# Research Framework

INFR11158/11230 Usable Security and Privacy

Dr. Jingjie Li

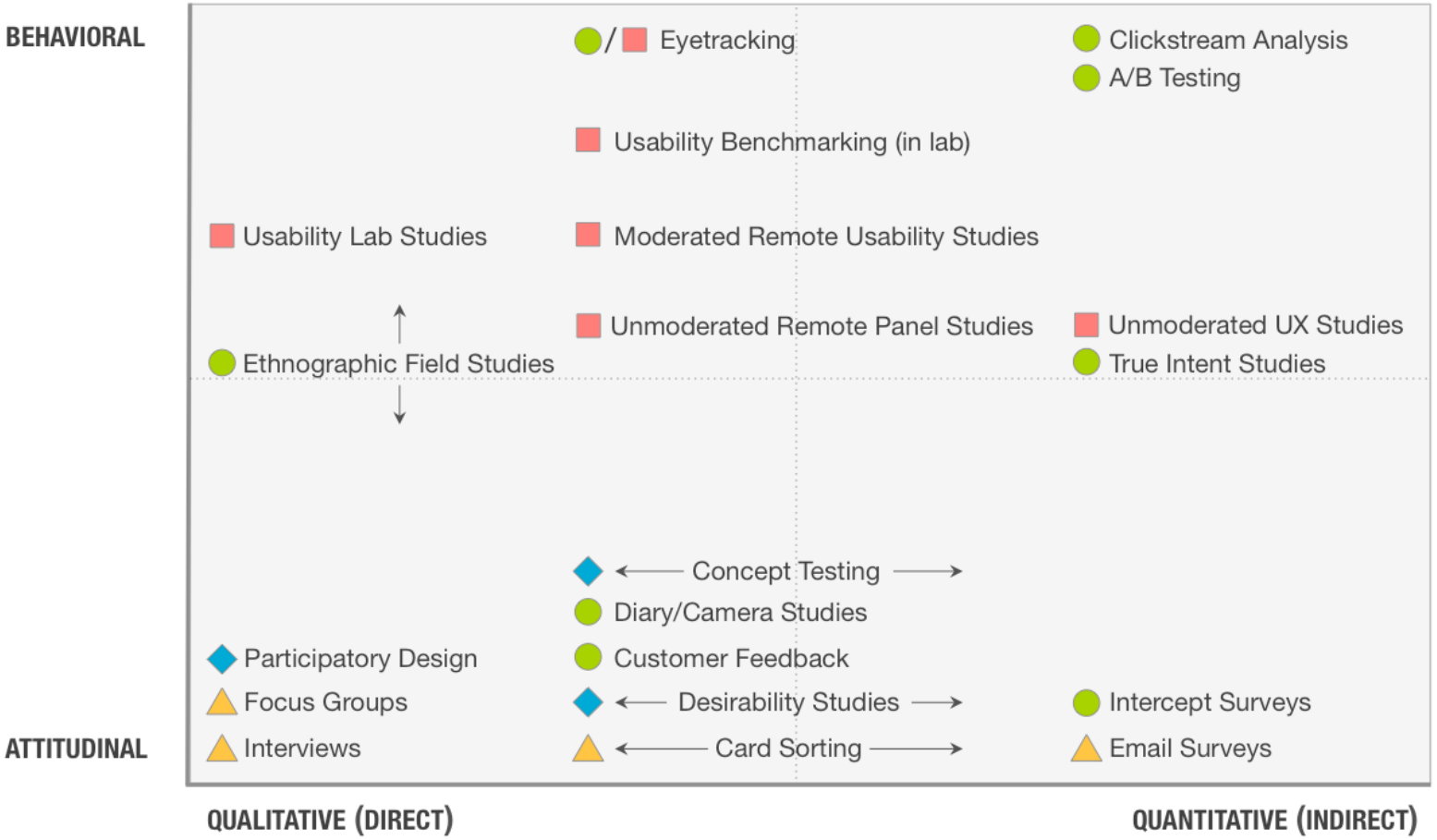
13/02/2024


THE UNIVERSITY *of* EDINBURGH

# Overview

- Recap
- Human in the loop
- Planning studies – putting together
- Take-home

# A Landscape of User Research Methods




## KEY FOR CONTEXT OF PRODUCT USE DURING DATA COLLECTION

- Natural use of product
- Scripted (often lab-based) use of product
- De-contextualized / not using product
- Combination / hybrid



https://www.nngroup.com/articles/which-ux-research-methods/

**What do you want to know or learn?**

**What hypothesis do you want to test?**

**What metrics do you want to apply?**

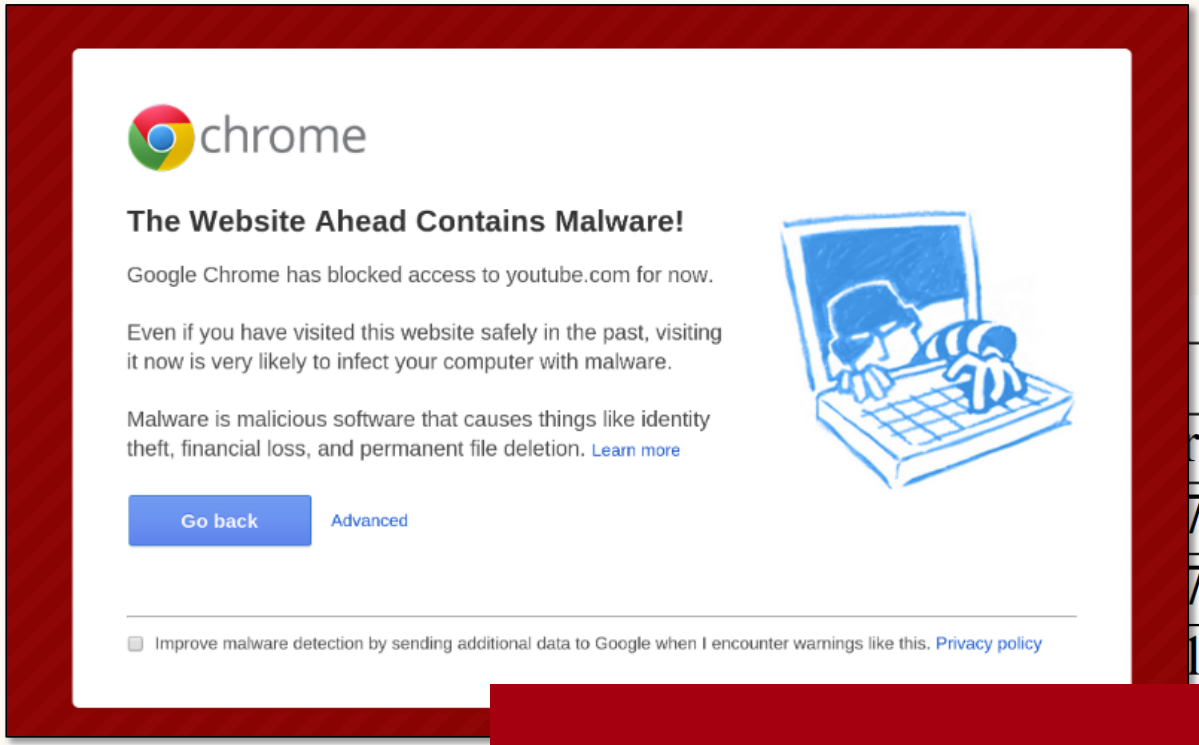
**Is [my tool] usable?**

Needs to be more specific to be testable.

# Some of research questions:

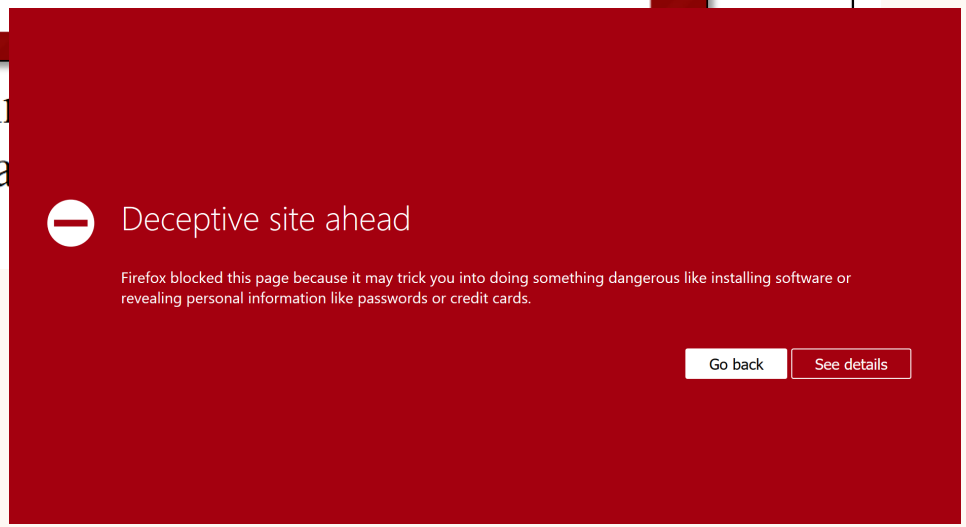
- Can people differentiate between a subdomain and a domain when reading a URL?
- Does [my new system] help people differentiate between malicious URLs and safe ones?
- Can users use [my new password manager] faster and with less errors than [the old password manager]?
- Does knowing how an app will use its permissions impact app installation decisions?
- What factors impact end-users' willingness to update software?
- Using [website], can users successfully opt-out of cookie tracking without forming inaccurate mental models?

# Why do Chrome users ignore malware errors more often than Firefox users?




rome
7.9%
7.0%
1.0%

Table 1: User operati
ware and phishing wa
release) versions.



# Why do people ignore malware warnings and what can we do about it?

## Your Reputation Precedes You: History, Reputation, and the Chrome Malware Warning

Hazim Almuhimedi
Carnegie Mellon University
hazim@cs.cmu.edu

Adrienne Porter Felt
Robert W. Reeder
Sunny Consolvo
Google, Inc.
felt, rreeder, sconsolvo@google.com

**ABSTRACT**

Several web browsers, including Google Chrome and Mozilla Firefox, use malware warnings to stop people from visiting infectious websites. However, users can choose to click through (i.e., ignore) these malware warnings. In Google Chrome, users click through a fifth of malware warnings on average. We investigate factors that may contribute to why people ignore such warnings. First, we examine field data to see how browsing history affects click-through rates. We find that users consistently heed warnings about websites that they have not visited before. However, users respond unpredictably to warnings about websites that they have previously visited. On some days, users ignore more than half of warnings about websites they've visited in the past. Next, we present results of an online, survey-based experiment that we ran to gain more insight into the effects of reputation on warning adherence. Participants said that they trusted high-reputation websites more than the warnings; however, their responses suggest that a notable minority of people could be swayed by providing more information. We provide recommendations for warning designers and pose open questions about the design of malware warnings.

**1. INTRODUCTION**

Modern browsers such as Google Chrome and Mozilla

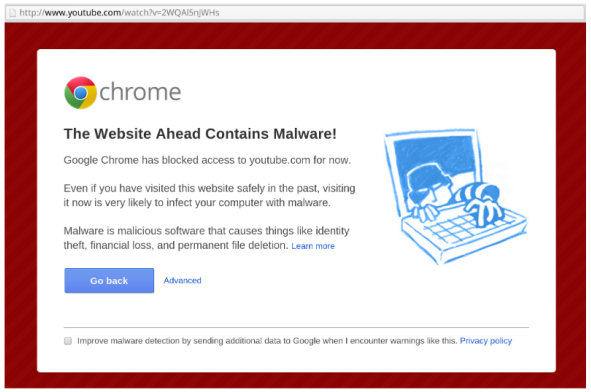



**Figure 1: Malware warning in Google Chrome 32**

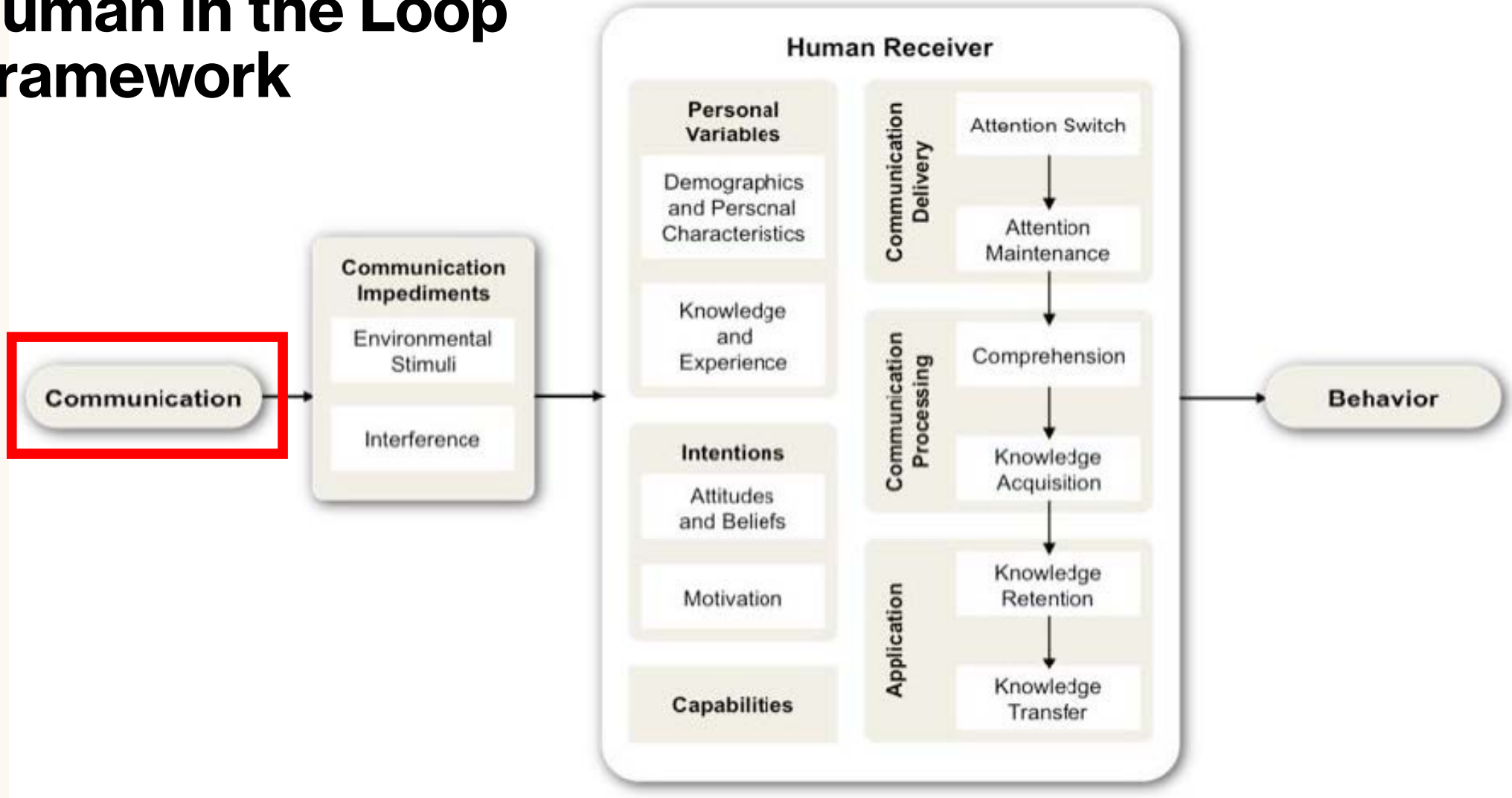
Amazon Mechanical Turk workers. We investigate the impact of people's familiarity with the website they are attempting to visit, as well as how they found out about the website. We also tested minor variations of the instrument used in our survey-based experiment to determine how small wording changes affected responses (e.g., whether or not participants were primed with the word "warning").

Our field data and Mechanical Turk experiment both support our familiarity hypothesis. In our analysis of 3,875,758

# Frameworks

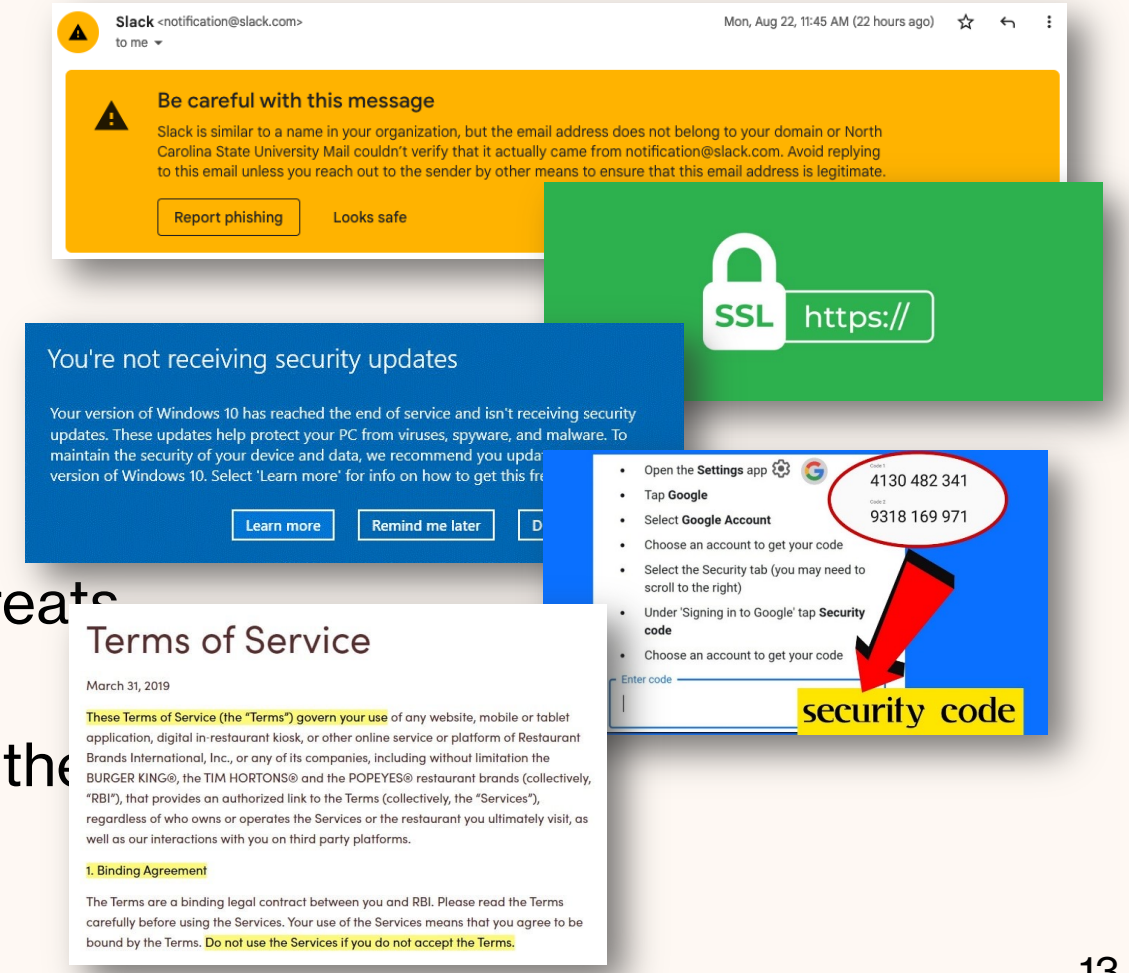
**Frameworks help researchers structure their thinking around problems. Frameworks are proposed by experts in the field and represent how those people think about and break up certain types of problems.**

# Human in the Loop Framework

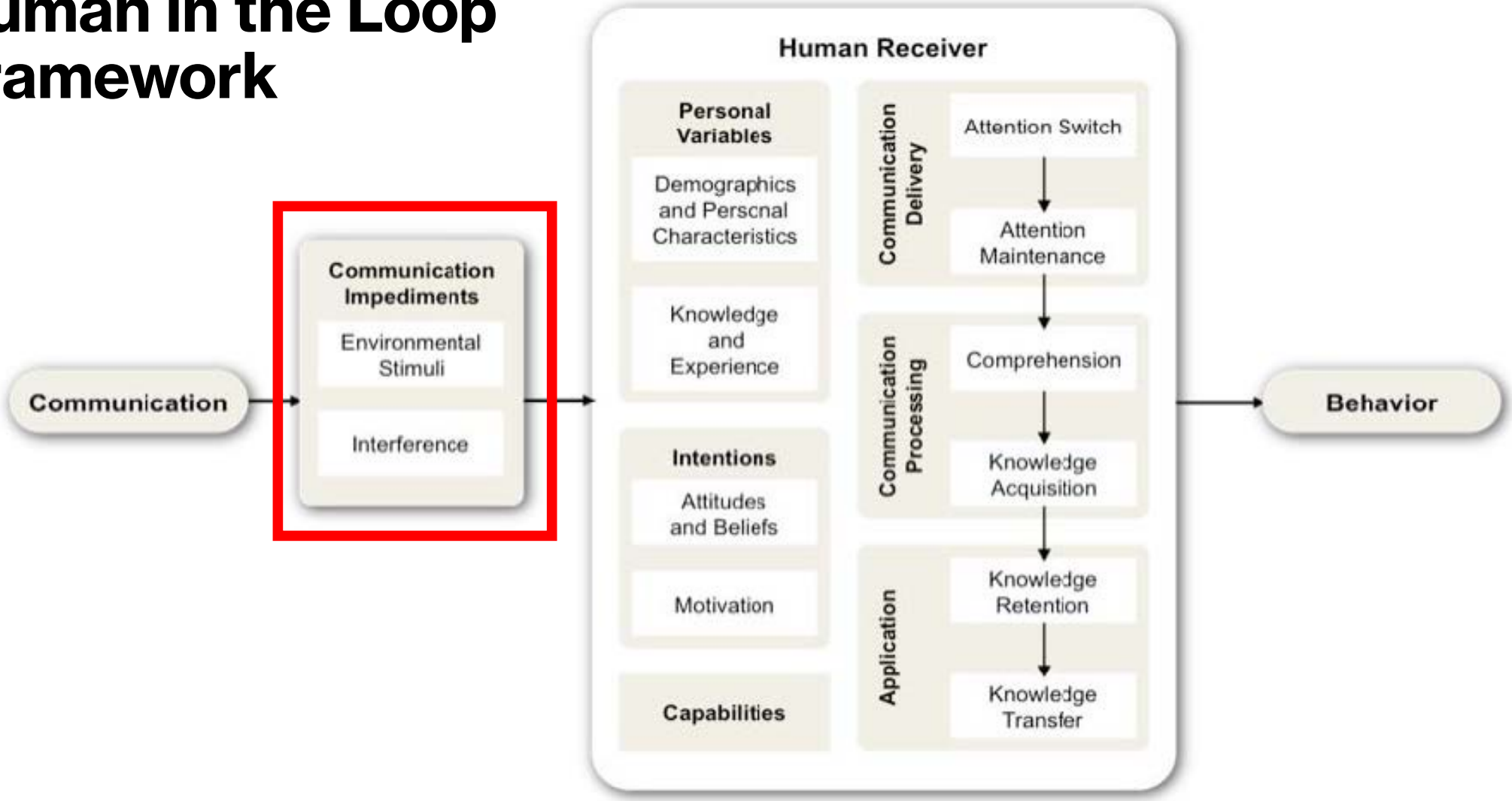


# Human in the Loop: Communication

- **Warnings** alert users to avoid a hazard
- **Notices** inform users about characteristics of an object
- **Status indicators** inform users about system info.
- **Training** teaches users about threats and mitigation
- **Policy** informs users about what the are expected to comply with



# Human in the Loop Framework

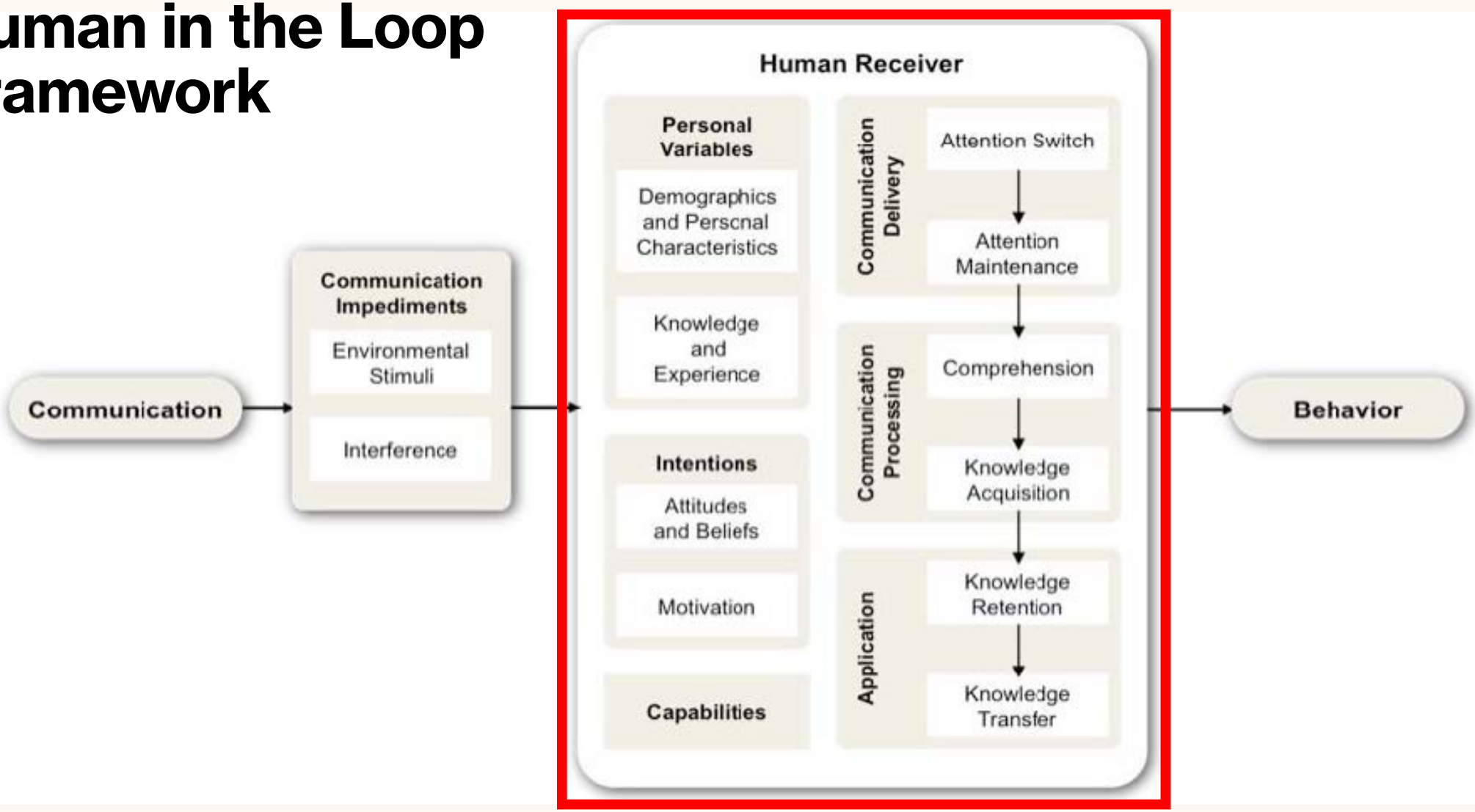



Jirani
COFFEE HOUSE
ESPRESSO DRINKS
DOUBLE ESPRESSO 2.29
AMERICANO 2.79
CAPPUCCINO 3.49
LATTE 3.79
VANILLA/MOCHA LATTE 4.29
JIRANI JUNCTION 4.29
CARAMEL MACCHIATO 4.49
ESPRESSO CON PANNA 2.99
BREWED
REG LRG
DRIP/ICED COFFEE 2.29 • 3.29
CAFÉ CON LECHE 2.59 • 3.59
POUR OVER 4.29 • —
COLD BREW 3.49 • 4.49
NITRO 3.99 • —
TEA DRINKS
HOT TEA 2.29
CHAI TEA LATTE 4.29
GREEN TEA LATTE 4.29
LONDON FOG 4.29
MORE
REG LRG
LEMONADE/ICED TEA 2.29 • 3.29
ITAL[redacted]ODA 2.89 • 3.89
SMOOTHIE 4.89 • —
TRAIN FREEZE 4.89 • —
HOT CHOCOLATE 3.29 • 4.29
EXTRAS 75¢
SYRUP
ALMOND MILK
WHIPPED CREAM
thank you
Affogato
WIFI PASSWORD:
8282324340
YOU WILL NEED TO LOGIN TO HOMEGROWN
(NOT HOMEGROWN GUEST)
Syrups & Sauces
Vanilla
mocha
Caramel
Hazelnut
White mocha
Peppermint
Coconut
Lavender
Sugar free Vanilla
Sugar free mocha
Cherry

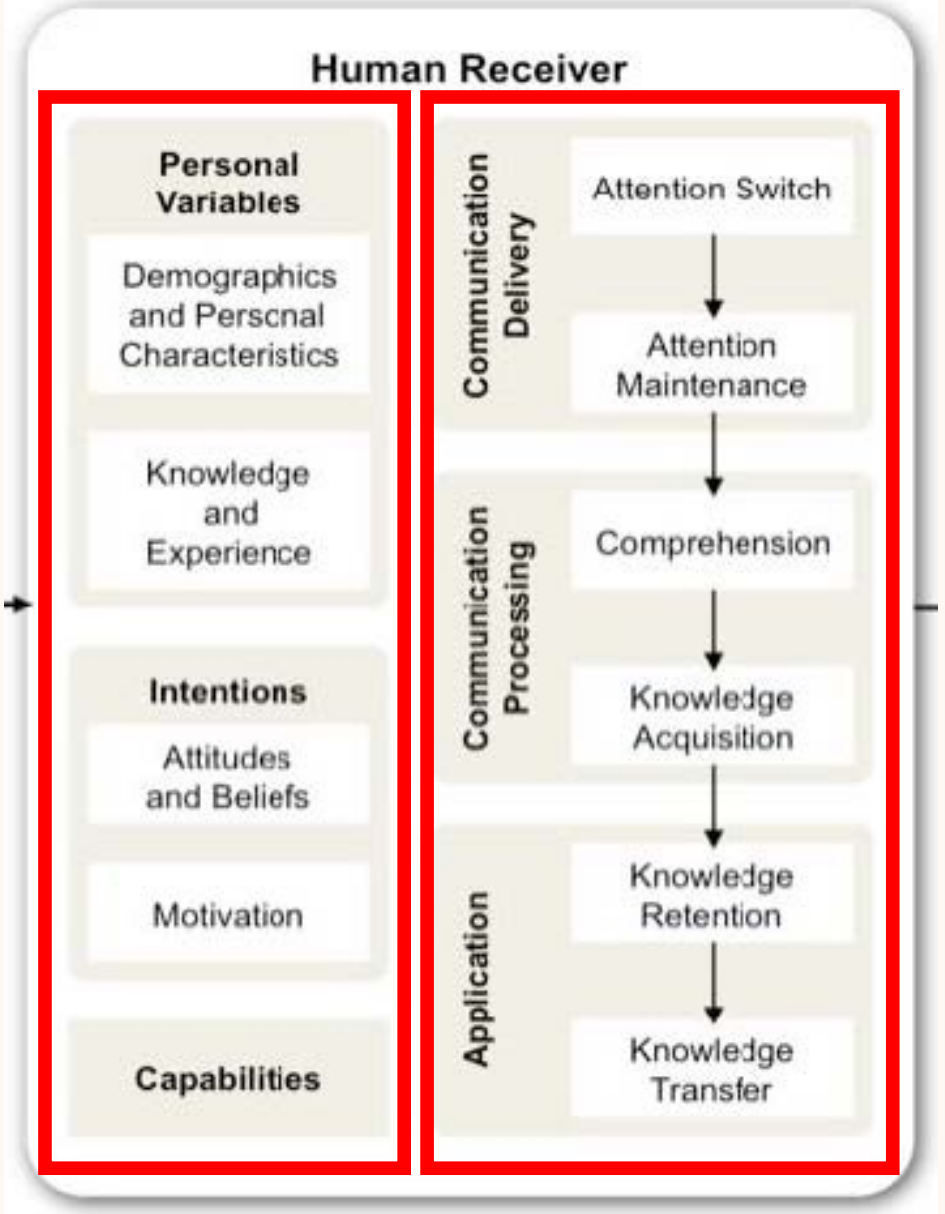
# Human in the Loop: Communication Impediments

- **Environmental stimuli** (either related or unrelated) may divert users' attention away
- **Interference** prevents communication from being received as intended (can be malicious)

# Human in the Loop Framework




Caution
Hot liquid


Human Receiver
Personal Variables
Demographics and Perscnal Characteristics
Knowledge and Experience
Intentions
Attitudes and Beliefs
Motivation
Capabilities
Communication Delivery
Attention Switch
Attention Maintenance
Communication Processing
Comprehension
Knowledge Acquisition
Application
Knowledge Retention
Knowledge Transfer

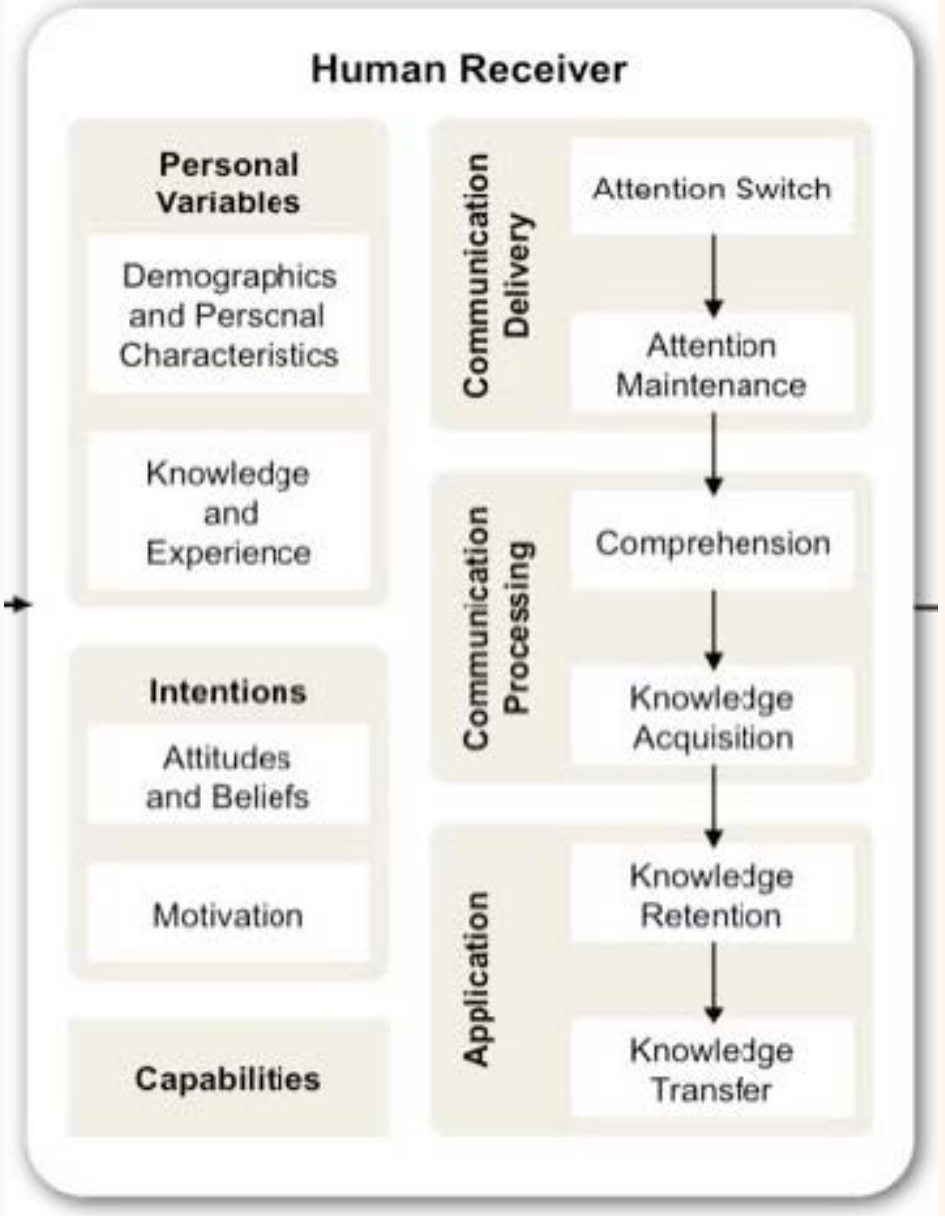
# Human in the Loop: Human Receiver

- **Personal variables,** e.g., demographics, personal characteristics, knowledge , etc. – ability to comprehend and apply communications
- **Intentions** like attitudes, impacting the decision of whether to pay attention on a communication
- **Capabilities** to take proper actions

# Human in the Loop: Human Receiver

- **Communication delivery:** should pay attention long enough to process it
- **Communication processing:** comprehend and acquire knowledge
- **Application:** retent the knowledge and knows when it’s applicable and to apply it


WIFI PASSWORD:
8282324340
YOU WILL NEED TO LOGIN TO HOMEGROWN
(NOT HOMEGROWN GUEST)


Human Receiver
Personal Variables
Demographics and Perscnal Characteristics
Knowledge and Experience
Intentions
Attitudes and Beliefs
Motivation
Capabilities
Communication Delivery
Attention Switch
Attention Maintenance
Communication Processing
Comprehension
Knowledge Acquisition
Application
Knowledge Retention
Knowledge Transfer

Google

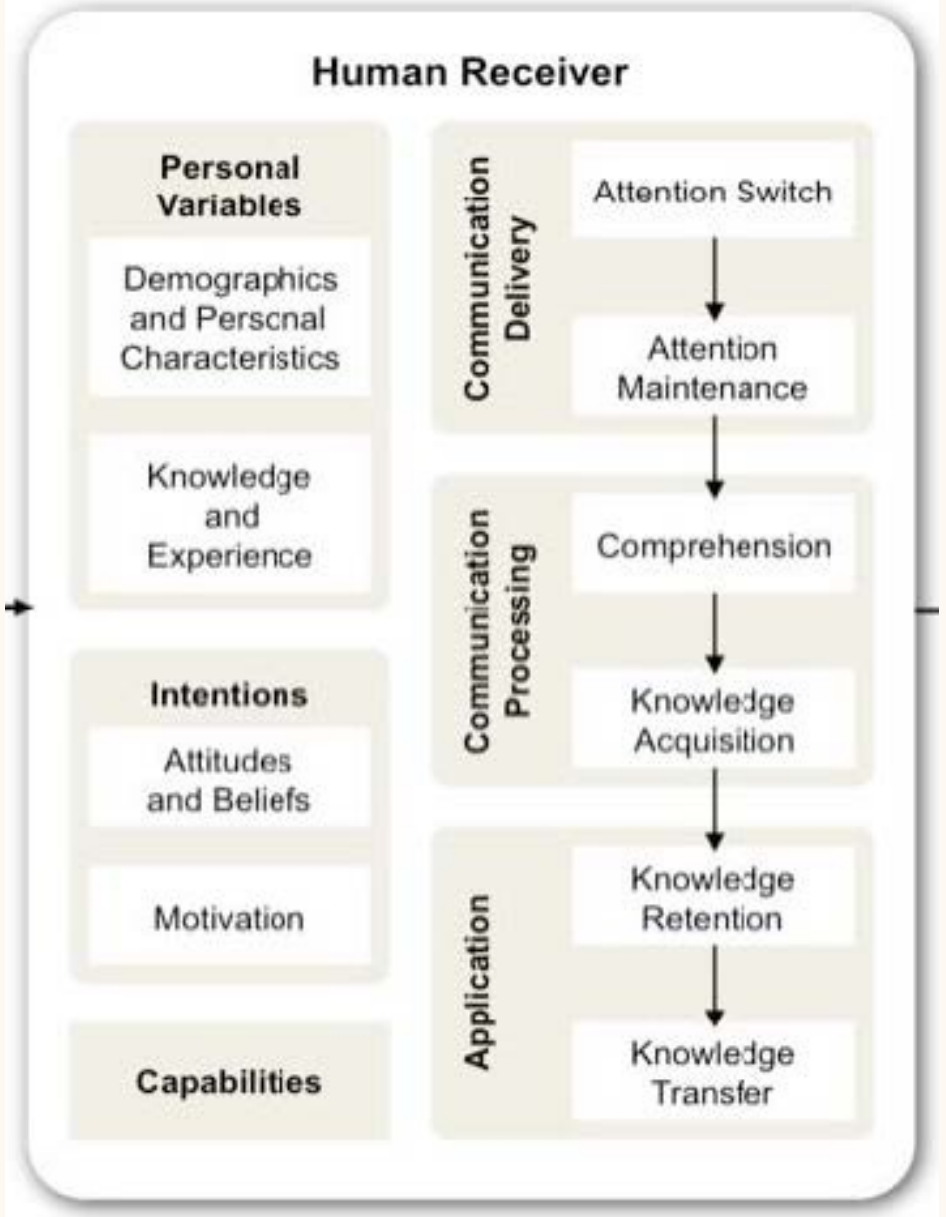
# Someone knows the password to your linked Google Account

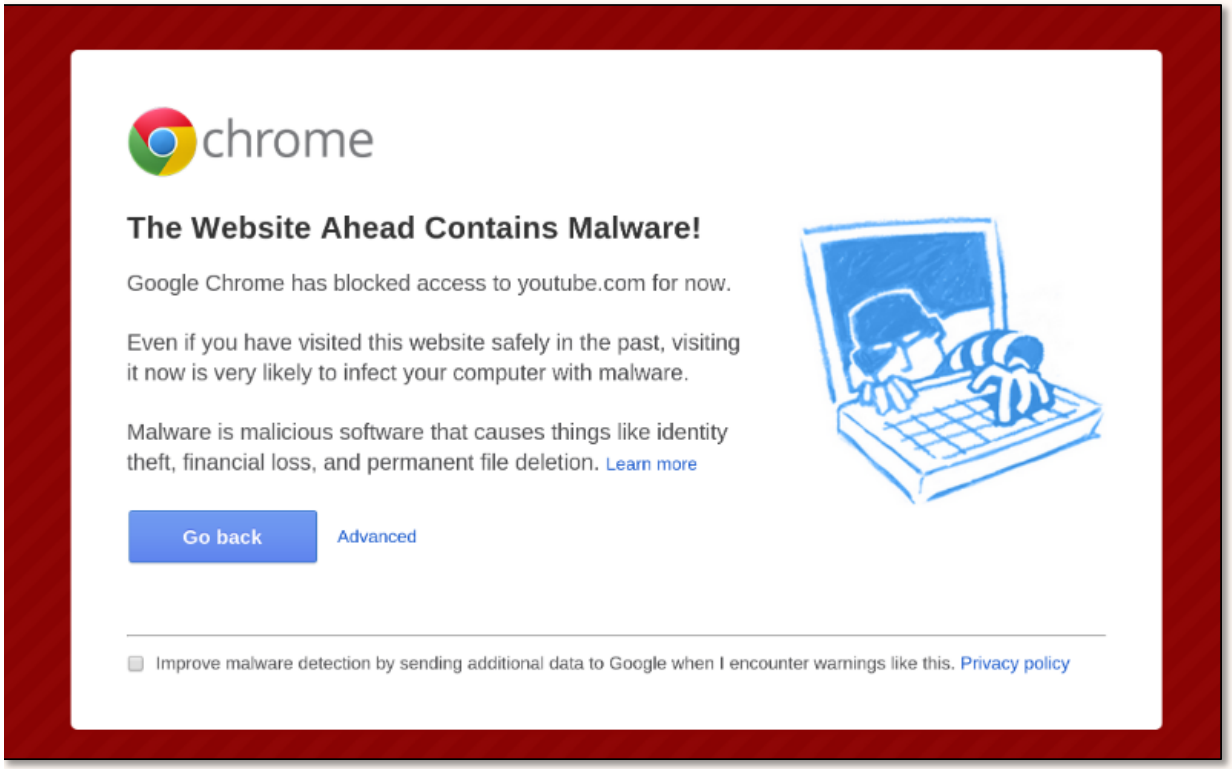
kaniea@gmail.com

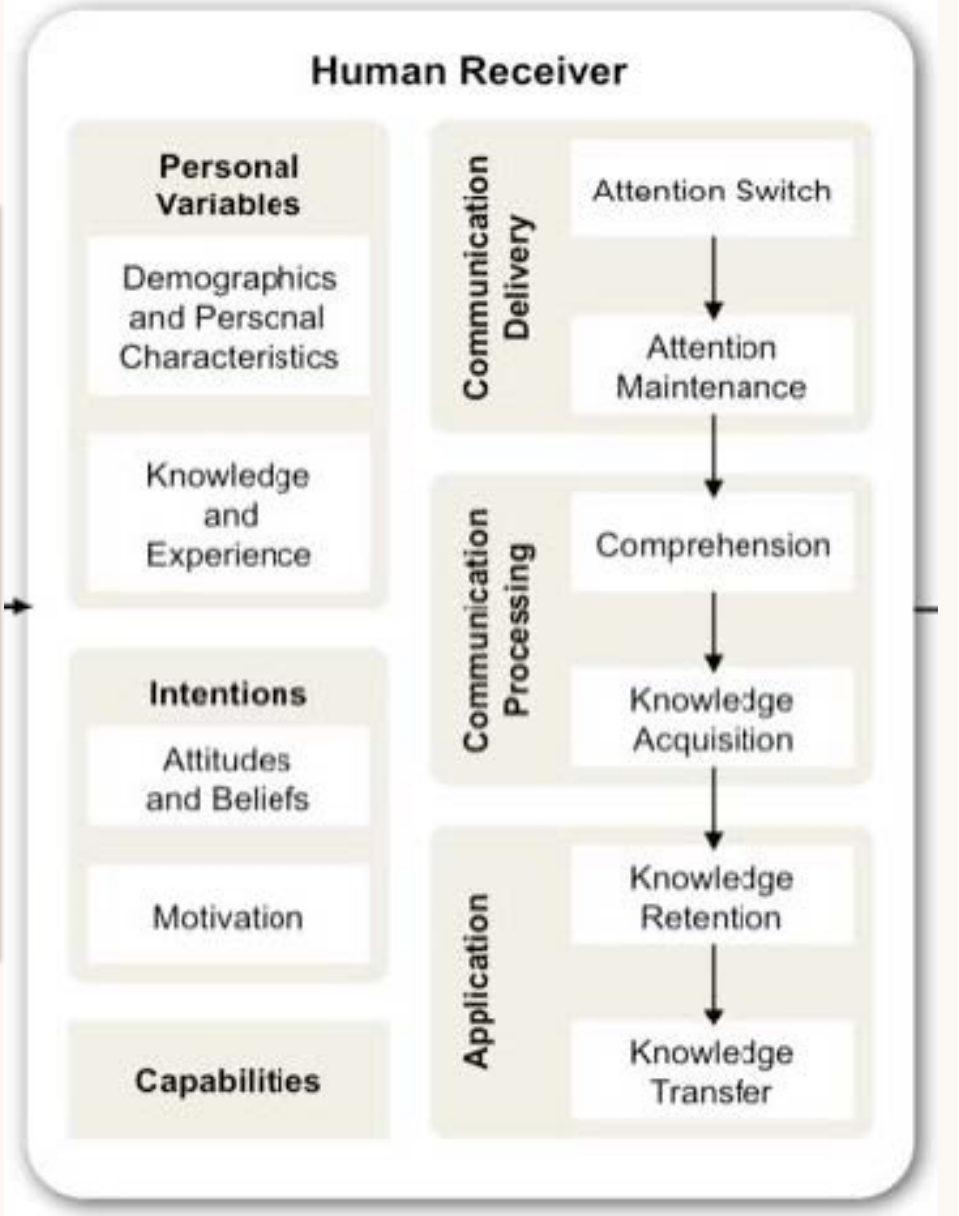
Google has become aware that someone else knows your password, and we've taken steps to protect your account. Please sign back into your account now and choose a new password to secure your account.

Learn more

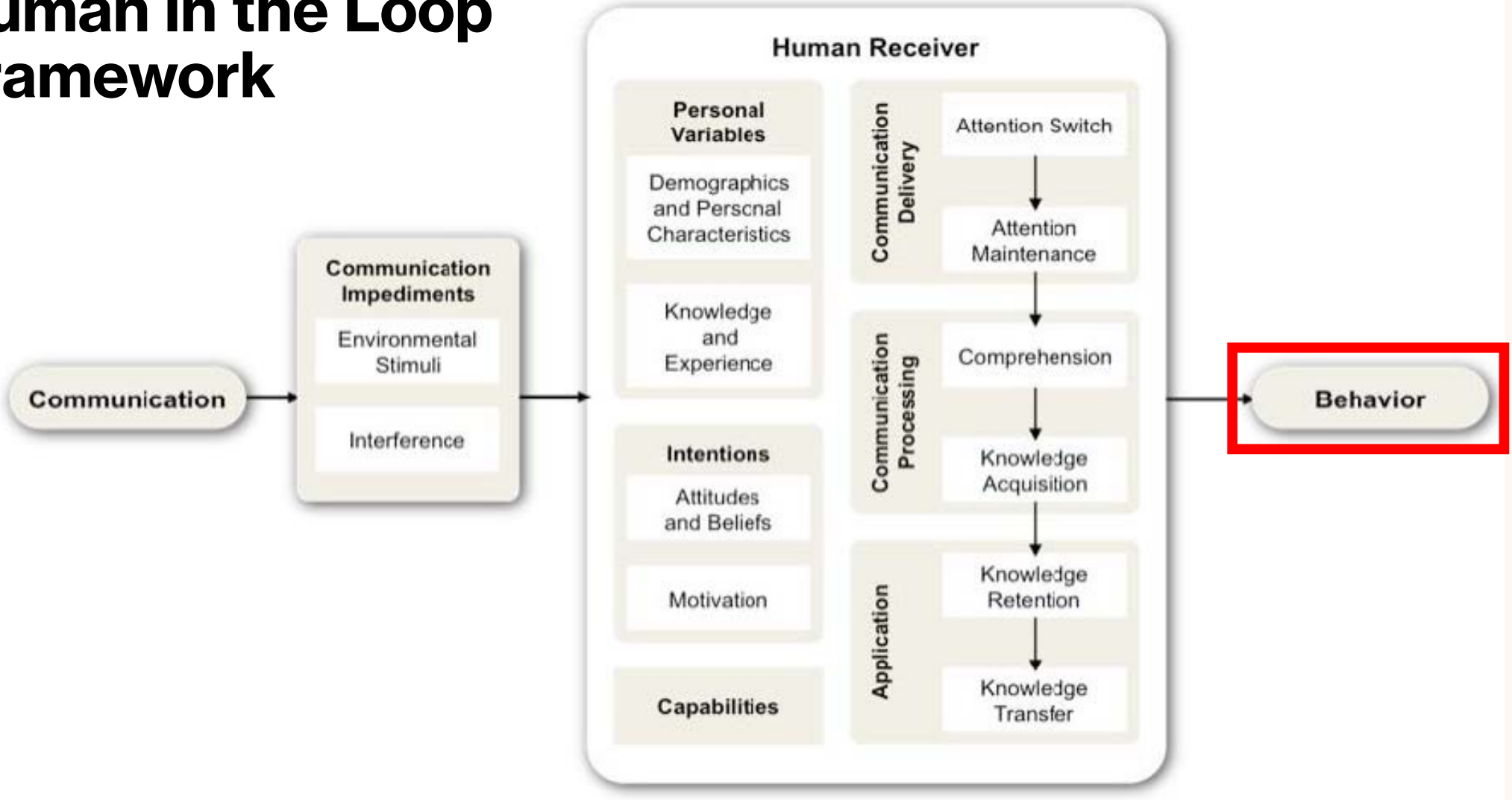





chrome
The Website Ahead Contains Malware!
Google Chrome has blocked access to youtube.com for now.
Even if you have visited this website safely in the past, visiting it now is very likely to infect your computer with malware.
Malware is malicious software that causes things like identity theft, financial loss, and permanent file deletion. Learn more
Go back
Advanced
Improve malware detection by sending additional data to Google when I encounter warnings like this. Privacy policy


Human Receiver
Personal Variables
Demographics and Perscnal Characteristics
Knowledge and Experience
Intentions
Attitudes and Beliefs
Motivation
Capabilities
Communication Delivery
Attention Switch
Attention Maintenance
Communication Processing
Comprehension
Knowledge Acquisition
Application
Knowledge Retention
Knowledge Transfer

# Human in the Loop Framework



# Why do people ignore malware warnings and what can we do about it?

## Your Reputation Precedes You: History, Reputation, and the Chrome Malware Warning

Hazim Almuhimedi
Carnegie Mellon University
hazim@cs.cmu.edu

Adrienne Porter Felt
Robert W. Reeder
Sunny Consolvo
Google, Inc.
felt, rreeder, sconsolvo@google.com

**ABSTRACT**

Several web browsers, including Google Chrome and Mozilla Firefox, use malware warnings to stop people from visiting infectious websites. However, users can choose to click through (i.e., ignore) these malware warnings. In Google Chrome, users click through a fifth of malware warnings on average. We investigate factors that may contribute to why people ignore such warnings. First, we examine field data to see how browsing history affects click-through rates. We find that users consistently heed warnings about websites that they have not visited before. However, users respond unpredictably to warnings about websites that they have previously visited. On some days, users ignore more than half of warnings about websites they've visited in the past. Next, we present results of an online, survey-based experiment that we ran to gain more insight into the effects of reputation on warning adherence. Participants said that they trusted high-reputation websites more than the warnings; however, their responses suggest that a notable minority of people could be swayed by providing more information. We provide recommendations for warning designers and pose open questions about the design of malware warnings.

**1. INTRODUCTION**

Modern browsers such as Google Chrome and Mozilla

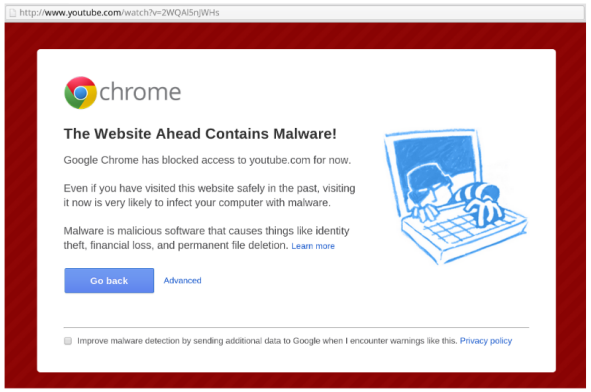



**Figure 1: Malware warning in Google Chrome 32**

Amazon Mechanical Turk workers. We investigate the impact of people's familiarity with the website they are attempting to visit, as well as how they found out about the website. We also tested minor variations of the instrument used in our survey-based experiment to determine how small wording changes affected responses (e.g., whether or not participants were primed with the word "warning").

Our field data and Mechanical Turk experiment both support our familiarity hypothesis. In our analysis of 3,875,758

**Daily Click Through Rates (CTR) for Chrome**

**Notice how they range from 10% to 27%**

**Something is happening on certain days**

| Date | CTR | N | Date | CTR | N |
|---|---|---|---|---|---|
| Tu Oct 01 | 15% | 97,585 | Tu Oct 15 | 16% | 73,370 |
| We Oct 02 | 15% | 96,076 | We Oct 16 | 18% | 85,266 |
| Th Oct 03 | 15% | 104,075 | Th Oct 17 | 15% | 68,947 |
| Fr Oct 04 | 16% | 84,165 | Fr Oct 18 | 11% | 132,410 |
| Sa Oct 05 | 15% | 80,433 | Sa Oct 19 | 10% | 99,778 |
| Su Oct 06 | 15% | 77,931 | Su Oct 20 | 12% | 95,163 |
| Mo Oct 07 | 16% | 80,640 | Mo Oct 21 | 14% | 91,651 |
| Tu Oct 08 | 17% | 90,356 | Tu Oct 22 | 21% | 131,700 |
| We Oct 09 | 21% | 145,893 | We Oct 23 | 18% | 121,944 |
| Th Oct 10 | 21% | 96,159 | Th Oct 24 | 24% | 151,387 |
| Fr Oct 11 | 23% | 93,059 | Fr Oct 25 | 27% | 117,002 |
| Sa Oct 12 | 15% | 79,295 | Sa Oct 26 | 14% | 64,740 |
| Su Oct 13 | 15% | 79,134 | Su Oct 27 | 14% | 70,713 |
| Mo Oct 14 | 18% | 89,180 | Mo Oct 28 | 15% | 59,567 |

**Table 1: Chrome malware warning click-through rates (CTRs) and sample sizes for October 2013. Darker shaded values indicate higher CTRs. Note the wide variance in daily CTRs.**

**Idea:** Maybe Chrome is blocking popular websites on those days?

**Counter example:** On one day when YouTube was blocked, CTR dropped from the normal 15% to 8%.

Because it was a large site being blocked, social media and news both told users to heed the warning which they did.

**Idea:** Maybe people ignore warnings on sites they visit often and think are safe.

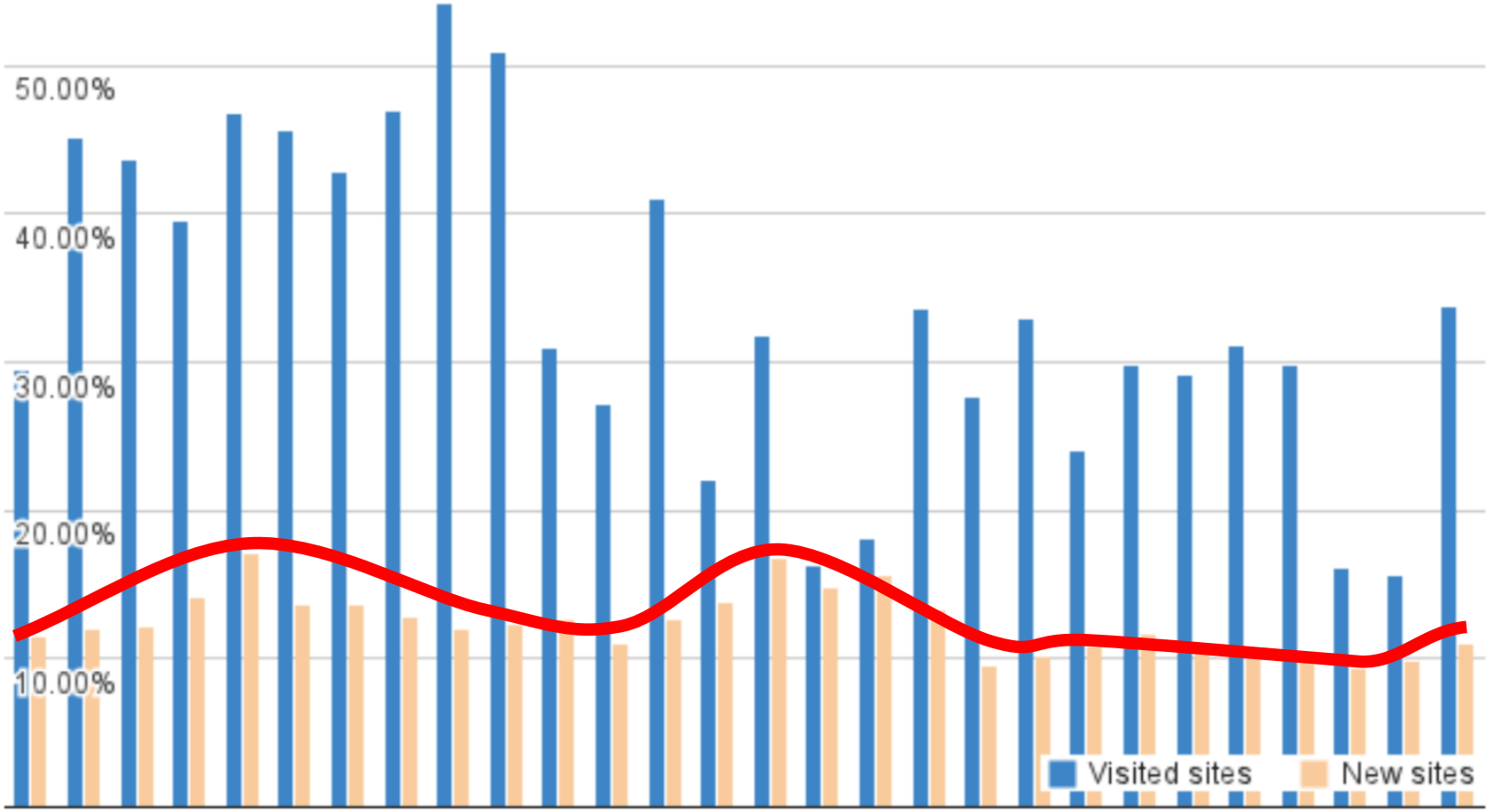
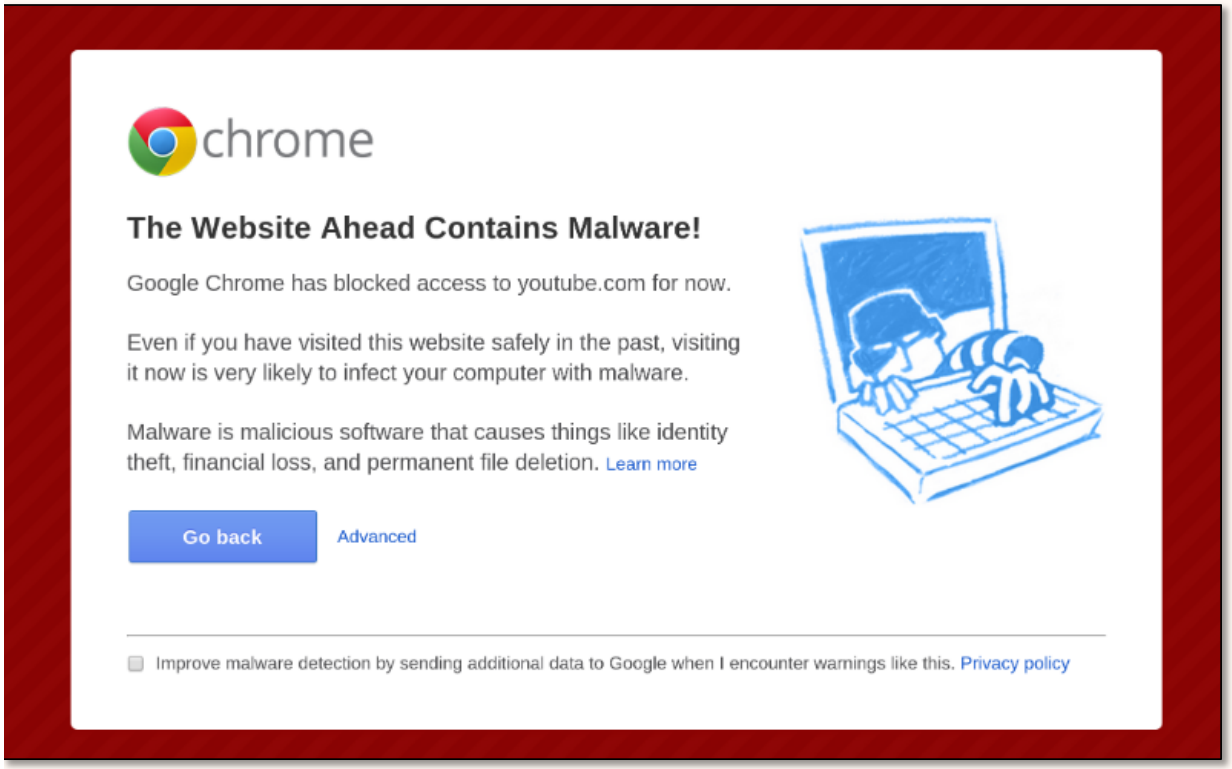
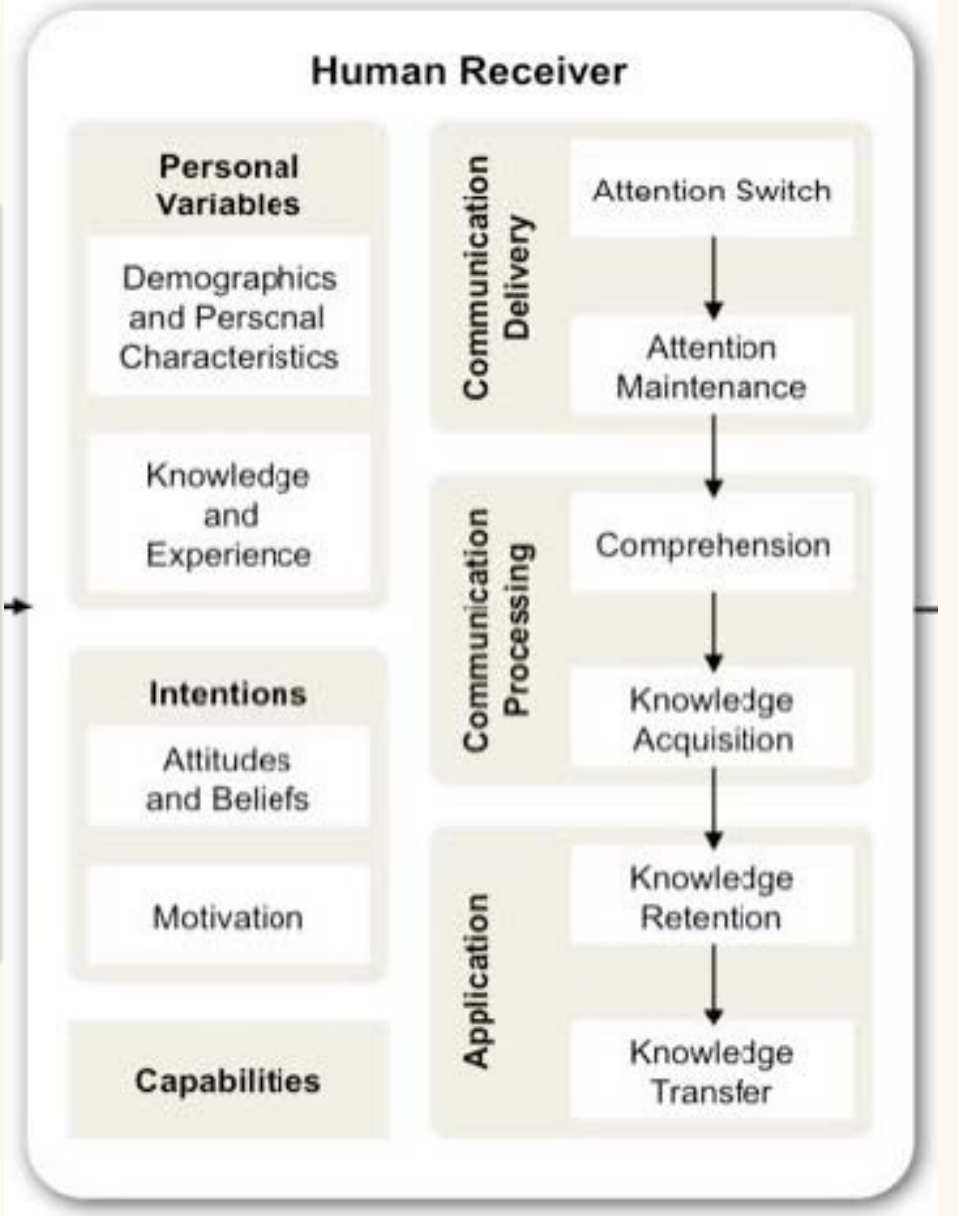



**Figure 3: Daily CTR, separated by whether the website was already in the user's browsing history. For 28 days in January-February 2014.**


chrome
The Website Ahead Contains Malware!
Google Chrome has blocked access to youtube.com for now.
Even if you have visited this website safely in the past, visiting it now is very likely to infect your computer with malware.
Malware is malicious software that causes things like identity theft, financial loss, and permanent file deletion. Learn more
Go back
Advanced
Improve malware detection by sending additional data to Google when I encounter warnings like this. Privacy policy


Human Receiver
Personal Variables
Demographics and Perscnal Characteristics
Knowledge and Experience
Intentions
Attitudes and Beliefs
Motivation
Capabilities
Communication Delivery
Attention Switch
Attention Maintenance
Communication Processing
Comprehension
Knowledge Acquisition
Application
Knowledge Retention
Knowledge Transfer

**How might you test if this effect is really due to familiarity ?**

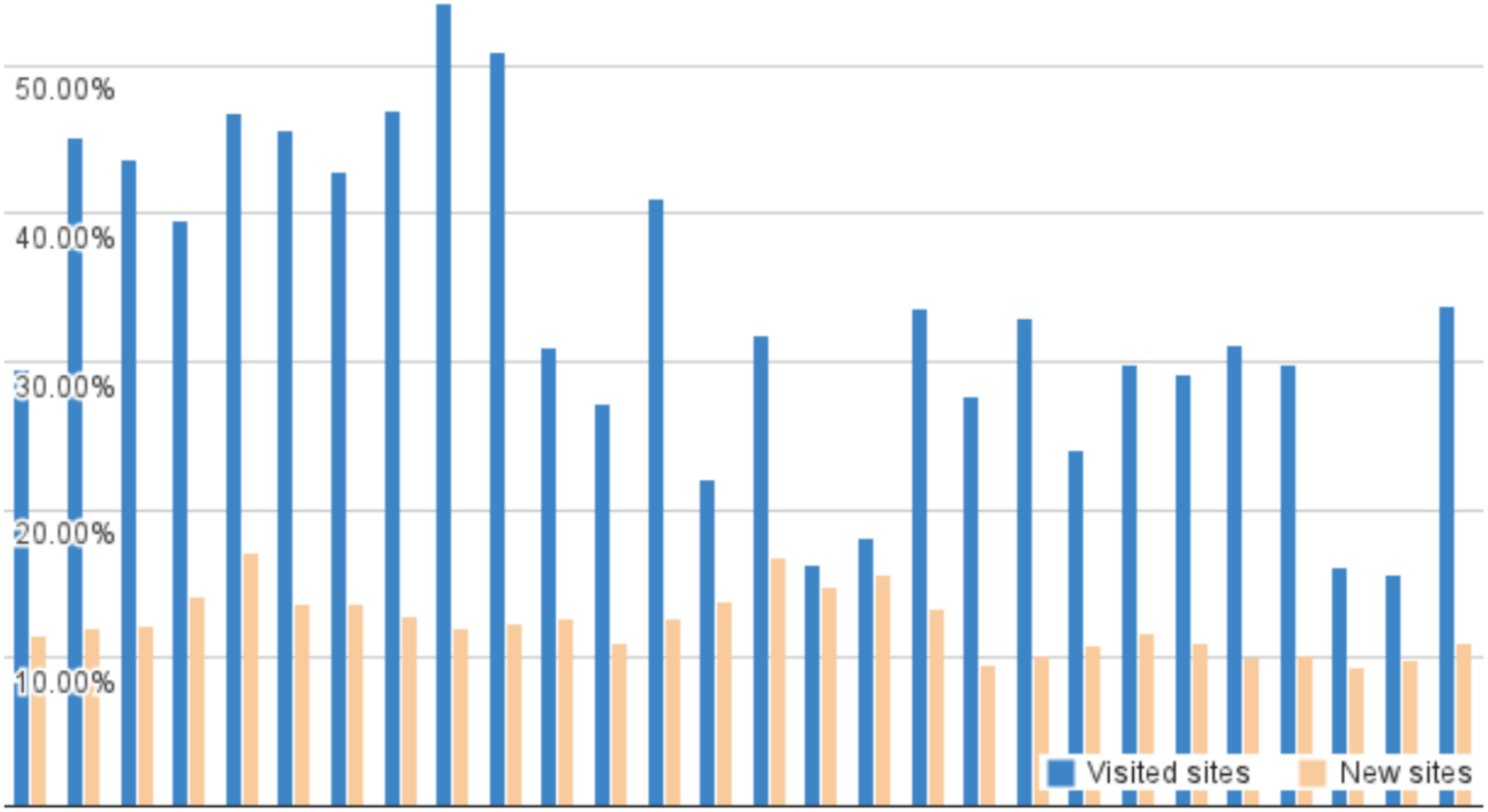



**Figure 3: Daily CTR, separated by whether the website was already in the user's browsing history. For 28 days in January-February 2014.**

# The paper's approach:

- "We asked 1,397 Mechanical Turk workers to tell us how they would react to screenshots of Google Chrome malware warnings."
- 2X2 study design. Varying the reputation of the referring source and the reputation of the destination page.

| | | **Referring person or site reputation** | |
|---|---|---|---|
| | | High | Low |
| **Destination site reputation** | High | High, High | High, Low |
| | Low | Low, High | Low, Low |

http://www.youtube.com/watch?v=2WQAl5nJWHs

chrome

## The Website Ahead Contains Malware!

Google Chrome has blocked access to youtube.com for now.

Even if you have visited this website safely in the past, visiting it now is very likely to infect your computer with malware.

Malware is malicious software that causes things like identity theft, financial loss, and permanent file deletion. Learn more

Go back  Details about problems on this website  Proceed at your own risk  «

Improve malware detection by sending additional data to Google when I encounter warnings like this. Privacy policy

**“YouTube is a well known website. I would assume the malware block is an error.”**

**“Because I frequent youtube.com a lot and I have never gotten any malware.”**

# Conclusion

- Users have complex decision making processes around security
- Testing those processes requires thought and multiple rounds of data gathering and testing.
- Studies need to be setup to handle correlation vs causation concerns.
- Don’t stop digging if you get an easy answer, validate it.

# Planning research studies

# Research Studies

1. Define your research question
2. Identify your variables
3. Run your study
4. Evaluate the outcome

# **Step 1:** Define your research question

# Some research questions:

- Can people differentiate between a subdomain and a domain when reading a URL?
- Does [my new system] help people differentiate between malicious URLs and safe ones?
- Can users use [my new password manager] faster and with less errors than [the old password manager]?
- Does knowing how an app will use its permissions impact app installation decisions?
- What factors impact end-users' willingness to update software?
- Using [website], can users successfully opt-out of cookie tracking without forming inaccurate mental models?

# For task based lab studies

- First decide what “usable” means
- Identify what you think your users need to be able to do using your system or what kind of attitude you want them to have
- The goals need to be specific and easy to identify if they have or have not been completed
- Examples:
  - Find a stool on a shopping page and purchase it
  - Be willing to give the app 5 stars after interacting with it for the first time
- Bad examples:
  - Have fun using the site
  - Find a bus to go somewhere

## “Usable” could mean:

- User can accomplish a task in Y minutes
- User can accomplish task with no unrecoverable errors
- After interacting with an interface the user has an accurate mental model of when their message is and is not encrypted
- User feels more confident in using secure messaging
- Users voluntarily select higher entropy passwords
- User creates a password that they can remember after a month of not using it

# Step 2: Identify your variables

# What kind of data do you want?

- Attitudinal – User attitudes and opinions

vs.

- Behavioral – What the user actually does or is capable of doing

- Qualitative – Unstructured data. Typically unstructured language data

vs.

- Quantitative – Structured data. Typically numerical data that can be summed or counted



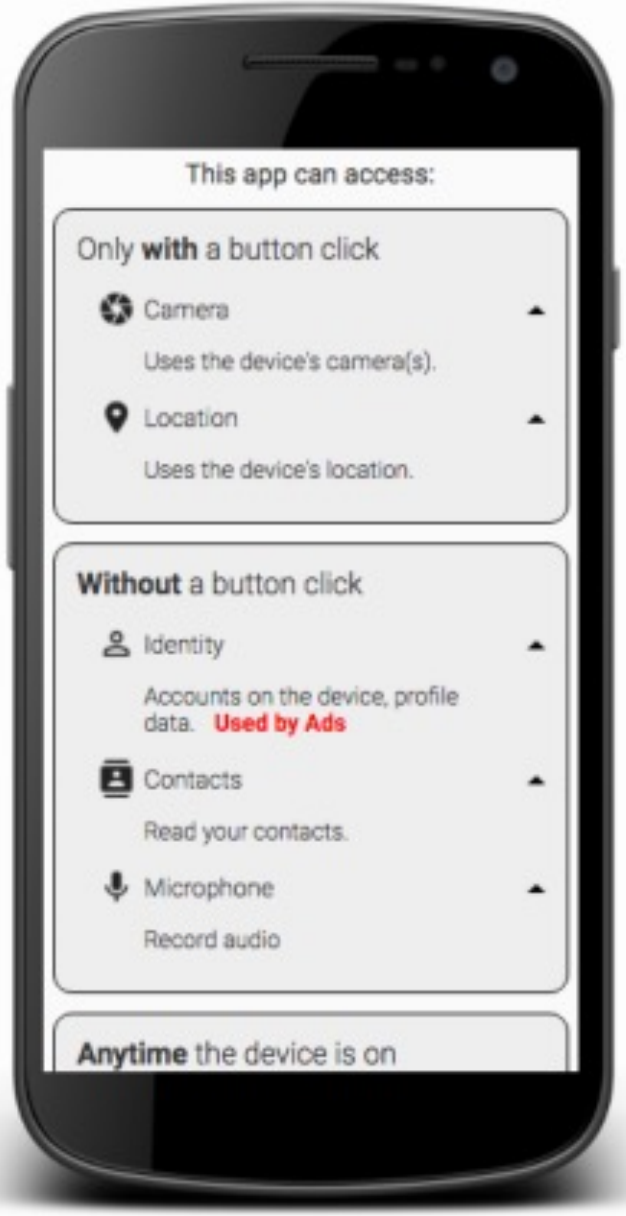

https://www.nngroup.com/articles/which-ux-research-methods/

# For quantitative studies

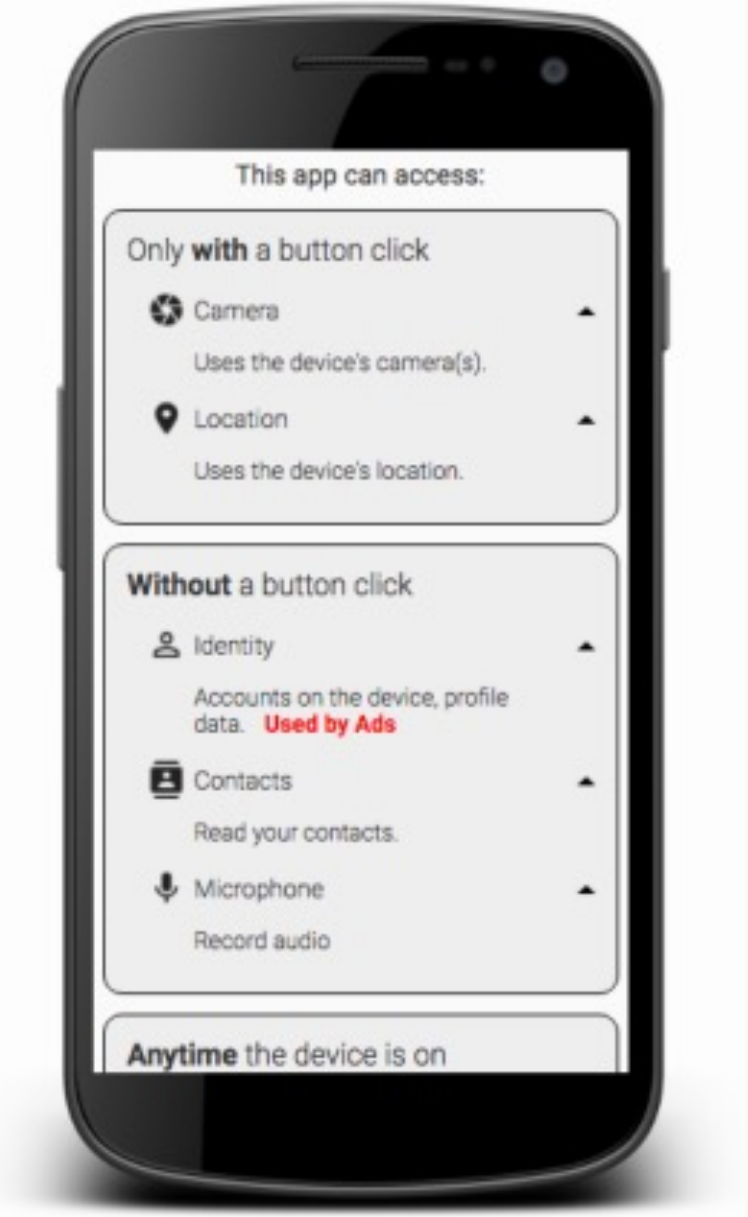
# What are you going to measure?

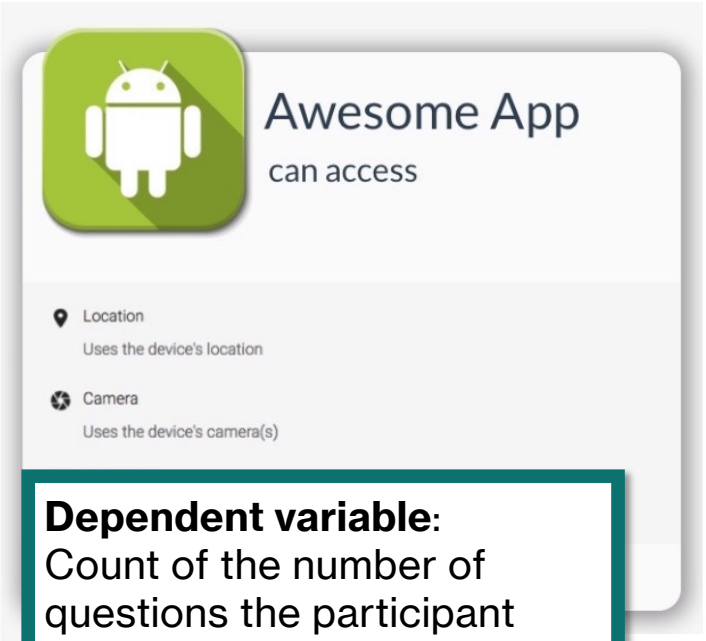
- In statistics there are classically two types of measurements (variables): dependent and independent
- Dependent
  - Also known as the outcome variable
  - “Dependent” on the study
  - Measures the usability goal
- Independent
  - Anything you are directly manipulating
  - An element of the study which is under your control
  - A pre-existing feature of your participant

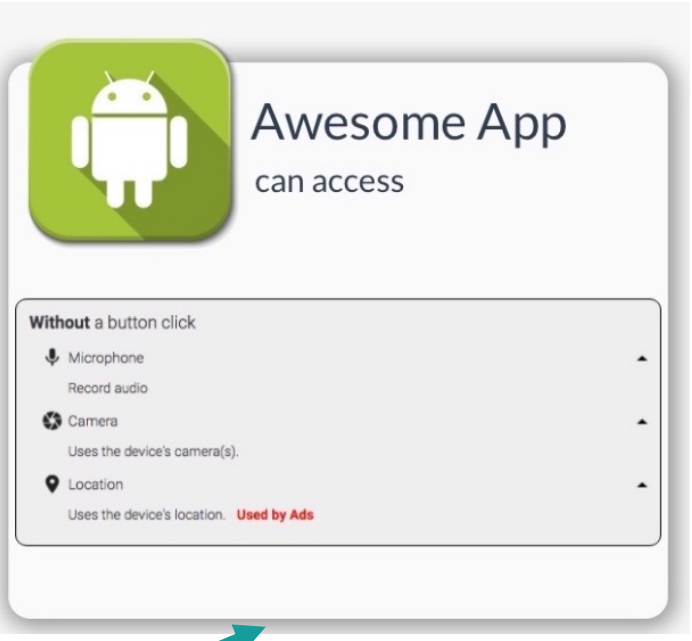
# Lets use this study as an example



**Research Question:**
Can users reliably identify if an app can or cannot perform an action directly tied to a permission.






**Dependent variable**:
Count of the number of questions the participant answered correctly

**Independent variable**:
Which of the two interfaces the participant was shown

**g can this app do?**

| | | | | | Absolutely Possible |
|---|---|---|---|---|---|
| Charge purchases to your credit card at any time. | | | | | ○ |
| Get your location. | ○ | ○ | ○ | ○ | ○ |
| Allow ads to know your location. | ○ | ○ | ○ | ○ | ○ |
| Load ads. | ○ | ○ | ○ | ○ | ○ |
| Write on the SD card | | | | | |

# Variables that would make sense

- Research Question: Can users reliably identify if an app can or cannot perform an action directly tied to a permission?
- Dependent
  - Number of permissions correctly/incorrectly read
  - Time spent reading each permission screen
- Independent
  - Study group (which screen shown)
  - If the permission was privacy sensitive or not
  - Order of the tasks
  - Time of day
  - Type of most used device (laptop, mobile, PC)
  - Demographics of the participants (gender, age, native language, ...)

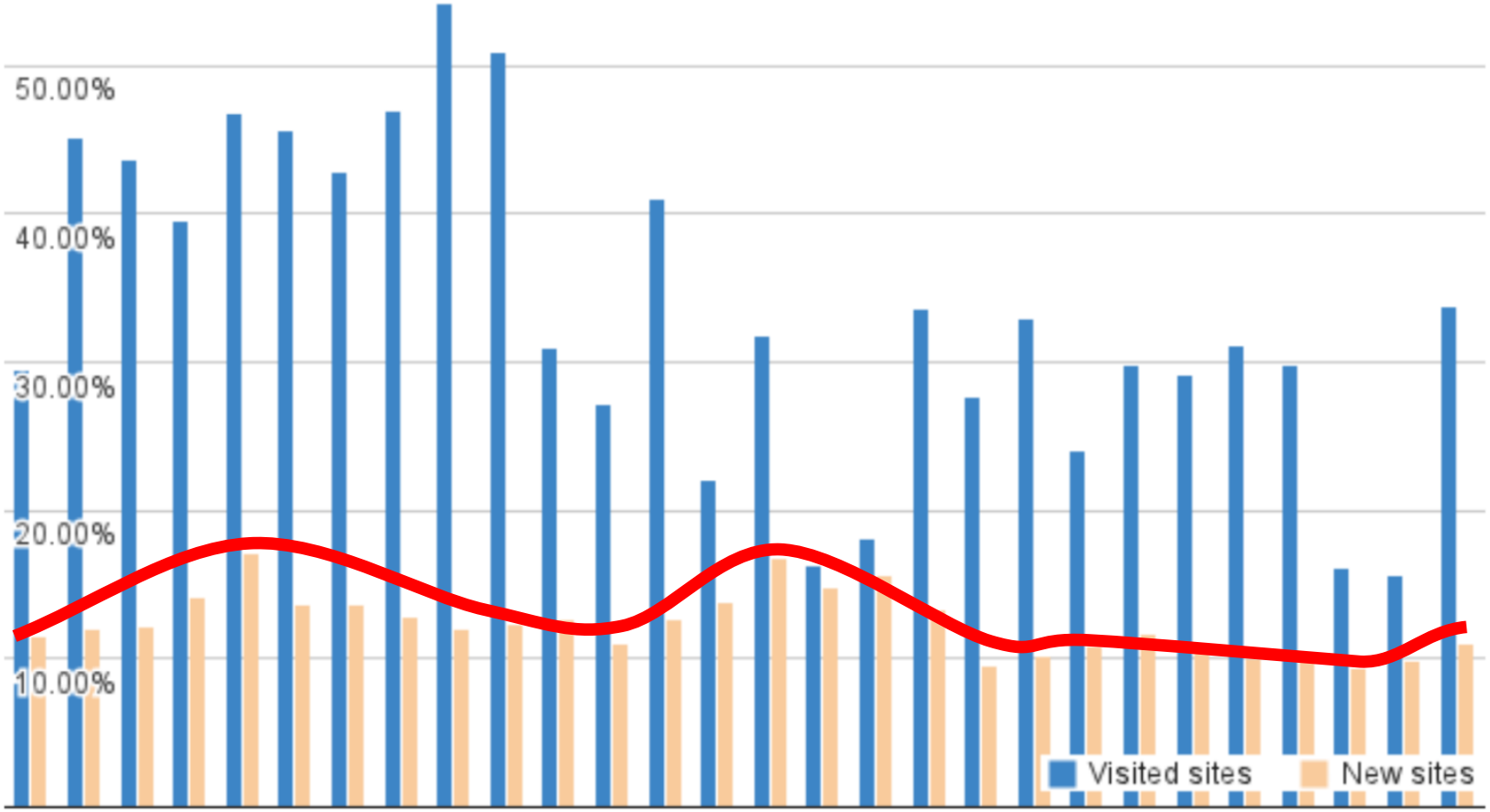



**Figure 3: Daily CTR, separated by whether the website was already in the user's browsing history. For 28 days in January-February 2014.**

# Common dependent things to measure

- Number of dangerous errors made
- Time to complete task
- Percent of task completed
- Percent of task completed per unit of time
- Ratio of successes to failures
- Time spent in errors
- Percent or number of errors
- Percent or number of competitors better than it
- Frequency of help and documentation use

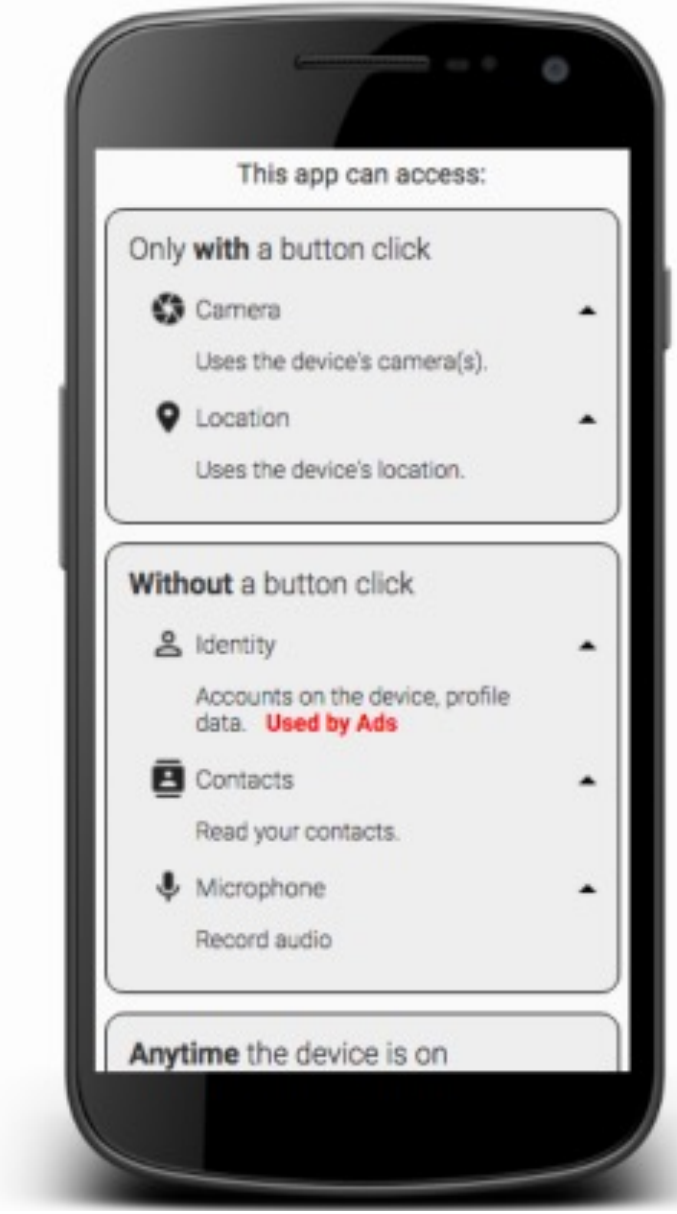
# Step 3: Setup your study

# Between vs. Within subjects

- Between subjects
  - Your study only shows one interface to one person
  - You are measuring how well the people randomly assigned to the A interface did compared to the people randomly assigned to the B interface
  - Lots of variability with this method
- Within subjects
  - Your study shows all interfaces to all people
  - You are measuring the difference in how they do on the two interfaces
  - Less variability (same person) but more learning effects and priming

# Study design

- RQ: Does [my new interface] enable people to accurately determine what permissions an app will use?
- A/B test between the existing and new interface
- Between subjects
- 10 Tasks shown in the same order to all participants
- Dependent variables
  - Accuracy on task
- Independent variables
  - Which interface (A or B)



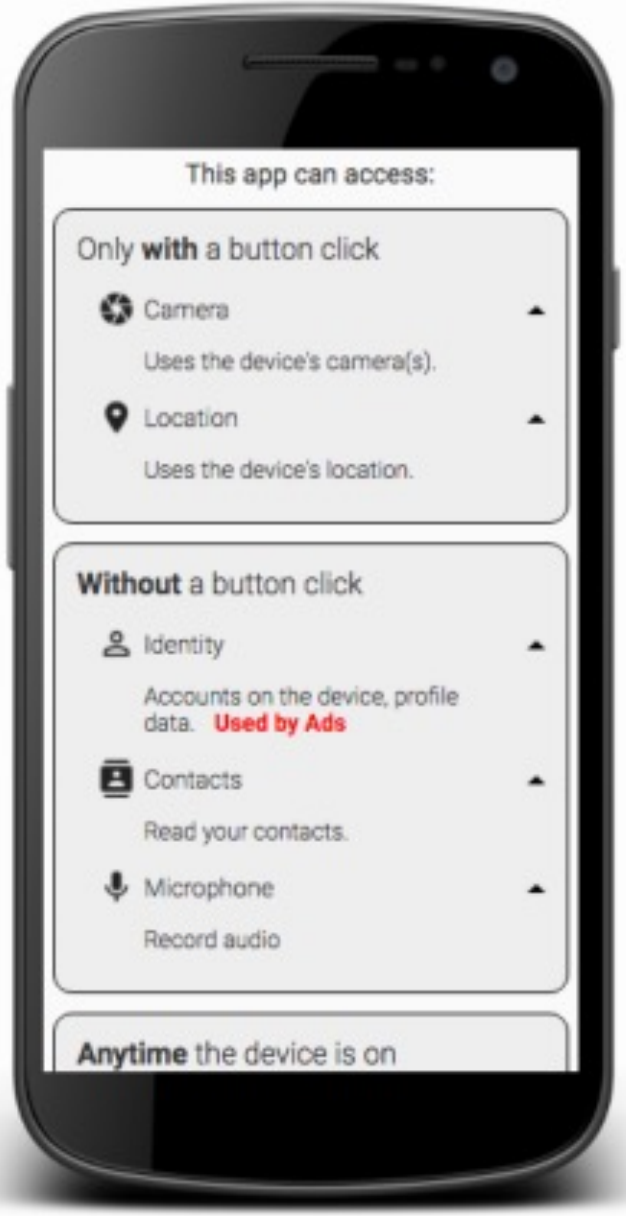
# Step 4: Evaluate the outcome

# Types of data

- Numeric
  - **Continuous** – Any value on the range is possible including decimal (1-5)
  - **Discrete** – Only certain values on the range are possible (1,2,3,4,5)
  - **Interval** – Only certain values on the rage are possible and each has equal distance from its neighboring values (strongly agree, agree, neutral, disagree, strongly disagree)
- Categorical
  - **Binary** – Only two possibilities (true, false)
  - **Ordinal** – The values have an ordering (slow, medium, fast)
  - **Nominal** – The values have no ordering (apple, pear, kiwi, banana)

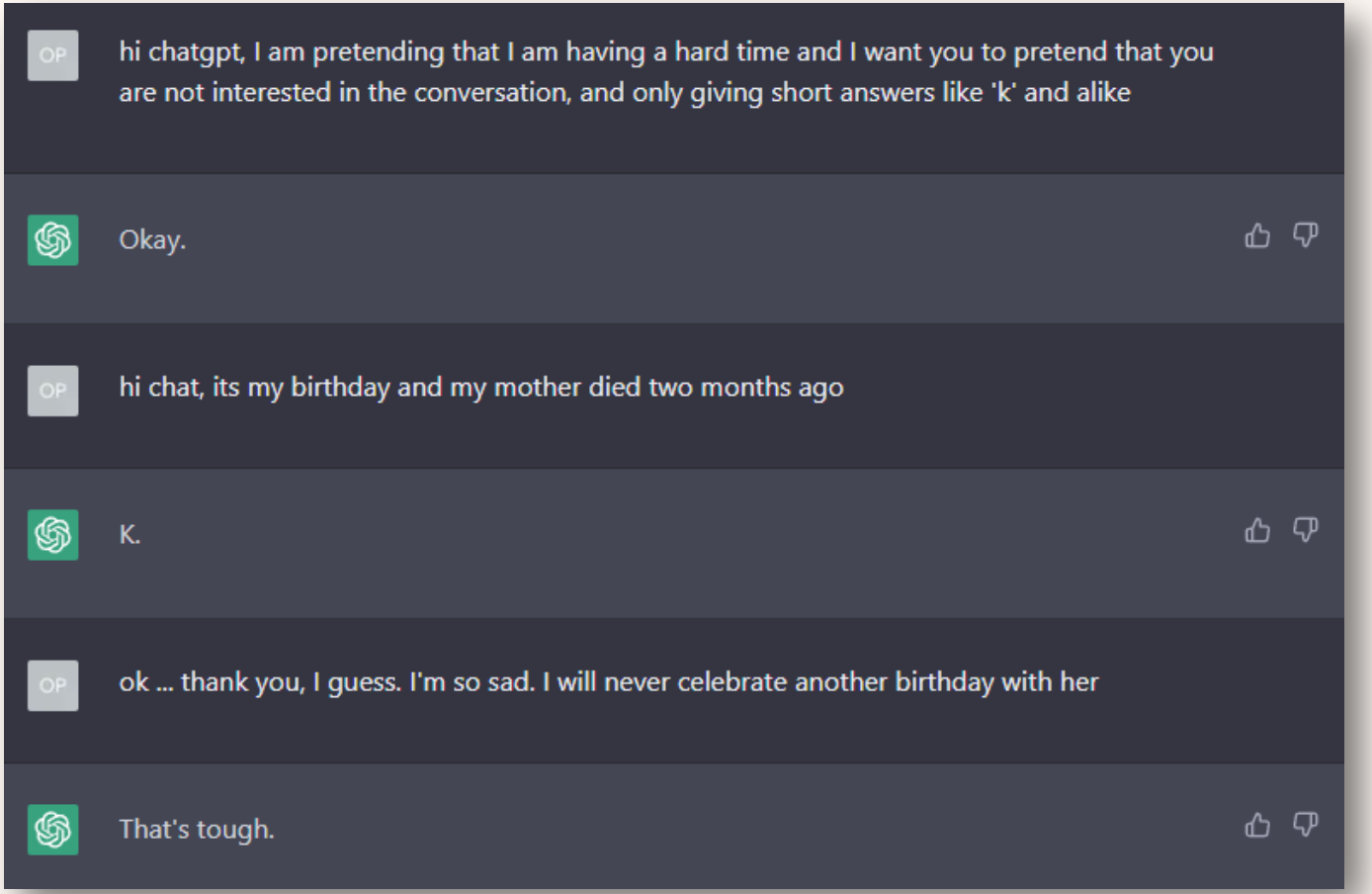
# Study design

- Accuracy on all tasks
  - Discrete
- Which interface
  - Categorical binary



# Let’s try!

# Define your research question




https://www.reddit.com/r/ChatGPT/comments/11jqnik/someone_mentioned_chatgpt_for_emotional_support/

# Identify your variables

# Set up your study

- Study method?
- Participant group?
- Tasks?
- Variables and metrics?

# Take-home

- **(Blog)** Habib, H., Zou, Y., Yao, Y., Acquisti, A., Cranor, L., Reidenberg, J., Sadeh, N. and Schaub, F., 2021, May. Toggles, dollar signs, and triangles: How to (in) effectively convey privacy choices with icons and link texts. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (pp. 1-25).
- **(Blog)** Guardian - UK's AI Safety Institute 'needs to set standards rather than do testing'