Evaluating Programming Languages and Tools in Studies with Human Participants

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Motivation

- Evaluate the **usability** of a programming language feature or tool for developers
    - usually productivity effects
- Given a context, what is effect on developer productivity

Challenges

- How many **participants** do I need?
- Is it ok to use students?
- What do I **measure**? How do I measure it?
- What's an IRB?
- Should I train participants?
- What **tasks** should I pick?

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A Practical Guide to Controlled Experiments Evaluating Software Engineering Tools with Human Participants

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Abstract Empirical studies, often in the form of controlled experiments, have been widely adopted in software engineering research as a way to evaluate the merits of new software engineering tools. However, controlled experiments involving *human* participants *using* new tools remain rare. When they are conducted, some have serious validity concerns. Recent research has also shown that many software engineering researchers view this form of tool evaluation as too risky and difficult to conduct, as it might ultimately lead to inconclusive or negative results. In this paper, we aim to help researchers design studies that minimize these risks and increase the quality of controlled experiments with developers by offering practical methodological guidance. We explain, from a practical perspective, options in the recruitment and selection of human participants, informed consent, experimental procedures, demographic measurements, group assignment, training, the selection and design of tasks, the measurement of common outcome variables such as success and time on task, and study debriefing. Throughout, we situate this guidance in the results of a new systematic review of the 345 tool evaluations with human participants that were reported in over 1,700 software engineering papers published from 2001-2011.

Keywords *Research methodology, tools, human participants, human subjects, experiments.*

1. Introduction

Over the past three decades, empirical studies have become widely accepted as a way to evaluate the strengths and weaknesses of software engineering tools (Zannier et al. 2006, Basili et al. 1986, Basili 1993, Basili 2007, Rombach et al. 1992, Fenton 1993, Tichy et al. 1995, Basili

[CodeExchange Supporting Reformulation of Internet-Scale Code Queries in Context]
Lee Martie, Thomas D. LaToza, and André van der Hoek
ASE 2015: International Conference on Automated Software Engineering
Introduces an online system for code search incorporating context and query reformulation and provides evidence for its value through a laboratory study and field deployment.
full paper (acceptance rate: 21%) **live site**

Ask the crowd: scaffolding coordination and knowledge sharing in microtask programming
Thomas D. LaToza, Arturo Di Lecce, Fabio Ricci, W. Ben Towne, André van der Hoek
VL/HCC 2015: Symposium on Visual Languages and Human-Centric Computing
Introduces a system for explicitly coordinating and sharing knowledge by asking, answering, and discussing questions about design decisions in code and reports evidence from a 30 hr crowd programming session.
short paper **local pdf**

Borrowing from the crowd: a study of recombination in software design competitions
Thomas D. LaToza, Micky Chen, Luxi Jiang, Mengyao Zhao, and André van der Hoek
ICSE 2015: International Conference on Software Engineering
Reports findings from an architecture and user experience design competition, examining where and how borrowing ideas from other designs helps to improve software designs.
full paper (acceptance rate: 19%) **local pdf, materials and data**

How software designers interact with sketches at the whiteboard
Nicolas Mangano, Thomas D. LaToza, Marian Petre, and André van der Hoek
TSE: Transactions on Software Engineering, Feb 2015
Using a manually coded dataset of 4,000 sketch-related events, examines how sketches support informal design 'in the moment' through an analysis of the relationships between sketches and the reasoning activities they help to enable.
journal article **local pdf, doi, materials and data**

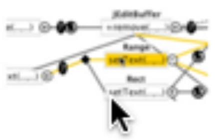
Microtask programming: building software with a crowd
Thomas D. LaToza, W. Ben Towne, Christian M. Adriano, and André van der Hoek
UIST 2014: Symposium on User Interface Software and Technology
Introduces an approach for programming through microtasks and presents CrowdCode, an online IDE for microtask programming.
full paper (acceptance rate: 22%) **local pdf, doi, youtube, slides**

Supporting informal design with interactive whiteboards
Nicolas Mangano, Thomas D. LaToza, Marian Petre, and André van der Hoek
CHI 2014: Conference on Human Factors in Computing Systems
Identifies 14 behaviors to support in informal design at the whitebord, and reports on three field deployments of an interactive whiteboard conducted to undersand the opportunities and challenges in supporting informal design.
full paper (acceptance rate: 23%) **local pdf, doi, youtube, github**

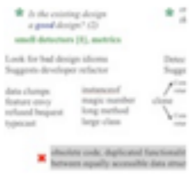
A study of architectural decision practices
Thomas D. LaToza, Evelina Shabani, and André van der Hoek
CHASE 2013: Workshop on the Cooperative and Human Aspects of Software Engineering
Reports findings from interviews of developers on their architectural decision practices. Results suggest that architectural decisions are often technology decisions and are sometimes revisited, causing software rewrites, following the discovery of an Achilles' heel.
workshop paper **local pdf, doi, poster**

Enabling a classroom design studio with a collaborative sketch design tool
Dastyni Loksa, Nicolas Mangano, Thomas LaToza, and André van der Hoek
ICSE 2013: International Conference on Sofware Engineering, Education Track
Reports findings from a deployment of a distributed interactive sketching tool - Calico - in a software design studio course. Results suggest that Calico enables students to work effectively in teams on design problems and quickly develop, refine, and evaluate designs.
full paper (acceptance rate: 27%) **doi**

Active code completion
Cyrus Omar, YoungSeok Yoon, Thomas D. LaToza, and Brad A. Myers
ICSE 2012: International Conference on Software Engineering
Introduces Graphite, an IDE plugin providing interactive and highly-specialized code generation interfaces through code completion. Reports survey and lab study data on the contexts in which such a system could be useful.
full paper (acceptance rate: 21%) **local pdf, doi, youtube, project website, github**



Visualizing call graphs
Thomas D. LaToza and Brad A. Myers
VL/HCC 2011: Symposium on Visual Languages and Human-Centric Computing
Introduces Reacher, an IDE plugin supporting code investigation. Lab study results suggest Reacher enables developers to answer reachability questions faster and more successfully.
full paper (acceptance rate: 33%) **local pdf, doi**

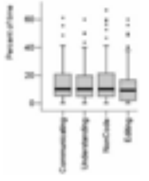


Hard-to-answer questions about code
Thomas D. LaToza and Brad A. Myers
PLATEAU 2010: Workshop on the Evaluation and Usability of Programming Languages and Tools
Reports results from a survey of hard-to-answer questions developers ask, revealing 94 questions across 24 categories, many of which are not addressed by exisiting SE tools.
workshop paper **local pdf, doi**

Developers ask reachability questions
Thomas D. LaToza and Brad A. Myers
ICSE 2010: International Conference on Software Engineering
Reports results from three studies examining challenges investigating code. Results suggest developers can spend tens of minutes answering a single question, get lost and disoriented, and erroneously make assumptions that result in bugs.
full paper (acceptance rate: 14%) **local pdf, doi**

Questions about object structure during coding activities
Marwan Abi-Antoun, Nariman Ammar, and T. LaToza
CHASE 2010: Workshop on Cooperative and Human Aspects of Software Engineering
Reports data from observations of developers performing maintenance tasks. Identifies typical questions about object structure, examining their frequency and context.
workshop paper **local pdf, doi**

Program comprehension as fact finding
Thomas D. LaToza, David Garlan, James D. Herbsleb, and Brad A. Myers
ESEC/FSE 2007: European Software Engineering Conference and the Symposium on the Foundations of Software Engineering
Reports results from observations of complex maintenance tasks. Describes a model of program comprehension and reports findings on the benefits of development experience.
full paper (acceptance rate: 17%) **local pdf, doi**



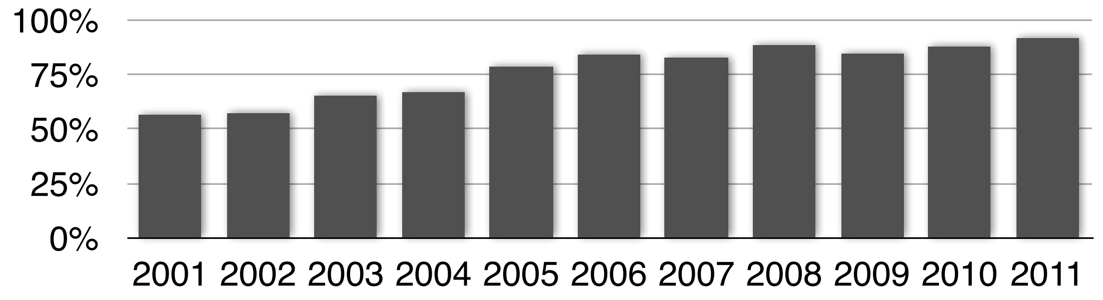
Maintaining Mental Models: A Study of Developer Work Habits
Thomas D. LaToza, Gina Venolia, and Robert DeLine
ICSE 2006: International Conference on Software Engineering, Experience Track
Reports results from surveys and interviews of professional software developers. Results reveal developers' use of tools, perceived problems, and practices involving code ownership, rationale, code duplication, and interruptions.
full paper (acceptance rate: 18%) **local pdf, doi**

Understanding and modifying procedural versus object-oriented programs: where does domain knowledge help more?
Thomas D. LaToza and Alex Kirlik
Cognitive Science 2004: Annual Meeting of the Cognitive Science Society
Experimentally tests if work with OO code benefits more from domain knowledge than work with procedural code. Results suggest domain knowledge benefits work with procedural code, rather than OO code.
poster **local pdf, conference pdf**

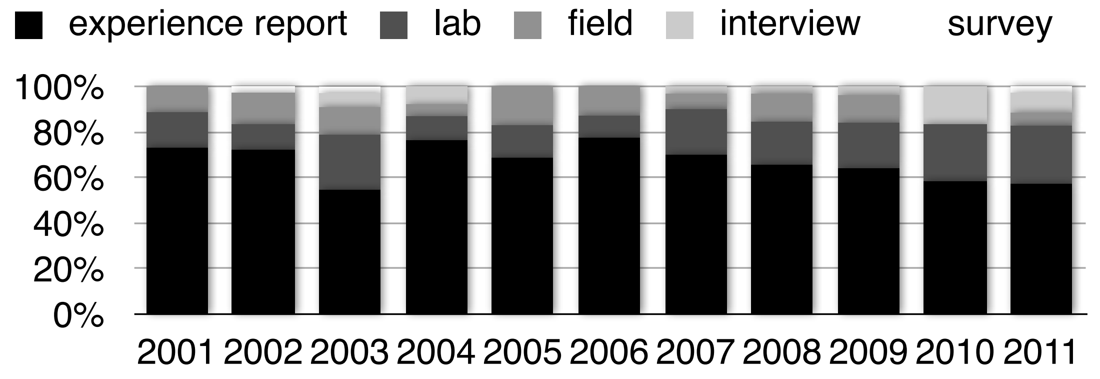
Data on how software engineering community conducts experiments w/ humans

- Systematic review of 1701 software engineering articles
  - All papers published at ICSE, FSE, TSE, TOSEM 2001 - 2011

82%	63%	17%
1392	1065	289
described tool	empirical eval	empirical eval w/ humans



% of papers w/ tools w/ empirical evals

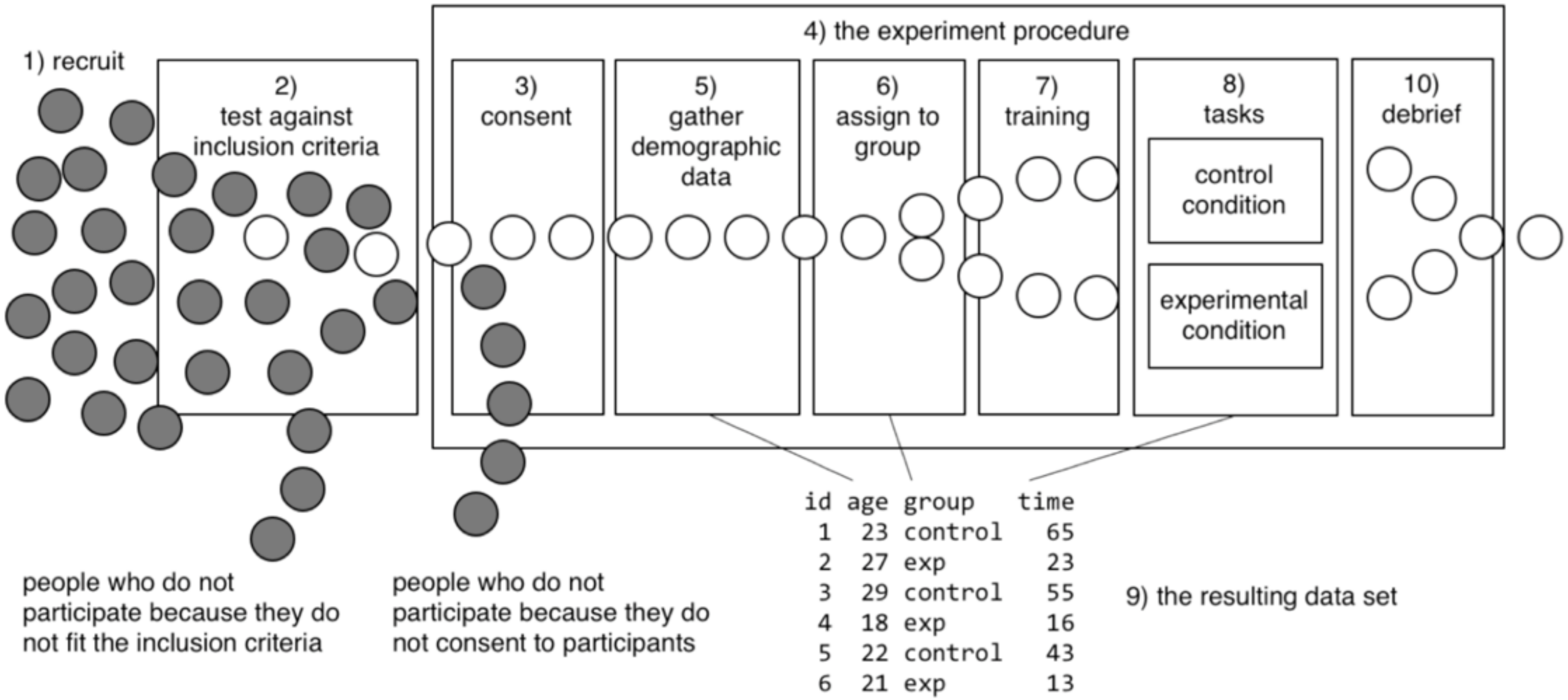


% of human evals by method

Controlled experiment

- Only way to argue **causality** - change in var x causes change in var y
- Manipulate **independent** variables
  Creates “conditions” that are being compared
  Can have >1, but # conditions usually exponential in # ind. variables
- Measure dependent variables (a.k.a measures)
  Quantitative variable you calculate from collected data
  E.g., time, # questions, # steps, ...
- **Randomly** assign participants to condition
  Ensure that participants only differ in condition
  Not different in other **confounding** variables
- Test hypotheses
  Change in independent variable causes dependent variable change
  e.g., t-test, ANOVA, other statistical techniques

Anatomy of controlled experiment w/ humans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2) test against inclusion criteria
4) the experiment procedure
3) consent
5) gather demographic data
6) assign to group
7) training
8) tasks
control condition
experimental condition
10) debrief
people who do not participate because they do not fit the inclusion criteria
people who do not participate because they do not consent to participants
9) the resulting data set

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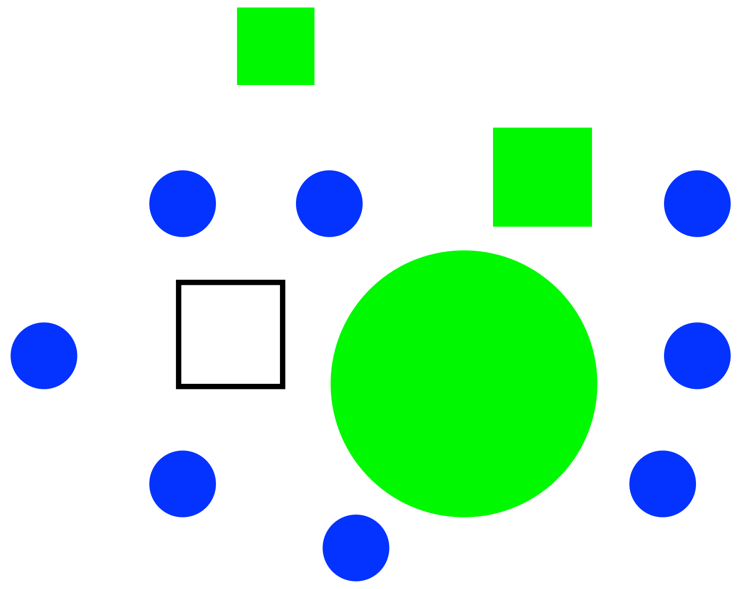
Terminology

- "Tool" — any **intervention** manipulating a software developer's work environment
    - e.g., programming language, programming language feature, software development environment feature, build system tool, API design, documentation technique, …
- Data — what you collected in study
- Unit of analysis — individual **item** of data
- Population — **all** members that exist
- Construct — some **property** about member
- Measure — **approximation** of construct computed from data

Example — Study of shapes

Real world

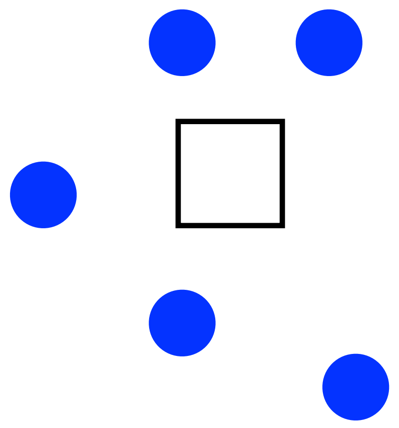


Population

shape
size
filled / empty
color

Constructs

Study



Sample of population

is blue?

size >10 or size < 10

Measure

(Some) types of validity

- **Validity** = should you believe a result
- **Construct** validity
  - Does measure correspond to construct or something else?
- **External** validity
  - Do results generalize from participants to population?
- **Internal** validity (experiments only)
  - Are the differences between conditions caused only by experimental manipulation and not other variables? (confounds)

Example: Typed vs. untyped languages

S. Hanenberg. (2009). What is the impact of static type systems on programming time? In the *PLATEAU workshop, OOPSLA 09*.

Participants 26 undergrads **Task** write a parser 27 hrs

Setup new OO language 16 hr instructions

Conditions type system vs. no type system

found errors at compile time errors detected at runtime

RESULTS

Developers with untyped version significantly faster completing task to same quality level (unit tests).

Example: Study validity

- **Construct** validity
  Does measure correspond to construct or something else?

- **External** validity
  Do results generalize from participants to population?

- **Internal** validity (experiments only)
  Are the differences between conditions caused only by experimental manipulation and not other variables? (confounds)

- **Other** reasons you're skeptical about results?

Good (not perfect) study designs

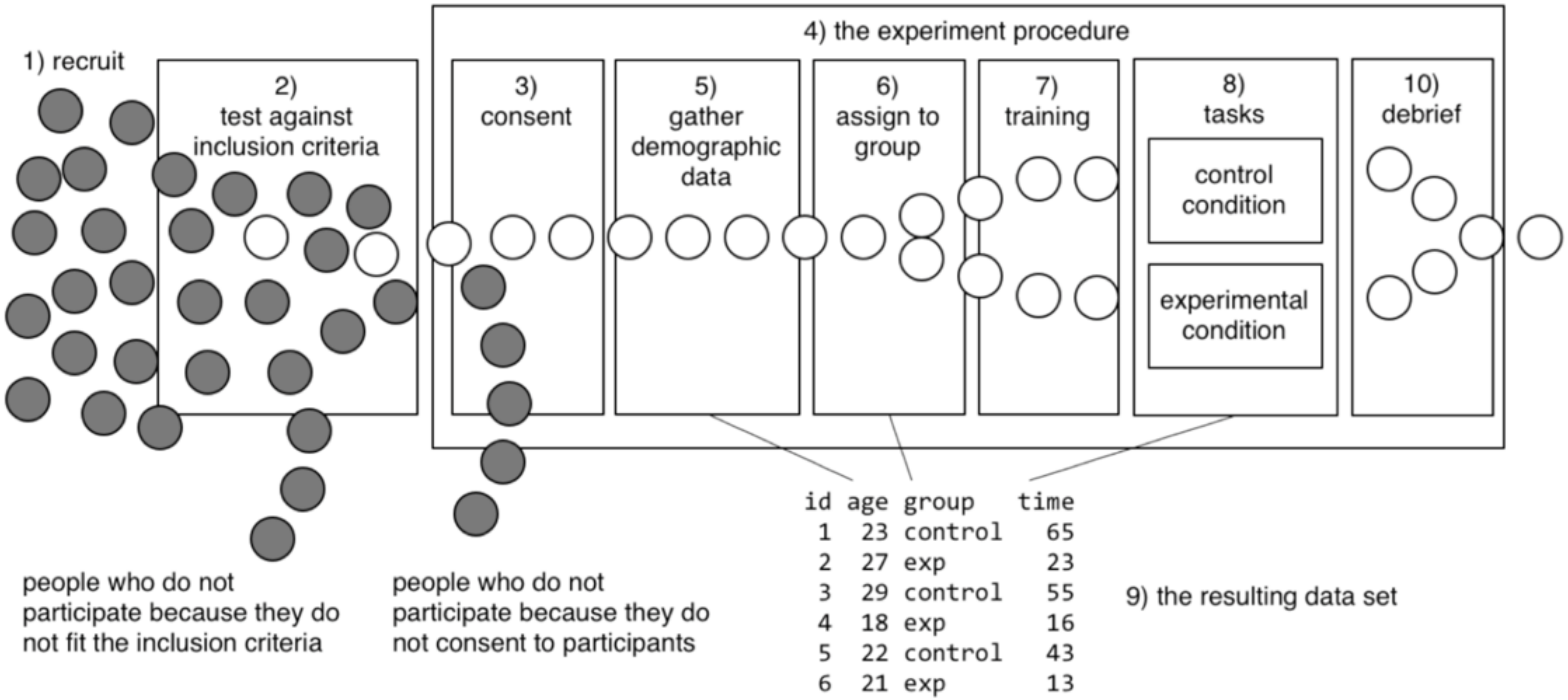
- Goals
    - Maximize **validity** - often requires more
        - more participants, data collected, measures
        - longer tasks
        - more realistic conditions

- Minimize **cost** - often requires
    - fewer participants, data collected, measures
    - shorter tasks
    - less realistic, easier to replicate conditions

- Studies are **not proofs** - results could always be invalid
    - don’t sample all developers / tasks / situations
    - measures imperfect

- Goal is to find results that are
    - **interesting**
    - **relevant** to research questions
    - **valid enough** your target audience believes them

Overview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Deciding who to recruit

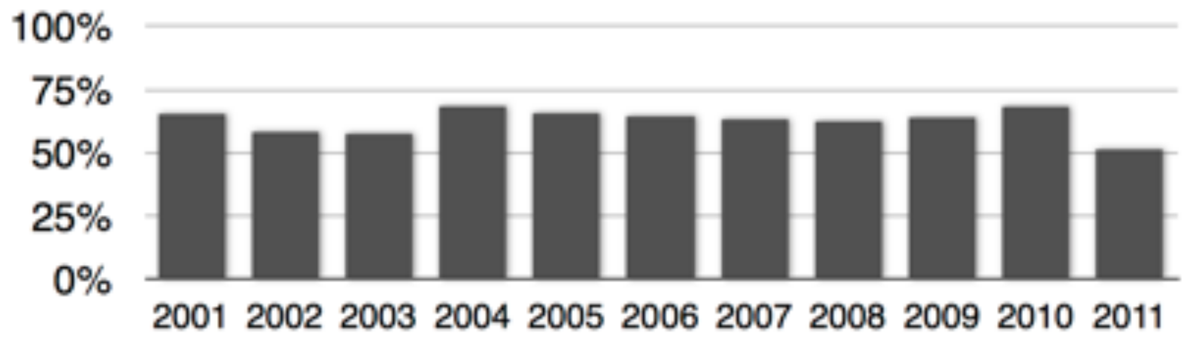
- **Inclusion criterion**: attributes participants must have to be included in study
- Goal: reflect characteristics of those that researchers believe would benefit
- Example - Nimmer & Ernst (2002)
    - Support those w/ out experience w/ related analysis tools
    - Chose graduate students
    - Developed items to assess (1) did not have familiarity w/ tool (2) Java experience (3) experience writing code

Common inclusion criteria

- Experience w/ a programming language
  - Self-estimation of **expertise**; time
- Experience w/ related **technologies**
  - Important for learning new tool
- **Industry experience**
  - Indicator of skills & knowledge; could also ask directly
- (Natural) language proficiency

Poor criteria: Paper authors

- **62%** of studies evaluating a tool involved **tool's authors** using the tool & reporting personal experiences
- Tool designers far more likely to use own tool successfully than those new to tool
- More likely to overlook weaknesses of tool



Proportion of evaluations involving humans in which authors were study participants

To use students or not to use students?

- **72%** of 113 SE experiments 1993-2002 used students [Sjoberg 2005]
- 23% reported using students in studies from 2001 - 2011 (many did not report if or if not)
- Students can be too inexperienced to be representative of tools intended users; observer-expectancy effect
- But
  - depends on task & necessary expertise
  - professional masters students may have industry experience
  - can minimize observer-expectancy effect

How many participants to recruit?

- More participants —> more statistical power
  - higher chance to observe **actual** differences
  - **power analysis** — given assumptions about expected effect size and variation, compute participants number
- Experiments recruited median **36** participants, median **18** per condition
  - Some studies smaller

Recruiting participants

- Marketing problem: how to attract participants meeting inclusion criteria
- Questions:
  - Where do such participants pay **attention**?
  - What **incentives** to offer for participation?

Sources of participants

- Students
  - Class announcement, fliers, emailing lists
  - Incentives: small compensation & intrinsic interest
- Software professionals
  - Relationships w/ industry researchers
  - Studies by **interns** at companies
  - **Partnerships** or contracts with companies
  - **In-house** university software teams
  - **Meetup** developer groups, public mailing lists, FB groups
  - CS Alumni mailing lists, LinkedIn groups

Remote participants

- Online labor markets focused on or including developers (e.g., MTurk, oDesk, TopCoder)
- Pros
  - Can quickly recruit hundreds or **thousands** of participants
  - Use their own space & tools; work at own time
- Cons
  - May **misreport** levels of experience
  - Might leave task temporarily; more extraneous variation

Remote participants - MTurk example

- Recruited participants from MTurk across 96 hours
- Used **qualification test** to screen for programming expertise
  - multiple choice question about program output
- Paid $5 for <= 30 mins

Participant numbers:

4776	3699	999	777	489
completed informed consent	took qualification test	qualified	completed 1 task	completed all tasks

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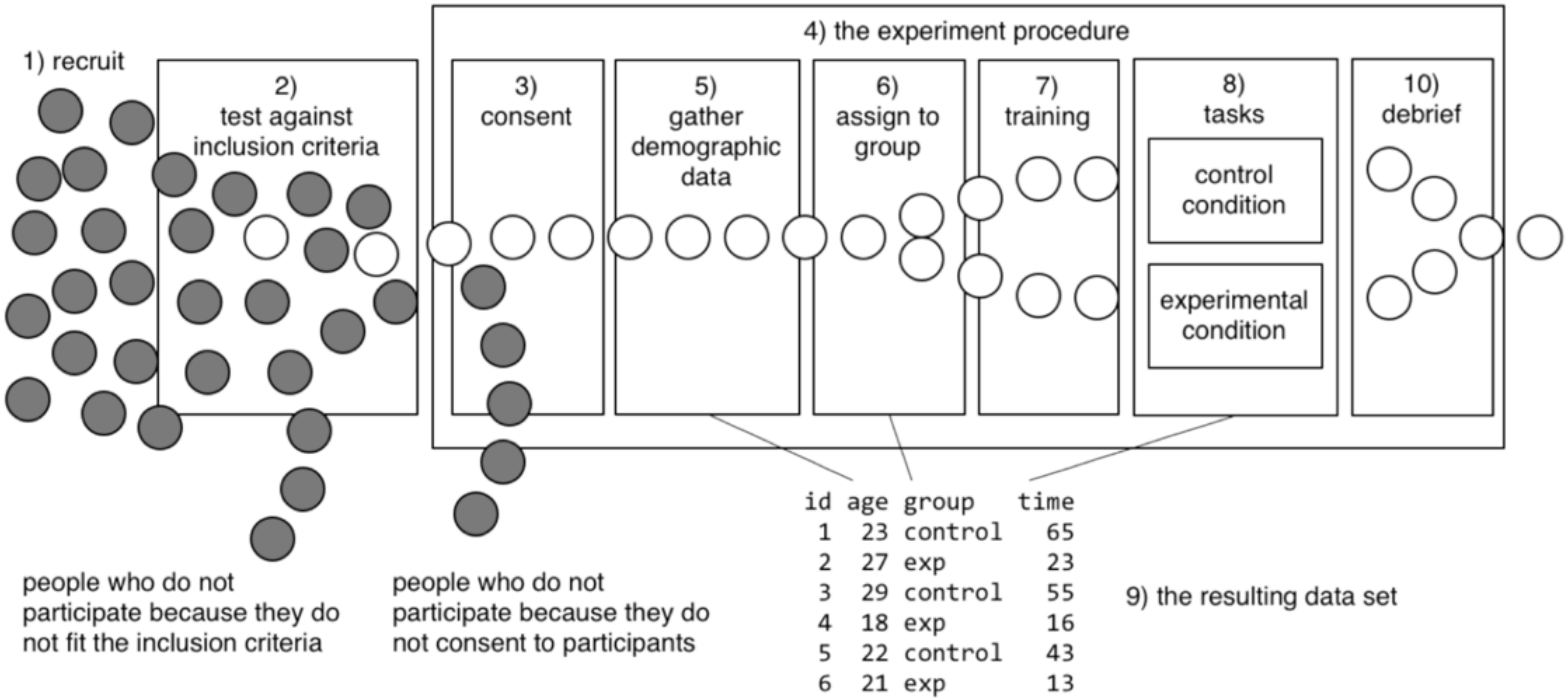
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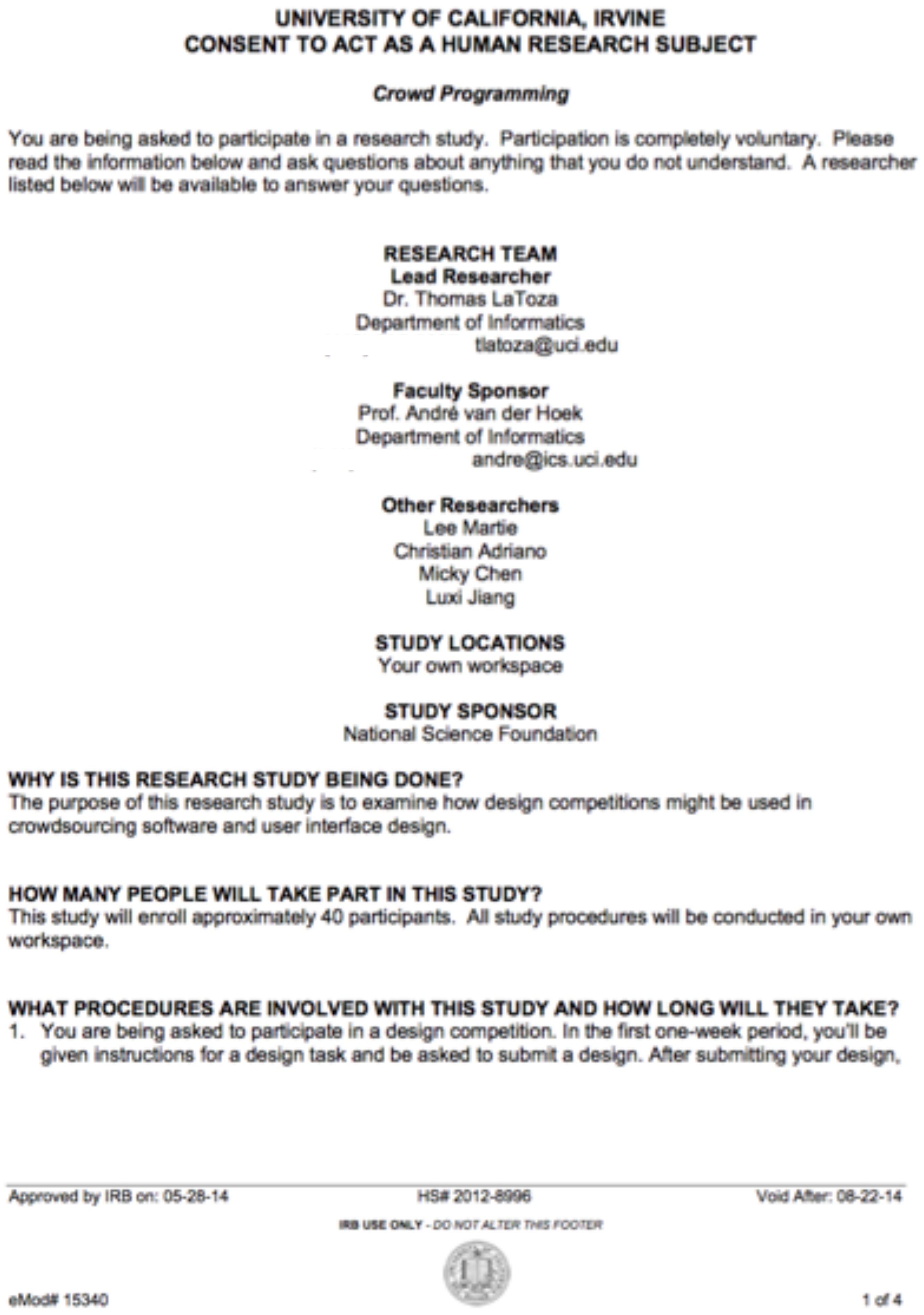
Informed consent

- Enables participants to **decide** to participate with a few page document
- Key elements
  - Names & contact info for you and other experimenters
  - **Purpose** of the study
  - Brief (one or two sentence) high-level description of the types of work participants will be asked to do
  - Expected **length** of the study
  - A statement of any possible **benefits** or compensation
  - A statement of any possible **risks** or discomforts
  - Overview of the data you will collect (thinkaloud, screencast, survey questions, etc.)
  - Clear statement on **confidentiality** of data (who will have access?)



UNIVERSITY OF CALIFORNIA, IRVINE
CONSENT TO ACT AS A HUMAN RESEARCH SUBJECT

Crowd Programming

You are being asked to participate in a research study. Participation is completely voluntary. Please read the information below and ask questions about anything that you do not understand. A researcher listed below will be available to answer your questions.

RESEARCH TEAM
Lead Researcher
Dr. Thomas LaToza
Department of Informatics
tlatoza@uci.edu

Faculty Sponsor
Prof. André van der Hoek
Department of Informatics
andre@ics.uci.edu

Other Researchers
Lee Martie
Christian Adriano
Micky Chen
Luxi Jiang

STUDY LOCATIONS
Your own workspace

STUDY SPONSOR
National Science Foundation

WHY IS THIS RESEARCH STUDY BEING DONE?
The purpose of this research study is to examine how design competitions might be used in crowdsourcing software and user interface design.

HOW MANY PEOPLE WILL TAKE PART IN THIS STUDY?
This study will enroll approximately 40 participants. All study procedures will be conducted in your own workspace.

WHAT PROCEDURES ARE INVOLVED WITH THIS STUDY AND HOW LONG WILL THEY TAKE?
1. You are being asked to participate in a design competition. In the first one-week period, you'll be given instructions for a design task and be asked to submit a design. After submitting your design,

IRB Approval

- US universities have an **Institutional Review Board** (IRB) responsible for ensuring human subjects treated ethically
- Before conducting a human subjects study
  - Must complete human subjects **training** (first time only)
  - Submit an application to IRB for **approval** (2 - ??? weeks approval time)
- During a study
  - Must administer “**informed consent**” describing procedures of study and any risks to participants

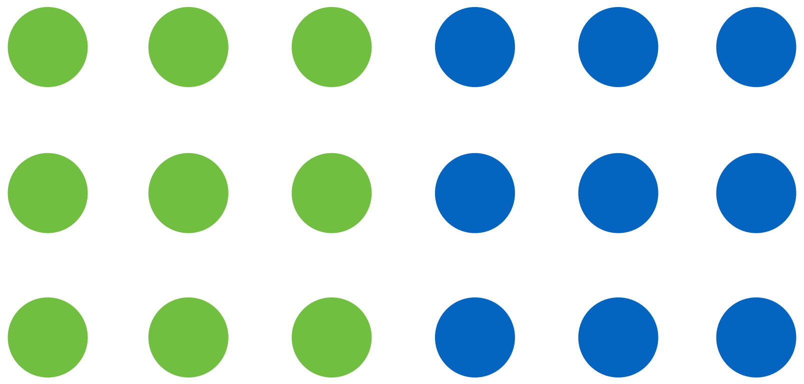
Collecting demographic data

- Goal: understand expertise, background, tool experience, …
- **Interviews** — potentially more comfortable
  - Before or after tasks
- **Surveys** — more consistent, can be used to test against inclusion criteria during recruiting

Assigning participants to an experimental condition

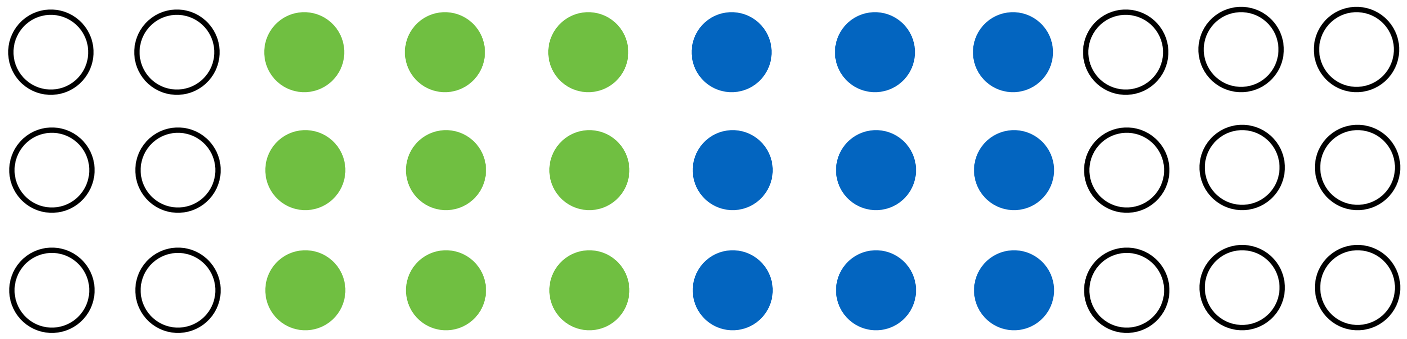
- Random assignment
  - distributes random **variation** in participant skills and behavior across all conditions
  - minimizes chance that observed difference is due to participant differences
- Used with a **between-subjects** experiment
- Are alternative designs that can reduce number of participants necessary to recruit

Within-subjects design



- All participants use all tools being compared one at a time across several tasks
  - e.g., participant uses tool in task 1 but not task 2
- **Learning effect** — doing first task may increase performance on second task
- —> **Counterbalancing** — randomize order of task & on which task participants use each tool
  - Latin Square design

Interrupted time-series design



- Measure outcome variable **before** tool introduced, **after** introduced, **after removing** tool
- Can see possible causal effects of tool
- Enables participants to articulate effects of tool
- Could be "trial run" of new tool in a field deployment of tool to a company

Training participants

- Knowledge participants need includes
  - how to use **tools** in the environment provided
  - terminology & domain **knowledge** used in task
  - design of programs they will work with during task
- Can provide background and **tutorial** materials to ensure participants have knowledge.

To train or not to train?

- Key study design question, creating assumptions about context of use results generalize to
- Training
    - Ensures participants are **proficient** and **focused** on the task
- No training
    - Generalizes directly to new users who don’t have training materials, but risks study being dominated by learning
- Studies often choose to provide training materials for tool

Design of training materials

- Goal: **teach** required concepts quickly & effectively
- Possible approaches
  - Background materials
  - Video instructions
  - Tutorial where participants complete example task w/ tool
  - Cheat sheets
- Can also include **assessment** to ensure learning
- Can be helpful for experimenter to answer participant questions

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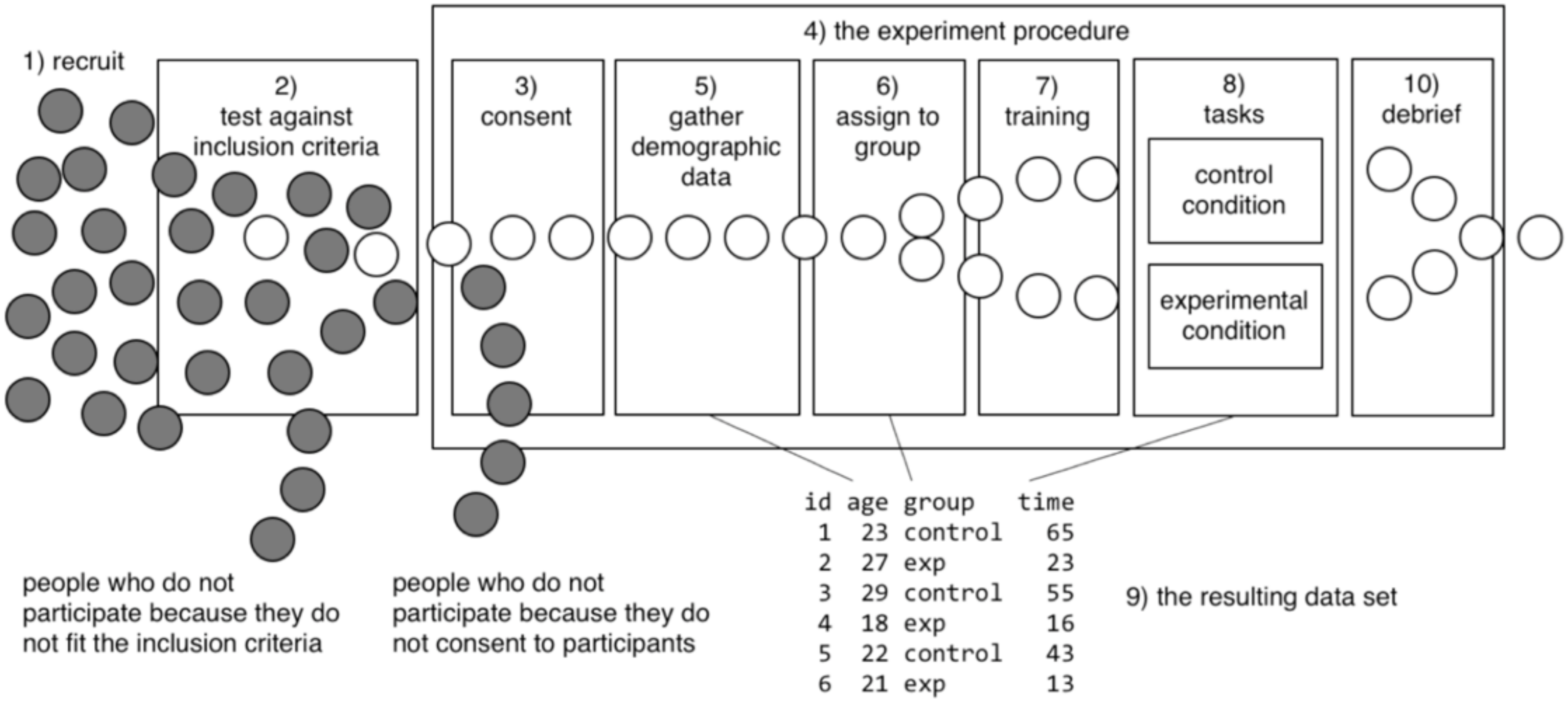
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Tasks

- Goal: design tasks that have **coverage** of work affected by tool
- Key tradeoff: realism vs. control
  - How are real, messy programming tasks **distilled** into brief, accessible, actionable activities?
- More realism —> messier, fewer controls
- More control —> cleaner, less realism
- Tradeoff often takes the form of tradeoff between bigger tasks vs. smaller tasks

Feature coverage

- Of all functionality and features of tool, which will receive **focus** in tasks?
- More features —> more to learn, more variation in performance, higher risk of undue negative results
- Fewer features —> less to learn, less ecological validity, more likely to observe differences

Experimental setting

- Experiments can be conduct in lab or in developer's actual workspace
- Experiments most often conducted in **lab** (86%)
    - Enables **control** over environment
    - Can minimize distractions
    - But less realism, as may have different computer, software, … from participants' normal setting

Task origin

- **Found** task — task from real project (15%)
    - e.g., bug fix task from an OSS project
    - More **ecologically** valid
    - May not exist for new tools
    - Can be hard to determine what feature usage found task will lead to
- **Synthetic** task — designed task (85%)
    - Can be easier to tailor for effective feature **coverage**
    - Must compare synthetic task to real tasks

Task duration

- **Unlimited** time to work on a task
  - Allow either participant or experimenter to determine when task is complete
  - Hard to find participants willing to work for longer time periods
- **Fixed** time limit
  - More **control** over how participants allocate time across tasks
  - Can introduce **floor effect** in time measures, where no one can complete task in time
- Typical length of **1 - 2** hours

Measuring outcomes

- Wide range of possible measures
  - Task completion, time on task, mistakes
  - Failure detection, search effort
  - Accuracy, precision, correctness, quality
  - Program comprehension, confidence
- Most frequent: **success** on task, **time** on task, tool **usefulness**

Measuring success on task

- Often multiple ways to succeed
  - e.g., several ways to implement feature or fix bug
- What is close enough to be **counted** as success?
- Might be binary success measure
- Might be measure of quality of change

Determining when goal is reached

- Experimenter **watches** participant for success
  - Requires **consistency**, which can be challenging
- Success is **automatically** measured (e.g., unit tests)
  - Requires researcher to identify all goal states in advance, which can be challenging
- **Participants** determine they believe they have succeeded
  - Most ecologically valid
  - Introduces variation, as participants may vary in confidence they obtain before reporting they are done

Defining success to participants

- Need to **unambiguously** communicate goal to participants
- When participants themselves determine, may ask experimenter about what is success
    - Experimenter can reiterate **instructions** from beginning
- When experimenter determines
    - Experimenter should respond “I unable to answer that question”

Measuring time on task

- Need to define task **start** and task **end** & who determines when task has finished
    - Choice of task framing
- What is **start**
    - When participant starts reading task — includes variation in time spent reading
    - When participants starts working
- What is **end**
    - What happens if participant succeeds but does not realize it?
    - What happens if they think they succeeded but failed?

Measuring usefulness

- Usefulness — does the tool provide functionality that satisfies a **user need** or provides a benefit
    - Not usability — ease of use for task
- Might **ask** developers
    - Did they find the tool useful
    - Would they consider using it in the future
- Technology Acceptance Model
    - **Validated** instrument for measuring usefulness through a questionnaire

Debriefing & compensation

- Explain to participant what study **investigated**
- Explain the correct solutions to tasks
- Instructions about information that should not be shared w/ others
  - e.g., don't share tasks with friends who might participate
- Get speculative **feedback** about tool
  - Can use semi-structured interview to get perceptions of tool

Piloting

- Most **important** step in ensuring useful results!

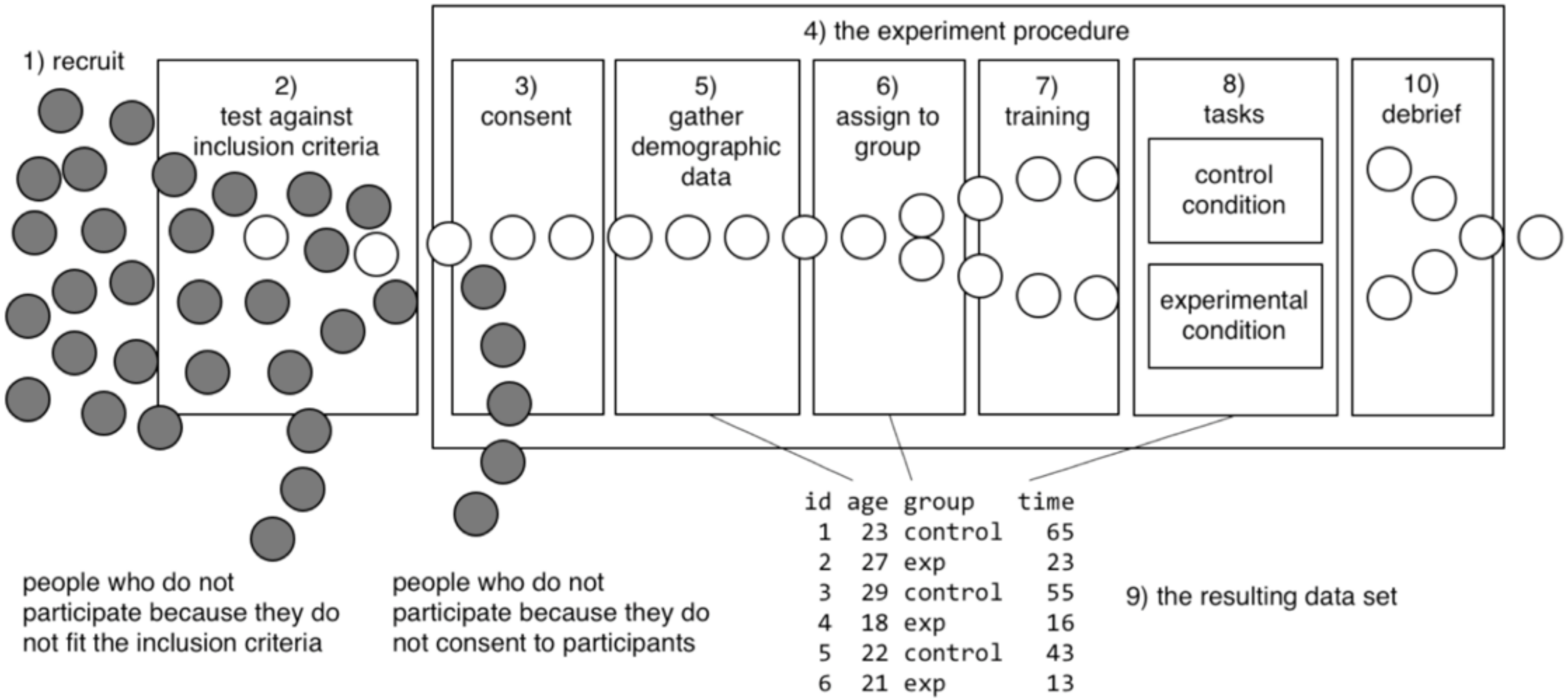
- (1) Run study on **small** (1 - 4) number of participants

- (2) Fix **problems** with study design
  - Was the tool tutorial sufficient?
  - Did tasks use your tool? Enough?
  - Did they understand your materials?
  - Did you collect the right data?
  - Are your measures correct?

  (3) Fix **usability** problems
  - Are developers doing the “real” task, or messing with tool?
  - Are users confused by terminology in tool?
  - Do supported commands match commands users expect?

- (4) **Repeat** 1, 2, and 3 until no more (serious) problems

Overview



4) the experiment procedure
1) recruit
2) test against inclusion criteria
3) consent
5) gather demographic data
6) assign to group
7) training
8) tasks
control condition
experimental condition
10) debrief
people who do not participate because they do not fit the inclusion criteria
people who do not participate because they do not consent to participants
9) the resulting data set

id	age	group	time
1	23	control	65
2	27	exp	23
3	29	control	55
4	18	exp	16
5	22	control	43
6	21	exp	13

Qualitative data

On the value of qualitative data

- Experiment may provide evidence that A is “better” than B
- But always generalizability questions about **why** and **when**
- Qualitative data offers possibility of explanation, making it possible to explain why result occurred.
- Can use **coding** to convert qualitative data to categorical data, which can be counted or associated with time to create quantitative data

Collecting qualitative data

- Screencasts
  - **Record** screen as participants do tasks
  - Many video recorders (e.g., SnagIt)
  - Offers insight into **what** participants did
    - What was time consuming
  - Permits quantitative analysis of **steps & actions**
    - Can code more fine-grained time data
  - Does not provide insight into why developers did what they did

Collecting qualitative data

- Think-aloud
  - Ask participants to **verbalize** what they are thinking as they work
  - **Prompt** participants when they stop talking for more than a minute or two
  - Offers insight into **why** participants are doing what they are doing
    - What barriers are preventing progress on task

Analyzing qualitative data

1. **open** coding - read through the text
   look for **interesting** things relevant to research questions
   add notes in the margin (or column of spreadsheet)
   add “**codes**” naming what you saw
   make up codes as you go, not systematic

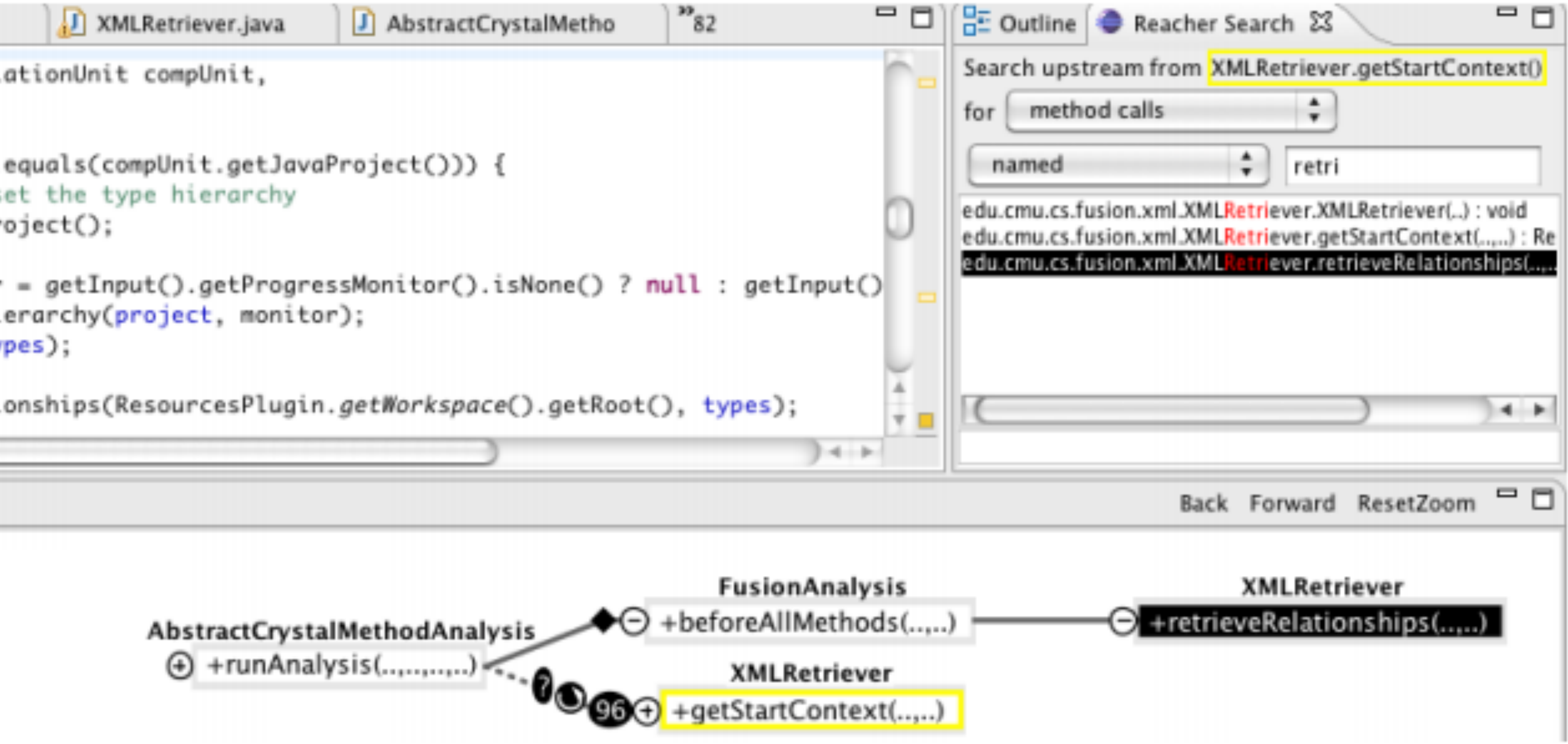
2. **axial** coding - how are codes related to each other?
   look for **patterns**: causality, ordering, alternatives

3. **selective** coding - from initial codes, select interesting ones
   which codes found interesting things?
   from initial examples, build definition on when they are applied
   systematically reanalyze data and apply codes

4. **second** coder (optional)
   2nd person independently applies codes from definitions
   check for interrater **reliability** - if low, iterate defns & try again

Example

REACHER: Interactive, compact visualization of control flow



```
ationUnit compUnit,

equals(compUnit.getJavaProject())) {
et the type hierarchy
oject();

 = getInput().getProgressMonitor().isNone() ? null : getInput()
erarchy(project, monitor);
pes);

onships(ResourcesPlugin.getWorkspace().getRoot(), types);
```

Search upstream from XMLRetriever.getStartContext()
for method calls
named retri

```
edu.cmu.cs.fusion.xml.XMLRetriever.XMLRetriever(..) : void
edu.cmu.cs.fusion.xml.XMLRetriever.getStartContext(..,..,..) : Re
edu.cmu.cs.fusion.xml.XMLRetriever.retrieveRelationships(..,..
```

XMLRetriever.java
AbstractCrystalMetho
»82
Outline
Reacher Search
Back
Forward
ResetZoom
AbstractCrystalMethodAnalysis
+runAnalysis(..,..,..,..,..)
FusionAnalysis
+beforeAllMethods(..,..,..)
XMLRetriever
+retrieveRelationships(..,..,..)
XMLRetriever
+getStartContext(..,..,..)
?
96

Evaluation

Does REACHER enable developers to answer reachability questions faster or more successfully?

Method

12 developers 15 minutes to answer **reachability** question x **6**

Eclipse only on 3 tasks Eclipse w/ REACHER on 3 tasks

(order counterbalanced)

Tasks

Based on developer questions in prior observations of developers.

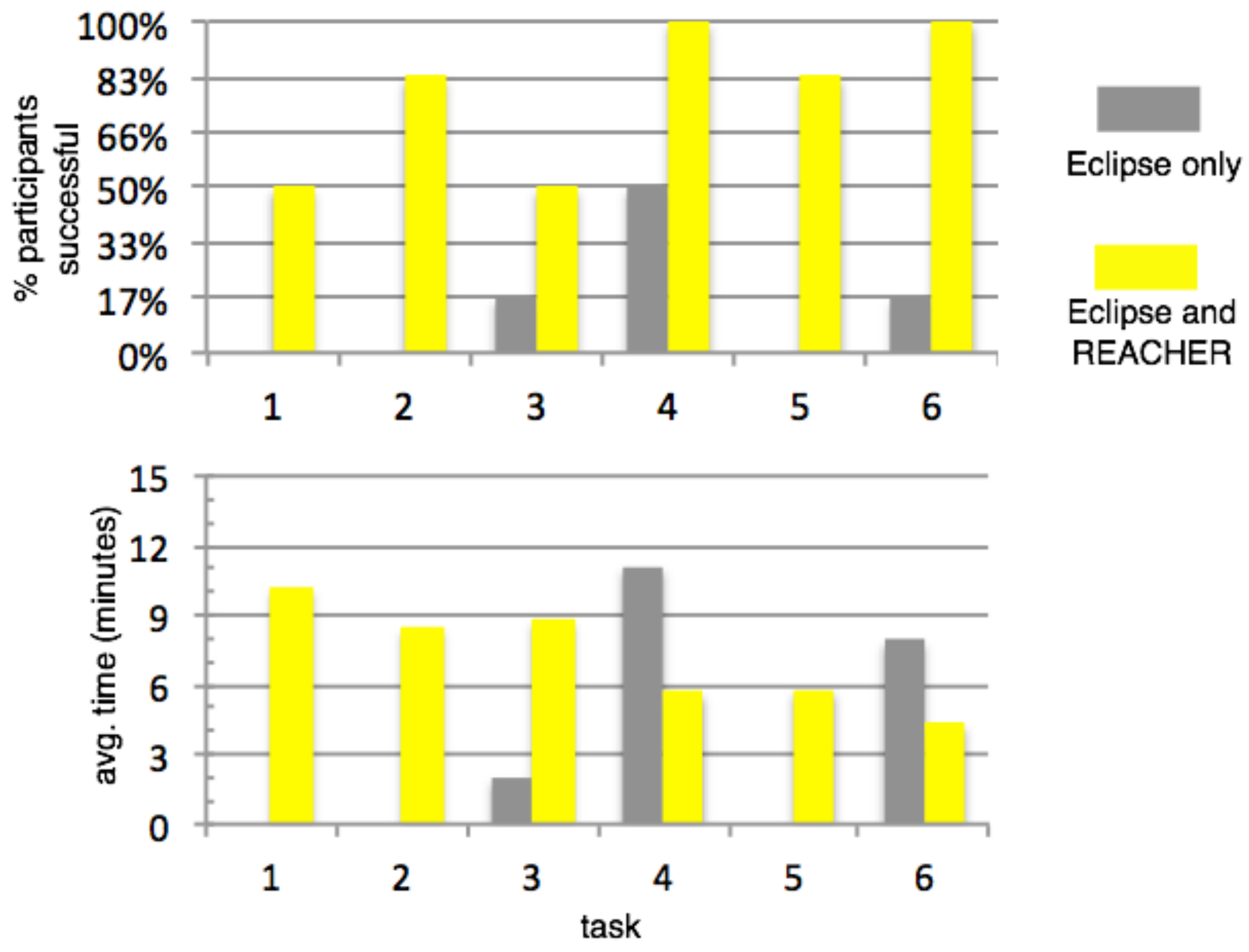
Example:

When a new view is created in jEdit.newView(View), what messages, in what order, may be sent on the EditBus (EditBus.send())?

Results

Developers with REACHER were **5.6** times more **successful** than those working with Eclipse only.

(not enough successful to compare time)



Task time includes only participants that succeeded.

REACHER helped developers stay oriented

Participants with **REACHER** used it to jump between methods.

"It seems pretty cool if you can navigate your way around a complex graph."

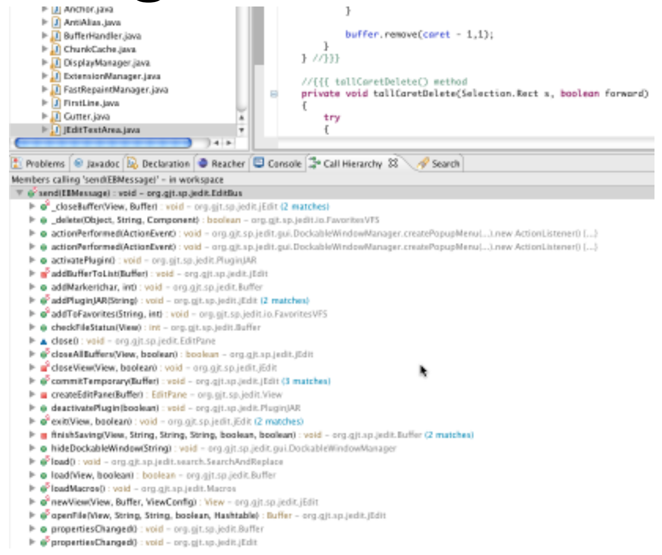
When **not** using REACHER, participants often reported being lost and confused.

"Where am I? I'm so lost."

"These call stacks are horrible."

"There was a call to it here somewhere, but I don't remember the path."

"I'm just too lost."



Participants reported that they liked working with REACHER.

"I like it a lot. It seems like an easy way to navigate the code. And the view maps to more of how I think of the call hierarchy."

"Reacher was my hero. … It's a lot more fun to use and look at."

"You don't have to think as much."

Conclusions

- Controlled experiments w/ humans can demonstrate **causal** relationship between tool & productivity effects of tool
  - But… observed in **context** where study conducted
- Key role for more research to understand **representativeness** of context
  - High value in qualitative understanding of productivity effects to help bridge this gulf

Resources

- Andrew J. Ko, Thomas D. LaToza, and Margaret M. Burnett. (2015) A practical guide to controlled experiments of software engineering tools with human participants. Empirical Software Engineering, 20 (1), 110-141.

- Robert Rosenthal & Ralph Rosnow. (2007). Essentials of Behavioral Research: Methods and Data Analysis. McGraw-Hill.

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- D. I. K. Sjoeberg, J. E. Hannay, O. Hansen, et al. (03 September 2005). A survey of controlled experiments in software engineering. IEEE Transactions on Software Engineering, Vol. 31, No. 9. pp. 733-753.