask-on-first-use* (AOFU) model is an improvement over ask-on-install (AOI). Prompting users the first time an application uses one of the designated permissions gives users a better sense of context: their knowledge of what they were doing when the application first tried to access the data should help them determine whether the request is appropriate. Despite that, Wijesekera et al. showed that AOFU fails to meet user expectations over half the time. This is because AOFU does not account for the varying contexts of future requests [43].

The notion of *contextual integrity* suggests that many permission models fail to protect user privacy because they fail to account for the context surrounding data flows [34]. That is, privacy violations occur when sensitive resources are used in ways that defy users' expectations. We posit that more effective permission models must focus on whether resource accesses are likely to defy users' expectations in a given context-not simply whether the application was authorized to receive data the first time it asked for it. Thus, the challenge for system designers is to correctly infer when the context surrounding a data request has changed, and whether the new context is likely to be deemed "appropriate" or "inappropriate" for the given user. Dynamically regulating data access based on the context requires more user involvement to understand users' contextual preferences. If users are asked to make privacy decisions too frequently, or under circumstances that are seen as low-risk, they may become habituated to future,

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Privacy paradox People say they care about privacy, but their behavior suggests otherwise

> image source: https://www.edweek.org/teaching-learning/science-denial-in-the-classroom-what-c it-how-should-teachers-respond/2021/11



Privacy preferences Self-reported - P3P

- A P3P statement comprises the purpose, data, recipients, retention, and consequence elements. A P3P policy contains one or more statements.
- A P3P Preference Exchange Language (APPEL)—provides syntax for encoding user preferences about privacy policies.
- Pros and cons of this method?

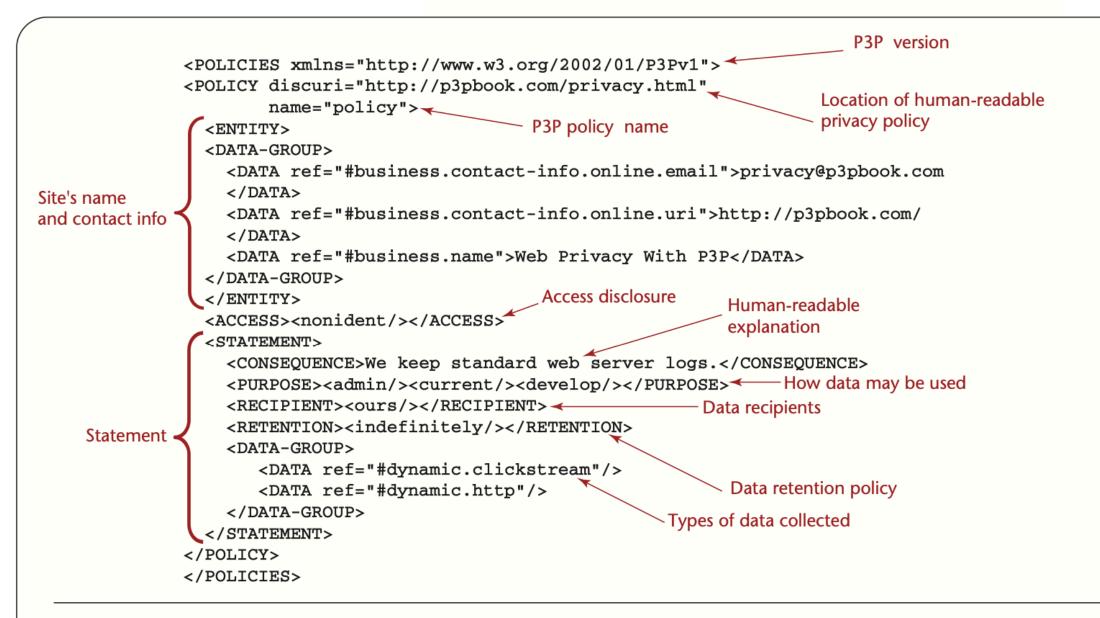
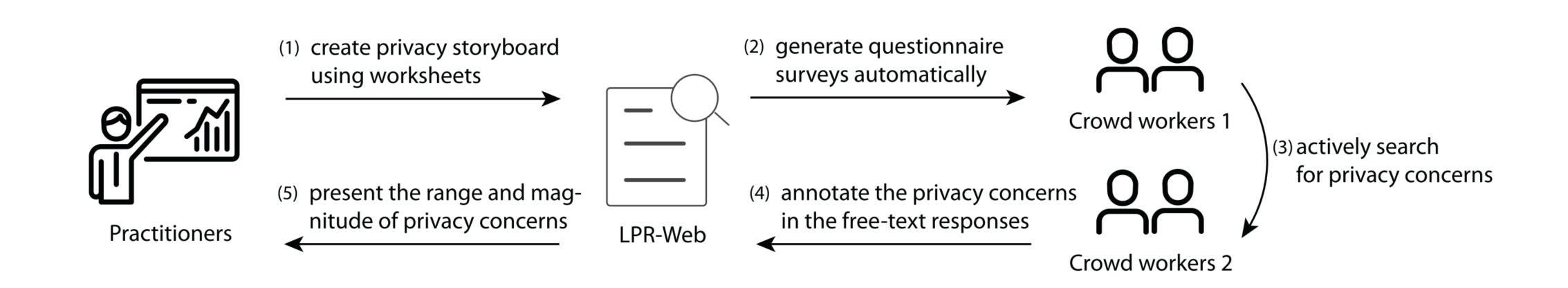
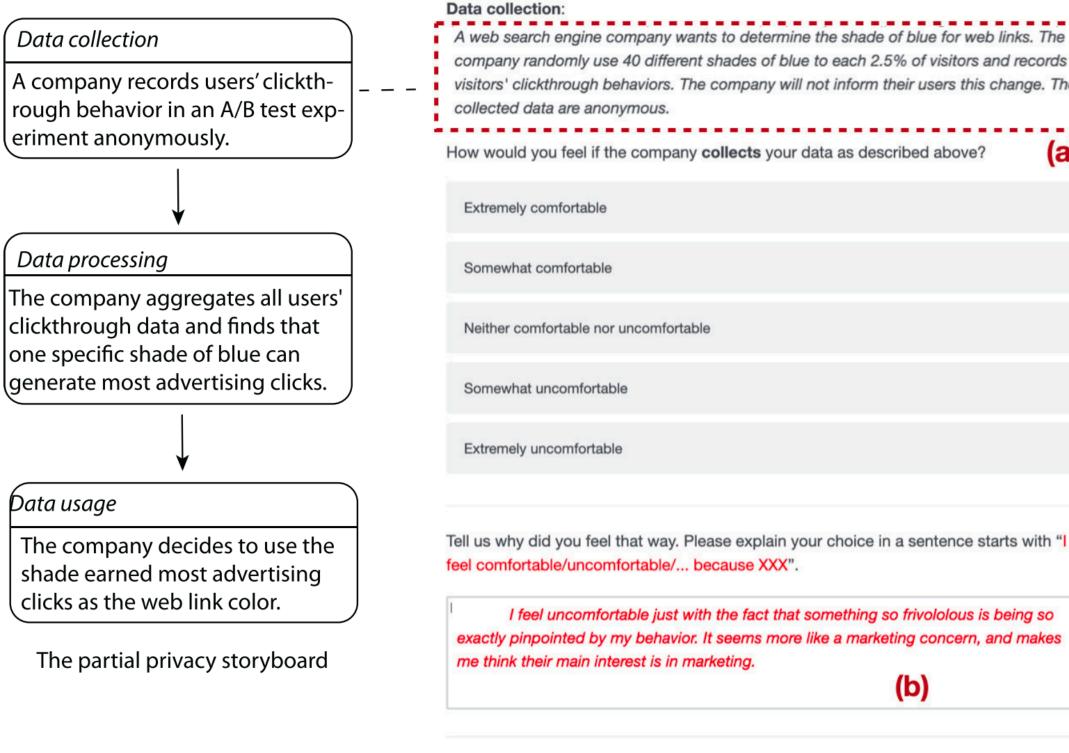


Figure 1. Example P3P policy. This relatively simple policy contains one statement, comprising purpose, data, recipients, retention, and consequence elements.





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Data processing: The company develops sophisticated artificial intelligence algorithms to analyze the video

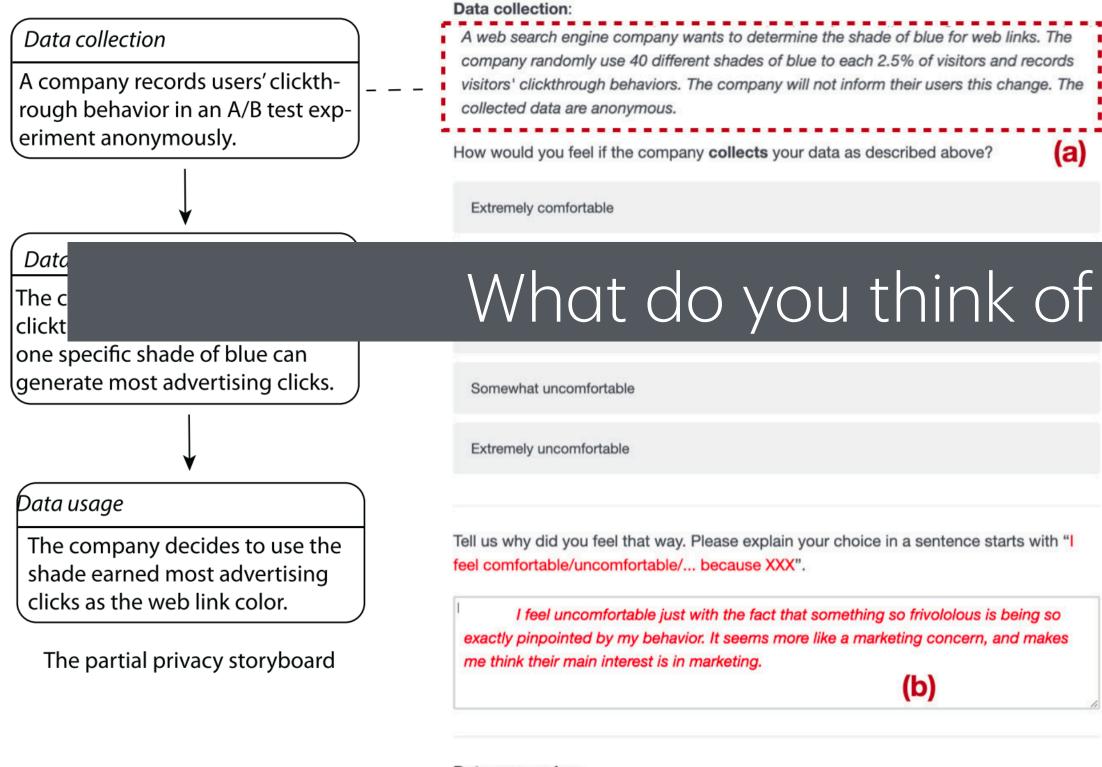
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| bed above? (a) | |
| Dod aboro. | |

(C) I feel uncomfortable just with the fact that something so frivololous is being so exactly pinpointed by my behavior. It seems more like a marketing concern, and makes me think their main interest is in marketing.

- Please check all the privacy concerns mentioned in the red text. 0. If there is no negative concern mentioned. You can skip the following questions and submit the form.
- 1. Invasive monitoring (e.g., too sensitive data, too much data) See examples
- 2. Violation of expectations/social norms (e.g., unexpected data collection, sharing, usages) See examples
- 3. Lack of respect for autonomy (e.g., decisional interference) See examples
- 4. Lack of informed consent (e.g., lack of transparency, lack of consent) See examples
- 5. Violation of consent See examples
- 6. Deceptive or misleading data practice See examples
- 7. Lack of protection for vulnerable population See examples
- 8. Lack of alternative option (e.g., no opt-out option) See examples
- 9. Insufficient data security (e.g., potential data breach) See examples

- 10. Insufficient anonymization See examples
- 11. Too high potential risks (e.g., it may result in finacial/opportunity/reputation loss.) See examples
- 12. Too low potential benefits See examples
- 13. Bias or discrimination See examples
- 14. Lack of trust for algorithms See examples
- 15. Lack of control of personal data See examples
- 16. Only beneficial to the company but not users See examples
- 17. Other concerns. Please summarize them in short phrases.

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Data processing: The company develops sophisticated artificial intelligence algo (C)

(a)

I feel uncomfortable just with the fact that something so frivololous is being so exactly pinpointed by my behavior. It seems more like a marketing concern, and makes me think their main interest is in marketing.

(C) Please check all the privacy concerns mentioned in the red text. 0. If there is no negative concern mentioned. You can skip the following questions and submit the form.

1. Invasive monitoring (e.g., too sensitive data, too much data) See examples

2 Violation of expectations/social norms (e.g. unexpected data collection sharing usages) See examples

What do you think of this method?

| | 5. Violation of consent See examples |
|--|--|
| | 6. Deceptive or misleading data practice See examples |
| | 7. Lack of protection for vulnerable population See examples |
| | 8. Lack of alternative option (e.g., no opt-out option) See examples |
| | 9. Insufficient data security (e.g., potential data breach) See examples |
| n a sentence starts with "I | 10. Insufficient anonymization See examples |
| | 11. Too high potential risks (e.g., it may result in finacial/opportunity/reputation loss.) See examples |
| so frivololous is being so ating concern, and makes | 12. Too low potential benefits See examples |
| (b) | 13. Bias or discrimination See examples |
| | 14. Lack of trust for algorithms See examples |
| | 15. Lack of control of personal data See examples |
| orithms to analyze the video | 16. Only beneficial to the company but not users See examples |
| | 17. Other concerns. Please summarize them in short phrases. |

Jin, Haojian, et al. "Lean privacy review: Collecting users' privacy concerns of data practices at a low cost." ACM Transactions on Computer-Human Interaction (TOCHI) 28.5 (2021): 1-55.

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Data processing: The company develops sophisticated artificial intelligence algorithms to analyze the video (C)

(a)

I feel uncomfortable just with the fact that something so frivololous is being so exactly pinpointed by my behavior. It seems more like a marketing concern, and makes me think their main interest is in marketing.

Please check all the privacy concerns mentioned in the red text. 0. If there is no negative concern mentioned. You can skip the following questions and submit the form.

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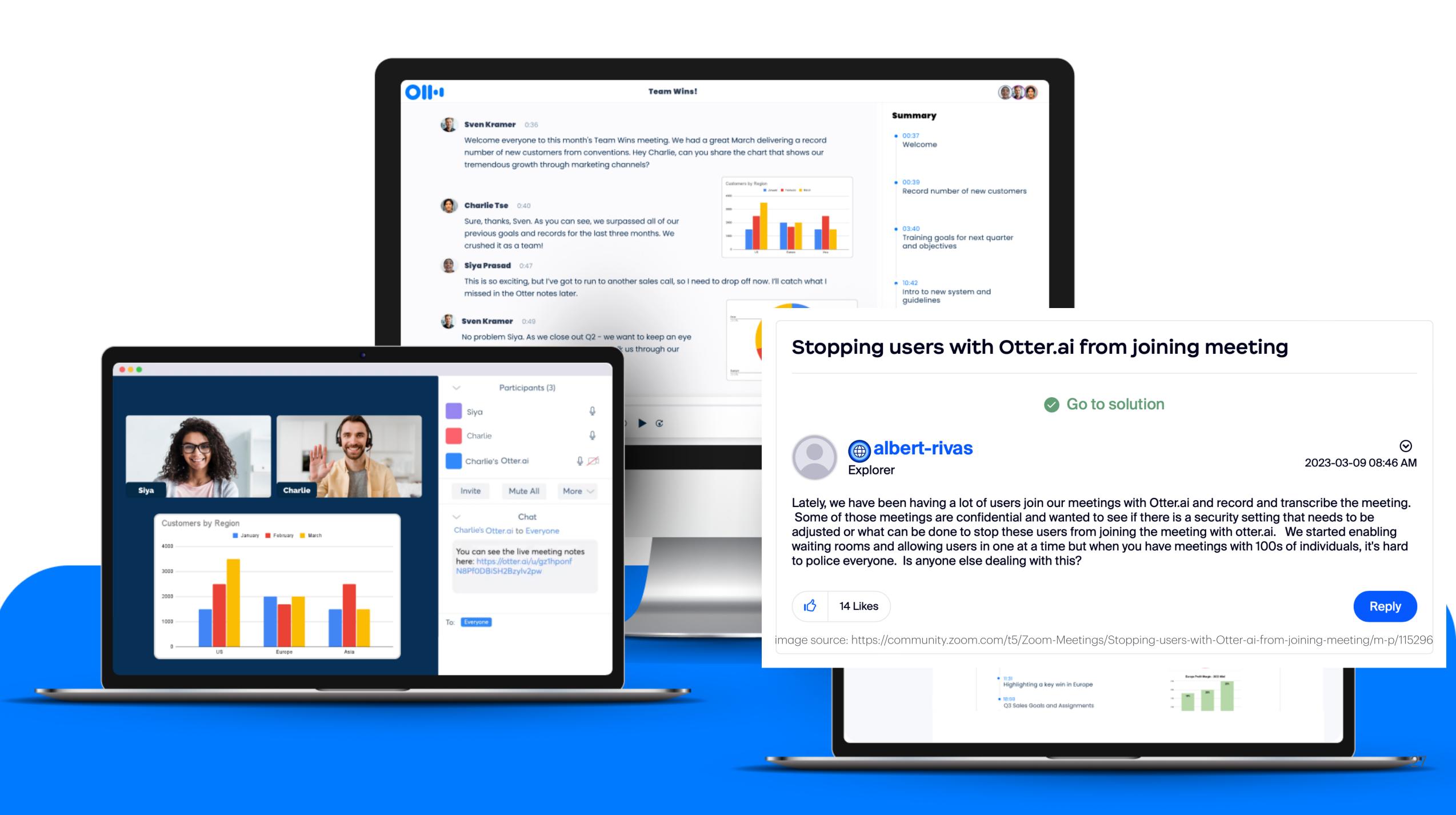
2 Violation of expectations/social norms (e.g. unexpected data collection sharing usages) See examples

How can we keep improving upon this?

(b)

- 5. Violation of consent See examples
- 6. Deceptive or misleading data practice See examples
- 7. Lack of protection for vulnerable population See examples
- 8. Lack of alternative option (e.g., no opt-out option) See examples
- 9. Insufficient data security (e.g., potential data breach) See examples
- 10. Insufficient anonymization See examples
- 11. Too high potential risks (e.g., it may result in finacial/opportunity/reputation loss.) See examples
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- 16. Only beneficial to the company but not users See examples
- 17. Other concerns. Please summarize them in short phrases.

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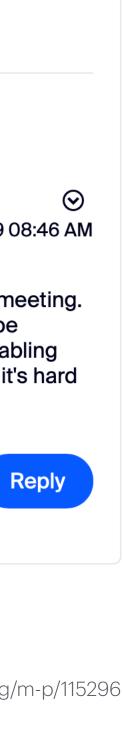


Think about privacy issues that are even more hidden OtterPilot automatically join zoom meetings, causing creepy experiences

- Why do people implement systems like this?
- How to identify and mitigate this issue?
 - Measure unintended consequences
 - Empathize with users

| Stopping users with Otter.ai from joining meeting | | | | |
|--|---|--|--|--|
| Go to solution | | | | |
| albert-rivas Explorer | 2023-03-09 08 | | | |
| Lately, we have been having a lot of users join our meetings with Ott Some of those meetings are confidential and wanted to see if there adjusted or what can be done to stop these users from joining the m waiting rooms and allowing users in one at a time but when you have to police everyone. Is anyone else dealing with this? | e is a security setting that needs to be neeting with otter.ai. We started enable | | | |
| 14 Likes | R | | | |

image source: https://community.zoom.com/t5/Zoom-Meetings/Stopping-users-with-Otter-ai-from-joining-meeting/m-p/115296



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Privacy preferences are malleable

\$12 gift card, linked with my name

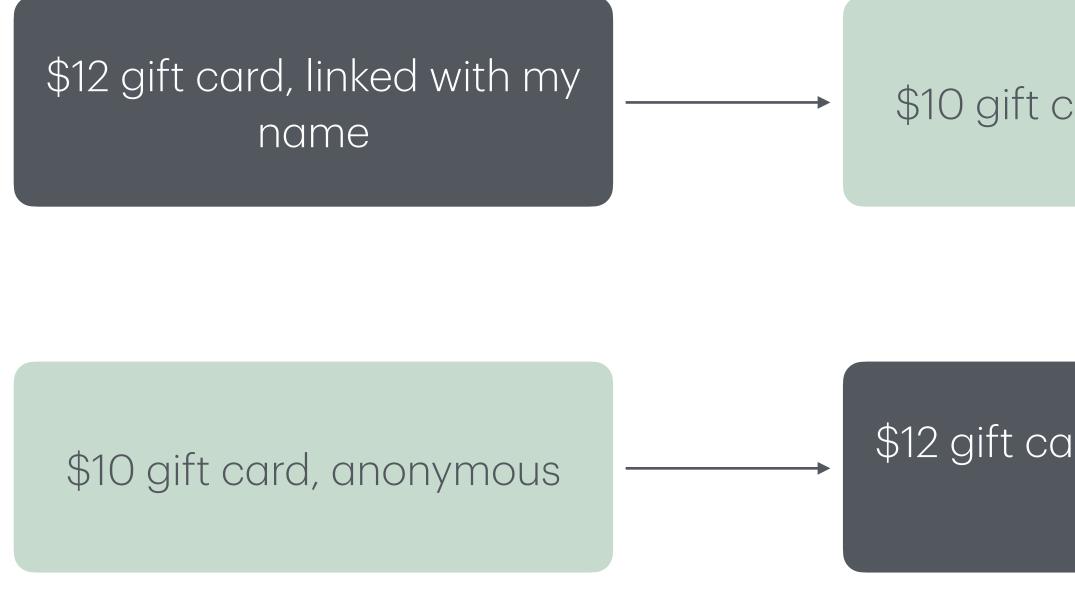
VS.

\$10 gift card, anonymous

Acquisti, Alessandro, Leslie K. John, and George Loewenstein. "What is privacy worth?." The Journal of Legal Studies 42.2 (2013)

29

Privacy preferences are malleable



Acquisti, Alessandro, Leslie K. John, and George Loewenstein. "What is privacy worth?." The Journal of Legal Studies 42.2 (2013)

\$10 gift card, anonymous

\$12 gift card, linked with my name

Five times more likely to reject cash offers and stay with the "\$10 gift card, anonymous" than paying money for increased privacy

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Recap

- Approaches to (proactively) identifying users' privacy concerns and collect privacy preferences
- Can we weave these two threads together?

• Factors that affect users' adoption of good privacy behaviors: awareness, ability, motivation

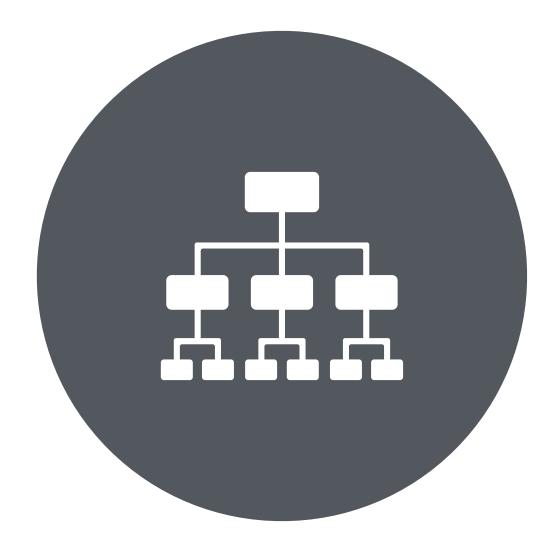
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Paradigms of human-centered privacy design and system research

Part of the materials are adapted from the course "CS 4/8803 UPS - Spring 2022" taught by Dr. Sauvik Das at Georgia Tech



Project types for this class



SYSTEMS (ARTIFACTS)



SOCIAL SCIENCE (EMPIRICAL)

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Systems Projects



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What makes for good systems research?

- What is the problem that you are solving, and why is it **important**?
- - Are you "lowering the floor"?
 - Are you "raising the ceiling"?

• What is **new** and **unique** about what you are proposing to build relative to what exists?



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Prior art

- Systems research must go beyond what has already been built in some way.
- a demonstrably novel approach

• This doesn't mean it must be "better engineered than"; it means that the system should take

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Validation

- Need to validate with user studies

• When building systems to solve human-centered problems, one must demonstrate that one's system is provably better for the humans who were supposed to be centered

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Contextualized in this class

- with privacy preferences?
- You don't have a lot of time; scoping is essential!
- Do a literature review to get up to speed on the state of the art
- Propose an **attack** or a **mitigation** that looks different from what has been done:
 - different technical approaches
 - targeting/serving different populations (e.g., older adults, the visually impaired)

• Example RQs: How to foster good privacy behaviors, specifically addressing the issues of privacy awareness, knowledge, and motivation? How to measure or mitigate privacy harms/concerns and align

• 9 weeks: 1 week literature search + 4-5 weeks implementations + 3-4 weeks evaluation and analysis

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Social Science Projects

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What makes for good social science research?

- important to learn?
- you are trying to learn?
- people?
- world?

• Research question: What are you trying to learn that is not already known and why is it

• Methodological considerations: Is the approach you are proposing appropriate for what

• **Sample appropriateness:** Are the people from whom you are collecting data the right

• Ecological validity: Do the conditions within which you are collecting data match the "real"

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Exploratory vs Confirmatory

- Confirmatory research: top-down, guided by theories or prior research
 - Generate specific, measurable, and falsifiable hypotheses. For example: "Users' level of selfesteem affects their intentions to hide the use of LLMs"
 - Run controlled experiments to test the hypotheses
- Exploratory research: bottom-up, identifying patterns from observations
 - Still need some research questions, but can be more open-ended. For example: **"What are the people's primary concerns when interacting with LM agents? What's the role of privacy?"**
 - Data sources: User studies or publicly available data on social media, existing dataset, etc.



Sample

- Very important to get data from the right people
- Some possibilities:
 - Online study participant pools (e.g., prolific.com)
 - Partnering with advocacy groups to target specialized population
 - Other students (e.g., for education interventions)

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Contextualized in this class

- Example RQs: When and why do people exhibit good or bad privacy behaviors, especially when do they have issues of privacy awareness, knowledge, and motivation? What are people's privacy concerns and preferences in a specific application domain?
- You don't have a lot of time; scoping is essential!
- 9 weeks: 1 week literature search + 4-5 weeks protocol design and pilot studies + 3-4 weeks formal studies and analysis
- Do a literature review to get up to speed on the state of the art
- Propose a methodology that is specific and is appropriate to answer your research question





Qualitative analysis



Inductive coding (most common in HCI research)

- the qualitative data itself.
- that are relevant to the research question within that data segment.

• Inductive coding, also called open coding, starts from scratch and creates codes based on

• Open codes are created when the researcher examines qualitative data, selects a relevant segment of data, and attaches a code (or codes) that capture the meaning or the aspects



Deductive coding

might already know what themes you're interested in analyzing.

• Deductive coding means you start with a predefined set of codes, then assign those codes to the new qualitative data. These codes might come from previous research, or you

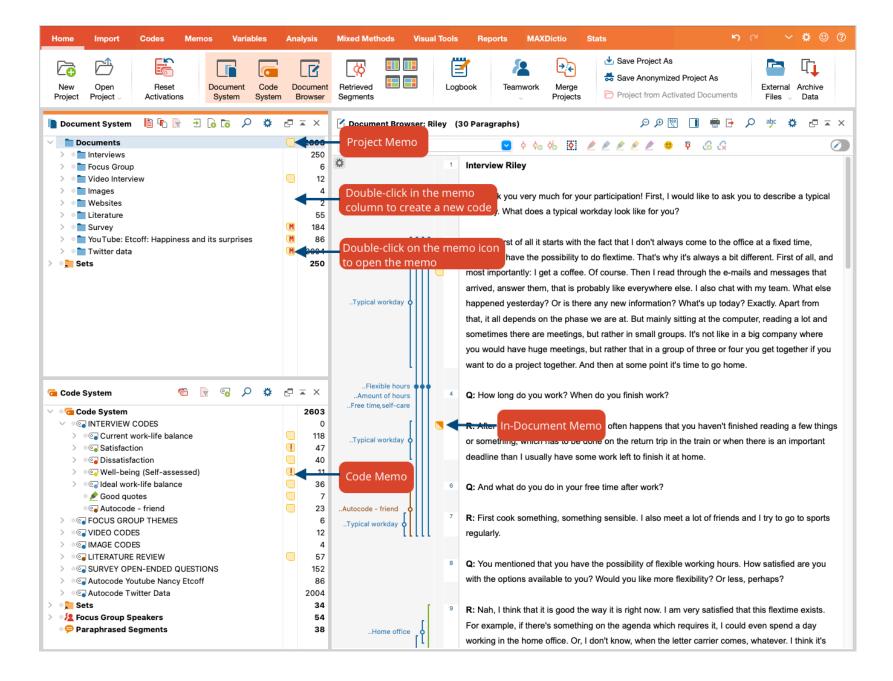
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Abductive coding

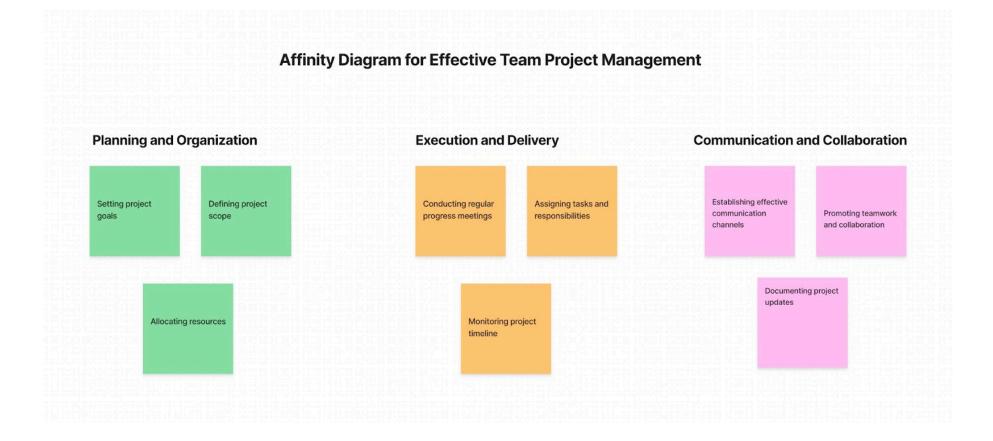
 Abductive coding combines what we already know with new observations to understand topics better and form more complete theories. It challenges the traditional dichotomy between induction and deduction by offering a blended approach to theory-building.

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Two common methods of open coding



Assign codes in text



Affinity diagramming

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What is coding?

A code in qualitative inquiry is most often **a word or short phrase** that symbolically assigns a summative, salient, essence-capturing, and/or evocative attribute for a portion of language-based or visual data.

Coding for patterns: look for what emerge **repeatedly** throughout

Coding filters: your interpretation can be affected by the **researcher's "filter" – your research questions, your personal involvement, etc.**

Coding as a heuristic: an **exploratory** problem-solving technique **without specific formula** to follow



Process

- Iterative process:
 - Codes: specific actions, behaviors, rationales, etc.
 - Categories: Synthesize codes into more abstract categories
 - Theory: Infer transferability from one sample to the general type of the scenario

Code: PEDAGOGICAL Code: SOCIO-EMOTIONAL Code: STYLE/PERSONAL EXPRESSION Code: TECHNICAL

Code: BEHAVIORIST TECHNIQUES Code: GROUP MANAGEMENT Code: SOCIO-EMOTIONAL Code: STYLE (overlaps with instructional style) Code: UNWRITTEN CURRICULUM





Process (continued)

• Develop a codebook, which usually follows a three-dimensional structure:

| Code | Definition | Example/Quote |
|------|------------|---------------|
| | | |

- Calculate inter-coder reliability, e.g., Cohen's Kappa, Gwet's AC1, Krippendorff's alpha
 - In some situations, multiple coders are required to code the same set of data and measure the inter-coder reliability. In HCI, an ICR > 0.8 is satisfactory.
 - A good ICR is a sign of comprehensive and well-defined codes/categories, and a consistent and rigorous process of applying the codes.
 - Not all the qualitative analysis requires ICR. If the goal is to generate themes rather than seek agreement, an ICR is not required [1].



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Quantitative analysis



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Descriptive statistics

- Min/Max
- Mean
- Median
- Standard deviation
- Distribution
- Visualization

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Inferential Statistics and Hypothesis Testing Acheatsheet

- T-test. "Are group A's completion times lower than group B?"
- ANOVA. "Are the completion times of the three groups different?"
- Chi-squared test. "Is the ratio of positive cases of group A higher than group B"
- Linear/logistic regression analysis. "Does the independent factor A correlate with the outcome factor B"
- Mediation analysis. "Does the independent factor A affect the outcome factor B via the mediator C?"



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Experimental design

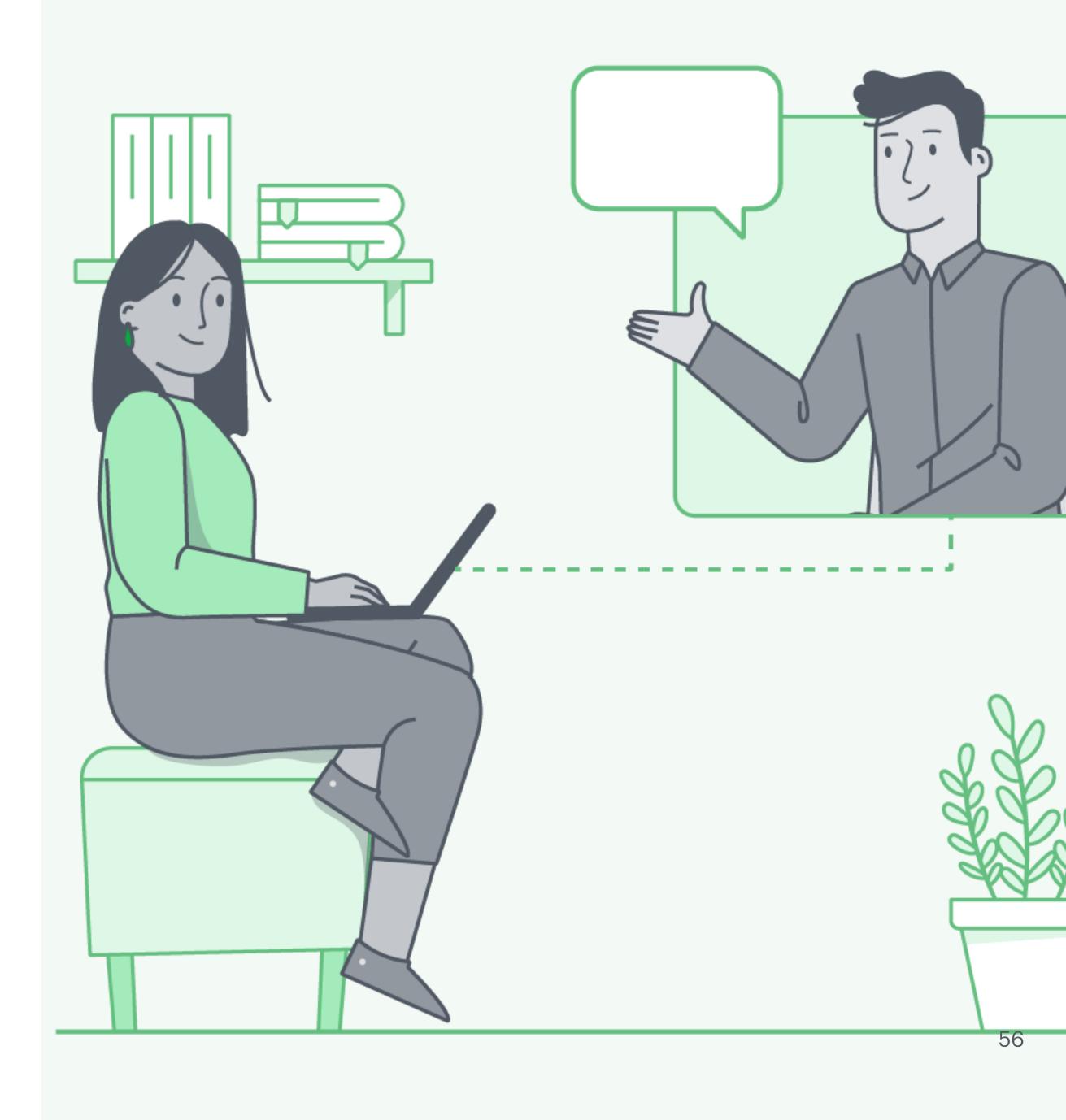
- Dependent variables
- Independent variables (Multicollinearity)
- Controlled experiment
 - variable; need to account for repeated measures in your statistical analysis
 - Between-subjects design: Every participant experiences only one condition.
 - people to groups with different levels of X between-subjects design

• Within-subjects design: All participants are exposed to every condition of the independent

• If you want to test whether X has a **causal relationship** with Y, you need to randomly assign

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How to conduct interviews?



Semi-Structured Interviews (most common)

- Seek a mix of constrained and unconstrained responses
- definitely needed to cover/get
- Flexibility for open-ended follow-up as situation evolves

• Make sure to cover bases (semi-structured questions) e.g. list of items/responses that are



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Structured Interviews

- Predetermined and closed questions: like questionnaire, often with a flowchart
- Questions: short and clearly worded
- Confirmatory
- Pros: Replicable, Not time-consuming
- Cons: Potentially important detail can be lost



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Focus Group (group interviews)

- Group: 2-10 people at one time, interviewed by trained moderators (critical!).
- Usually has agenda (1-3 h), but may be either structured or unstructured (w/prompt or probe).
- Pros: Can accommodate diverse and sensitive issues; Opinions developed within a social context.
- Cons: Some participants may be reluctant to take opposing view; Time-consuming and difficult to organize.

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Interview guidelines: how to conduct interviews?

- Do not pre-suppose answers; Be open-ended
- Avoid:
 - Yes/No questions
 - Asking long questions
 - Using jargon
 - Interrupting the interviewees
 - Being defensive (especially when evaluating an artifact you created)

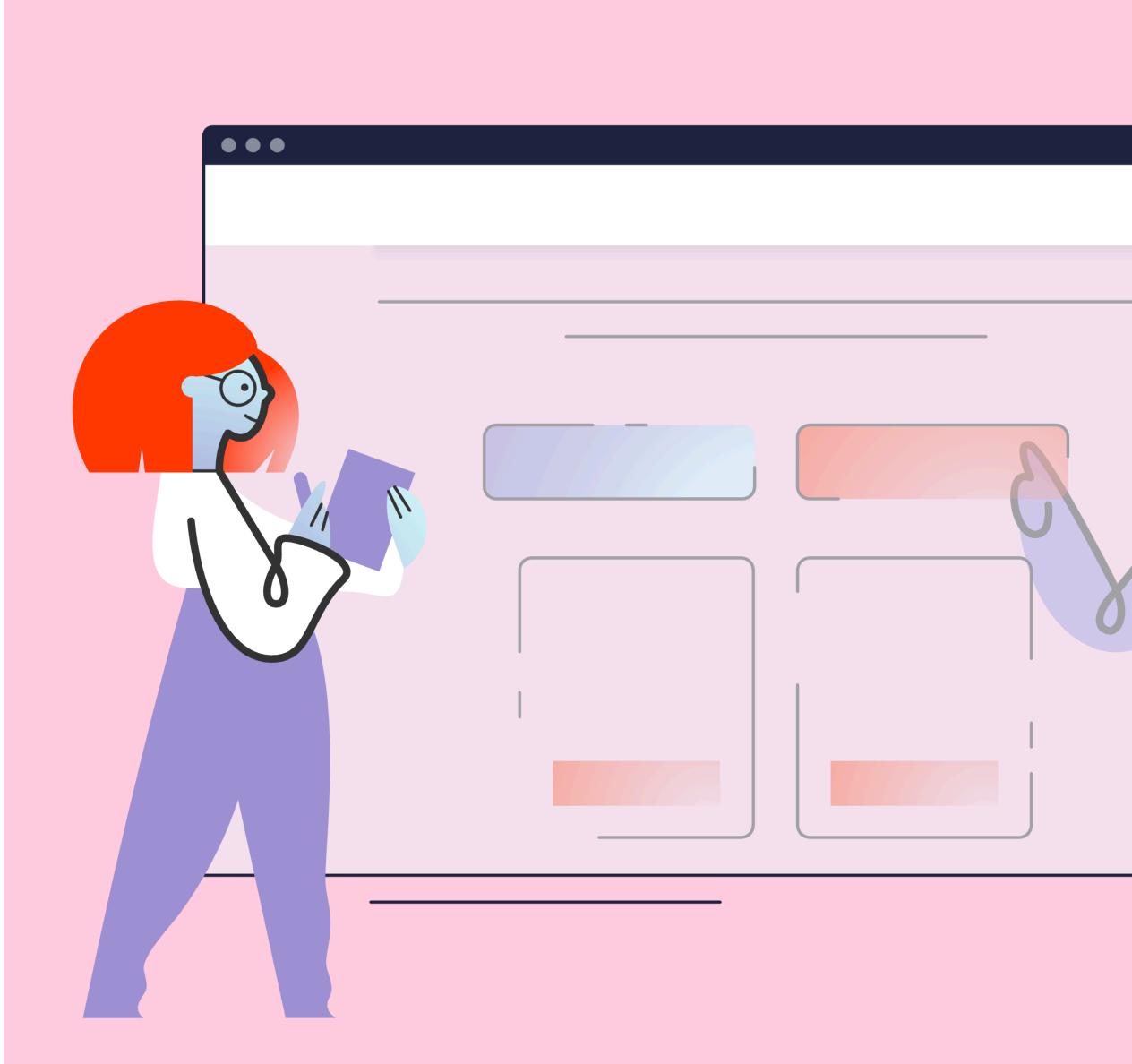
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What to prepare?

- Be **organized** BEFORE you start:
 - Consent forms
 - Screening forms
 - Study instruments: interview scripts, questionnaires, etc.
 - Audio/video equipment
 - Note-taking equipment

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How to conduct usability (testing) studies?





System evaluation

- Baseline vs. Experimental Conditions
 - (e.g., time, task completion, accuracy, SUS, NASA/TLX)

• Task-driven: Create tasks that represent common use cases for participants to complete

• Usually want to achieve statistically significant improvement in key performance metrics

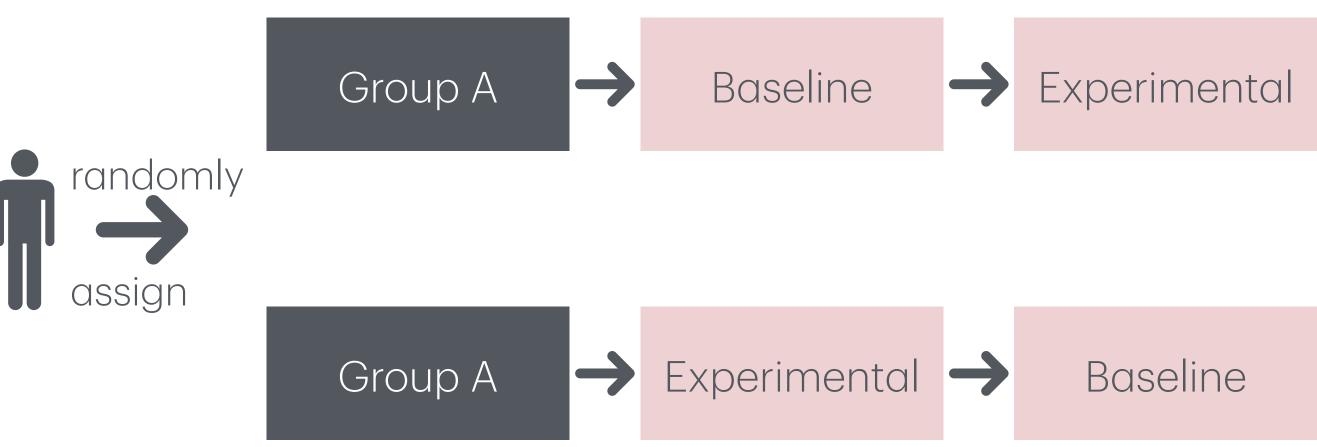
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Avoid confounding factors

Learning effect: In between-subjects studies, the tasks for the baseline and experimental condition are usually different to avoid learning effect

Treatment order: Counterbalanced study design

Hawthorne effect: Refer to the conditions as "system 1 and 2" rather than "baseline and experimental"



An example of counterbalanced design





Recap

- Types of projects suitable for this class: Systems (artifacts), Social sciences (empirical)
- Human-centered research methods
 - Qualitative
 - Quantitative
 - Interviews
 - Usability studies

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Action items

- By the noon this Wednesday (Sept 18)
 - Submit this week's reading commentaries
 - Two students will lead the first discussion
- Project proposal due one week later (Sept 25 midnight)
 - Book an office hour appointment with me (Wednesday 1-2pm)

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