THE UNIVERSITY OF TENNESSEE KNOXVILLE
SCHOOL OF INFORMATION SCIENCES

Foundations of User-Oriented Information Retrieval: User Interfaces & User-Centered Evaluation

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School of Information Sciences
University of Tennessee, USA

European Summer School in Information Retrieval
July 16, 2019

BIG ORANGE BIG IDEAS

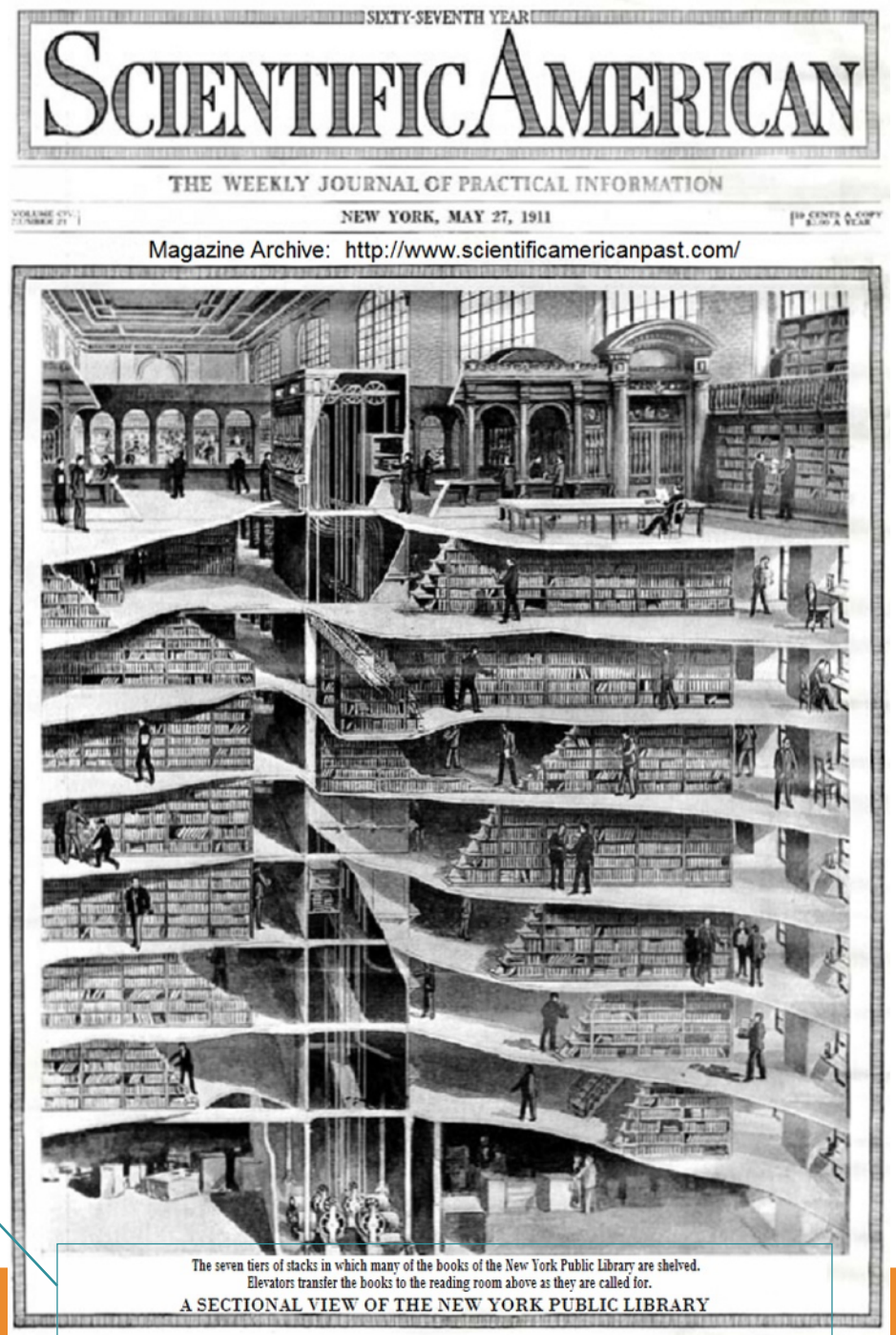
Agenda

- Search User Interfaces (30 minutes)
- User-Centered Evaluation (1 hour)
  - Deep dive into some details

Information Retrieval: Closed Stacks System

Scientific American
The Weekly Journal of Practical Information,
May 27, 1911

"The seven tiers of stacks in which many of the books of the New York Public Library are shelved. Elevators transfer the books to the reading room above as they are called for. "


SIXTY-SEVENTH YEAR

SCIENTIFIC AMERICAN

THE WEEKLY JOURNAL OF PRACTICAL INFORMATION

NEW YORK, MAY 27, 1911

Magazine Archive: http://www.scientificamericanpast.com/

The seven tiers of stacks in which many of the books of the New York Public Library are shelved.
Elevators transfer the books to the reading room above as they are called for.

A SECTIONAL VIEW OF THE NEW YORK PUBLIC LIBRARY

Information Retrieval: Closed Stacks System?

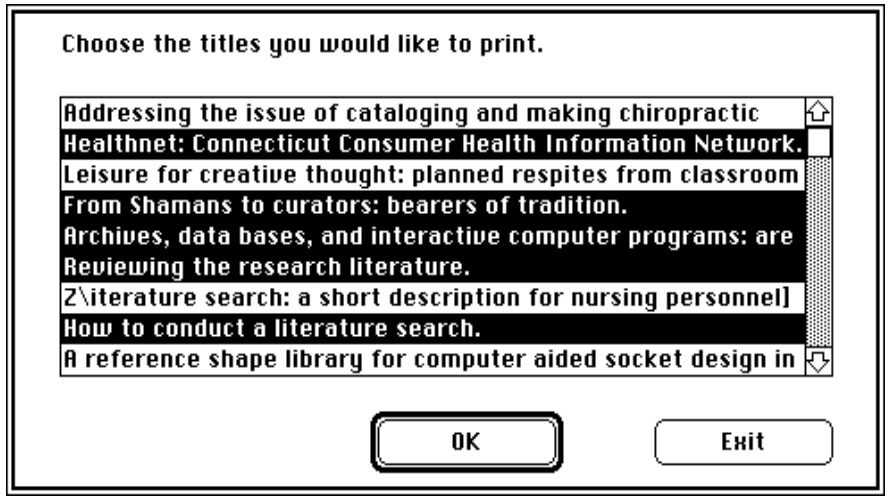
Interactive IR Evolution

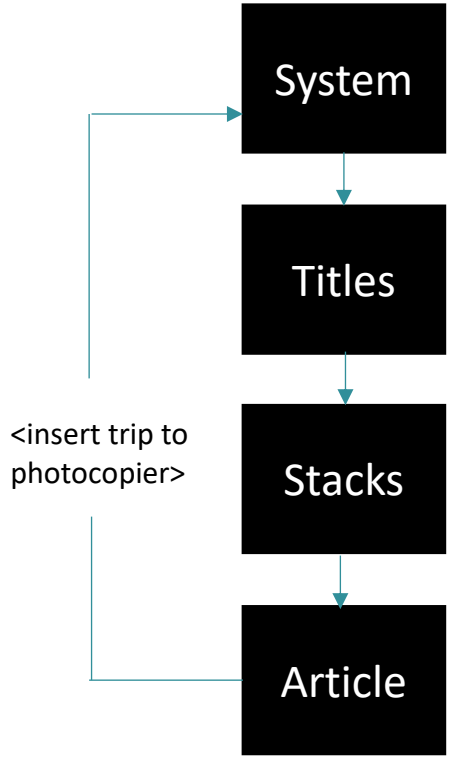
Query (Croft)			Data & Collections	Producers	Information Needs	Users
1970 CE (Boolean search)		NEGLECT! FAIL! NEGLIG! /5 MAINT! REPAIR! /P NAVIGAT! /5 AID EQUIP! LIGHT BUOY "CHANNEL MARKER"	Highly Regulated Highly Curated	Specialized	Homogenous Professional Serious	Specialized
1994 CE (web search)		negligence navigation aids				
2005 CE (CQA)		Are there any cases which discuss negligent maintenance or failure to maintain aids to navigation such as lights, buoys, or channel markers?	Highly Unregulated Curated and Uncurated	"Everybody"	Heterogenous Everyday Leisure/Causal	"Everybody"

Interaction Evolution

This is magnetic tape.

Search Interface





TODAY: Search applications, information, information needs and searchers are diverse!

- Users, characteristics, experiences, mental models
- Needs, tasks and goals
- ”Relevance” criteria
- Information objects and properties
- Indexing and retrieval techniques
- User environments
- …

Involving the User in Search

Since the user's original query is often inadequate, some sort of user interaction with the retrieval operation is desirable. The user of a manual retrieval system such as a library might at first ask a general and unclear question. The librarian, using his knowledge of the document collection, might then ask the user a few questions and show him a few books in an attempt to pinpoint his needs.

This study investigates relevance feedback, which is a procedure allowing user interaction with an automated information retrieval system. The user is given a small set of possibly relevant items, and is asked to judge each as relevant or non-relevant to his request. These user relevance judgments are then used for feedback to the information retrieval system, to produce a better subsequent set of retrieved items.

Ide, E. (1967, 1969). User interaction with an automated information retrieval system. In G. Salton (Ed.) *Information Storage and Retrieval: Scientific Report No. ISR-12 and ISR-15*.

Involving the User in Search

- By the mid-1960s, several techniques had been introduced to assist users, including the:
  - Display of online thesauri to help with query formulation
  - Choice of novice or experienced searcher interface mode
  - Ability to save search queries to rerun at a later time or on a different database
  - Relevance feedback
  - System prompts for further information from user about his/her information need
- In 1971, the first workshop was held about interactive searching.
  - Walker, D.E. (1971). *Interactive bibliographic search: The user/computer interface*. Montvale, NJ: AFIPS Press.

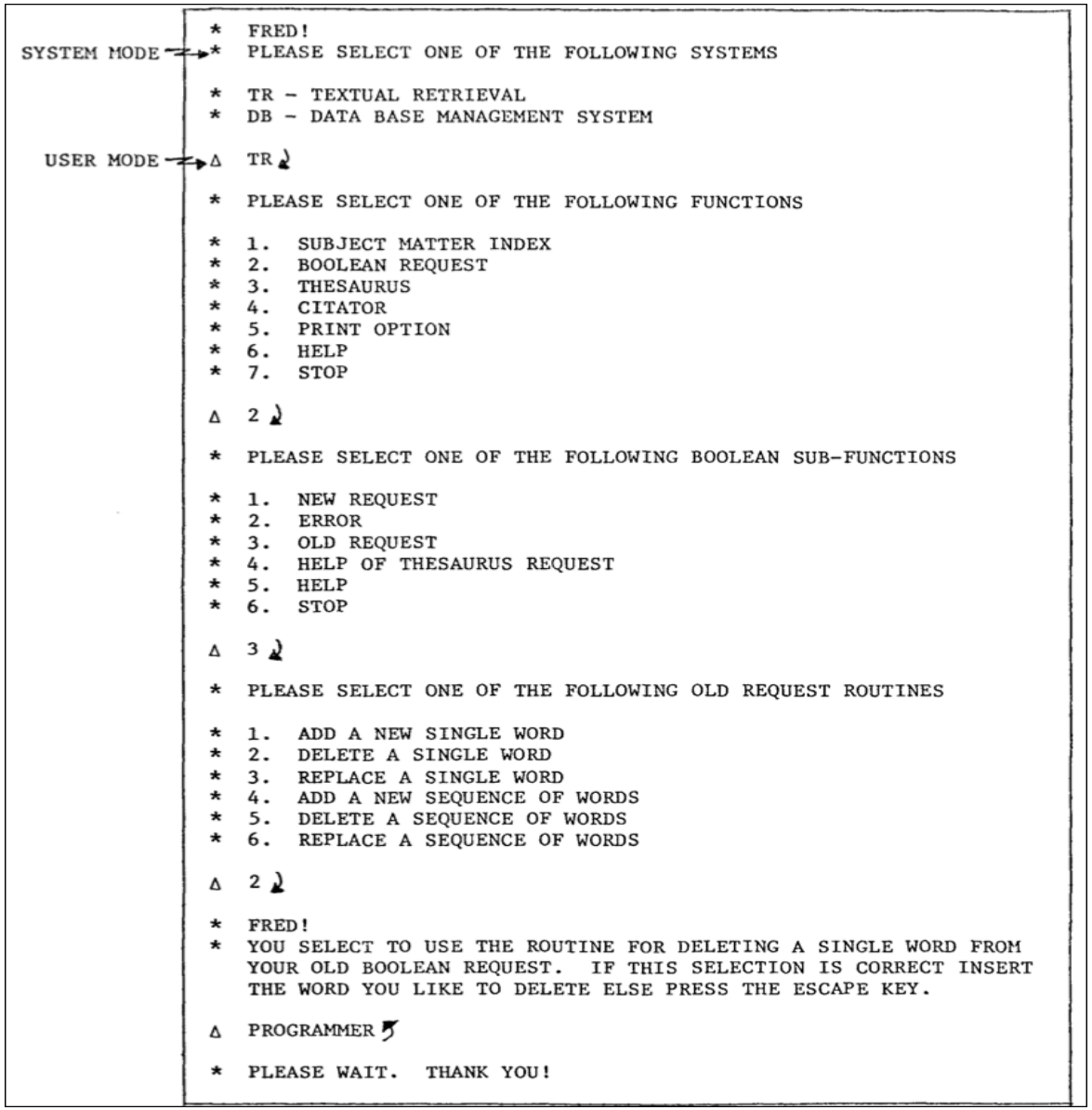
A Positive End-Expiratory Pressure—Nasal-Assist Device (PEEP-NAD) for treatment of respiratory distress syndrome.; Tummons, *Anesthesiology*, 38, 592–5, June 73

1. J L Tummons, 2. blood, 3. carbon dioxide, 4. human, 5. hydrogen-ion concentration. 6. infant, newborn, 7. masks, 8. methods, 9. nose, 10. oxygen, 11. oxygen inhalation therapy, 12. positive-pressure respiration, 13. respiration, 14. respiratory distress syndrome

Yes, 13, not 6

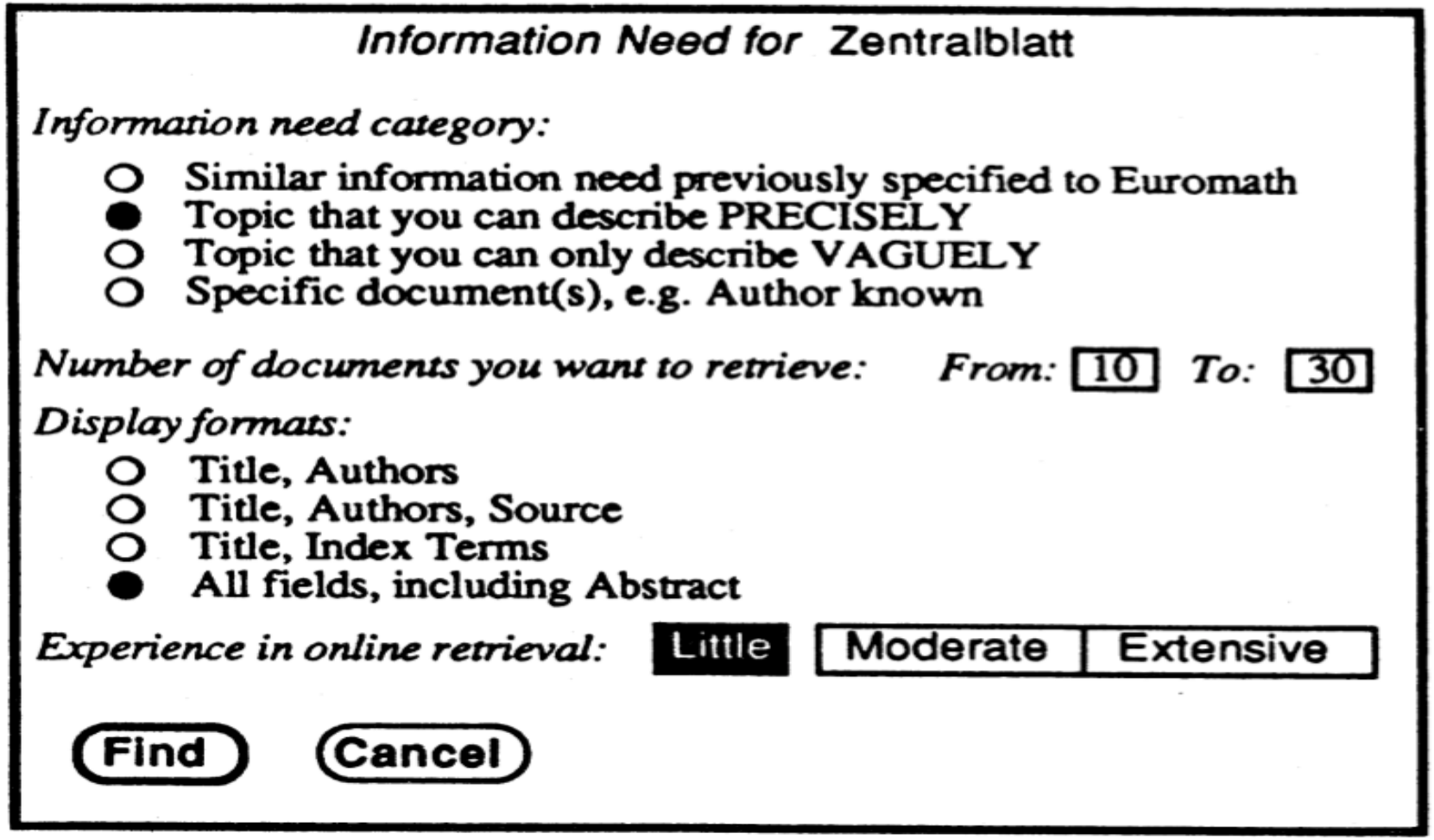
We are not doing so well now. You may already have the important references.

Oddy, R. N. (1977). Information retrieval through man-machine dialogue. *Journal of Documentation 33*(1), 1-14.



Slonim, J., Maryanski, F. J., & Fisher, P. S. (1978). Mediator: An integrated approach to information retrieval. *Proceedings of SIGIR*, 14-36.

Information Intermediary Modeling



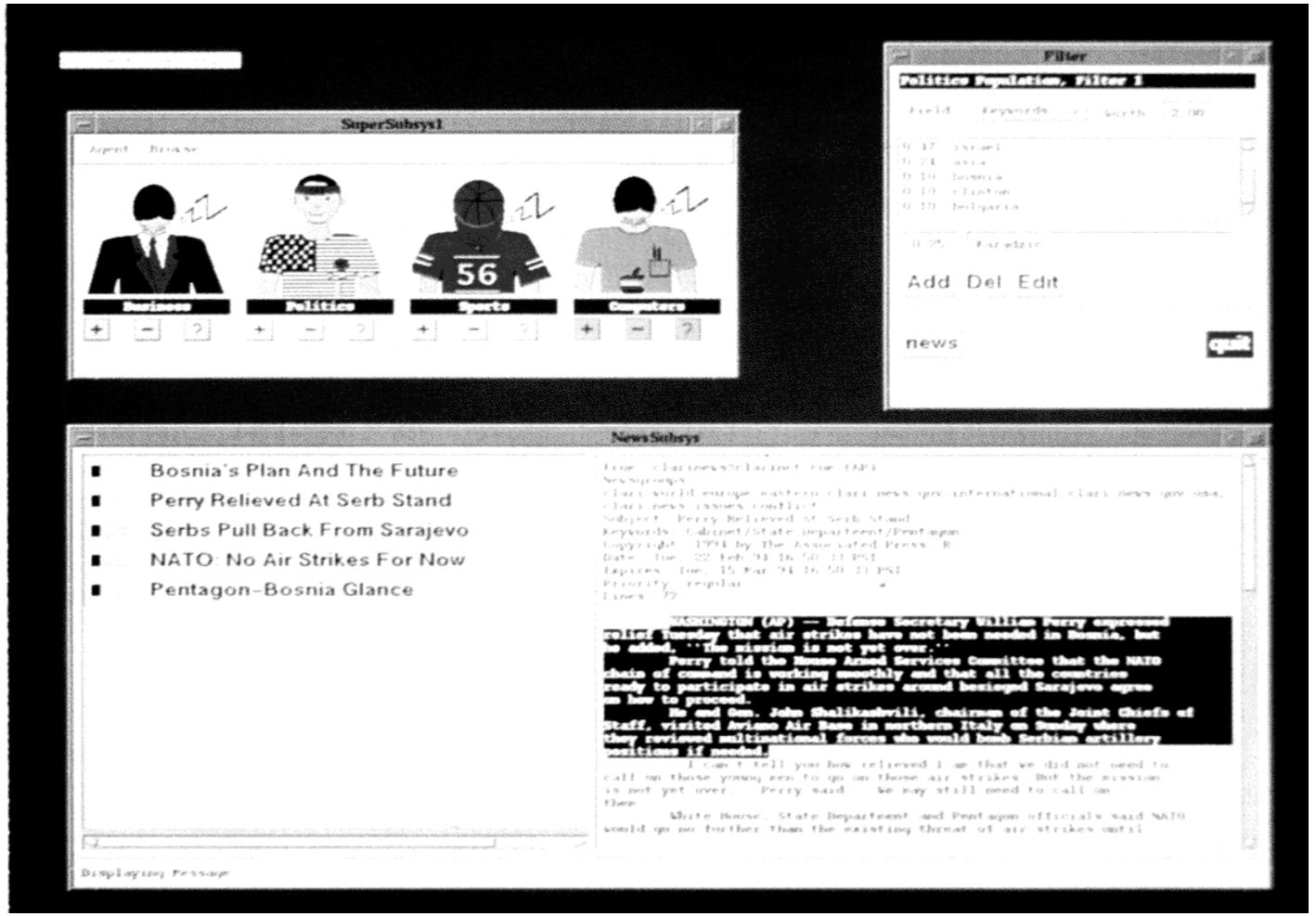
McAlpine, G. & Ingwersen, P. (1989). Integrated information retrieval in a knowledge worker support system. *ACM SIGIR Forum*, 48-57.

User Modeling and Profiles

FACET	VALUE	RATING
Activated-by	Athletic-w-trig	
Genl	ANY-PERSON	
Movitivations		
Excite	800	600
Interests		
Sports	900	800
Thrill	5	700
Tolerate-violence	4	600
Romance	−5	500
Education	−2	500
Tolerate-suffering	4	600
Strengths		
Physical-strength	900	900
Perseverance	800	600

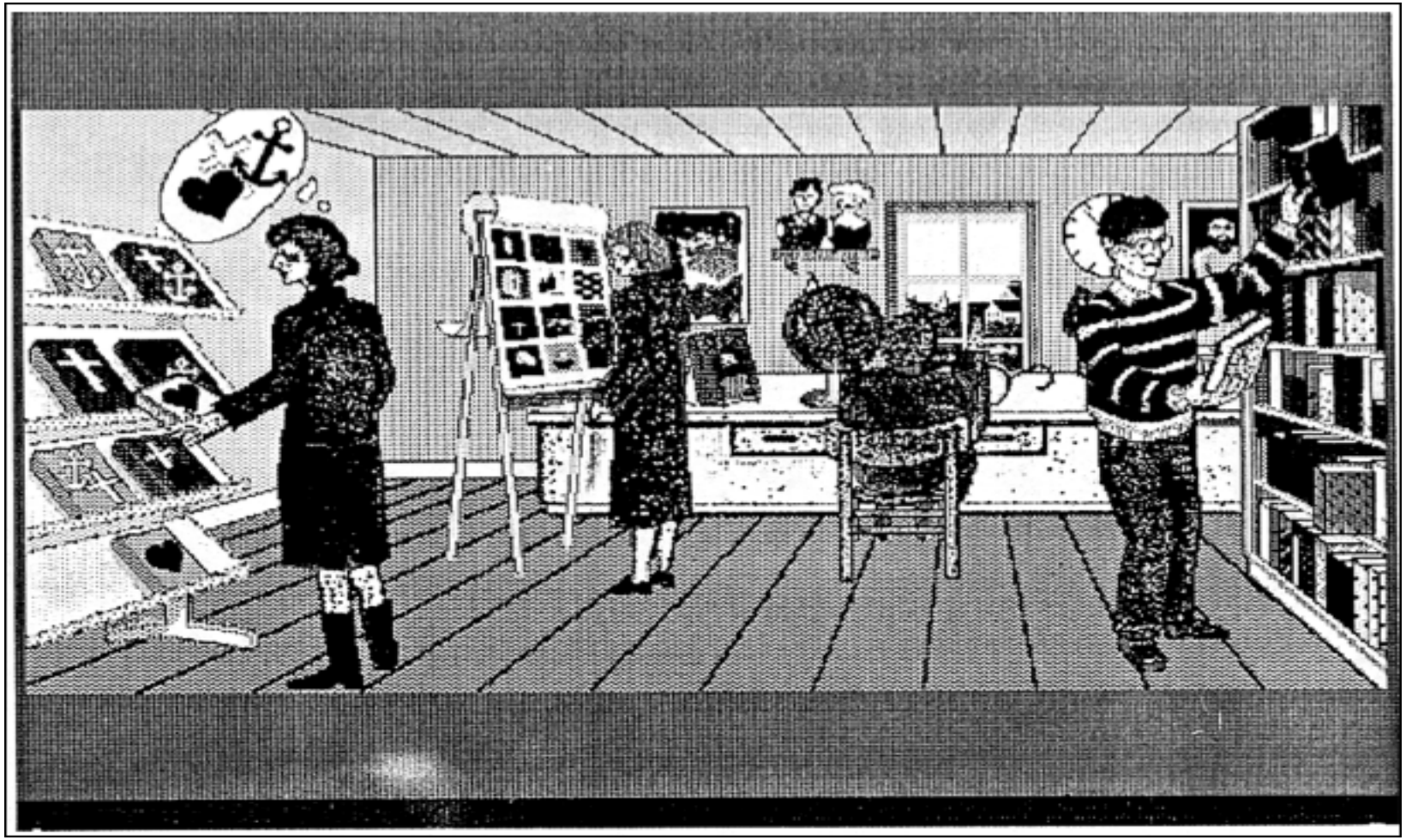
SPORTS-PERSON

Rich, E. (1983). Users are individuals: Individualizing user models. *International Journal of Human-Computer Studies, 51*, 323-338.



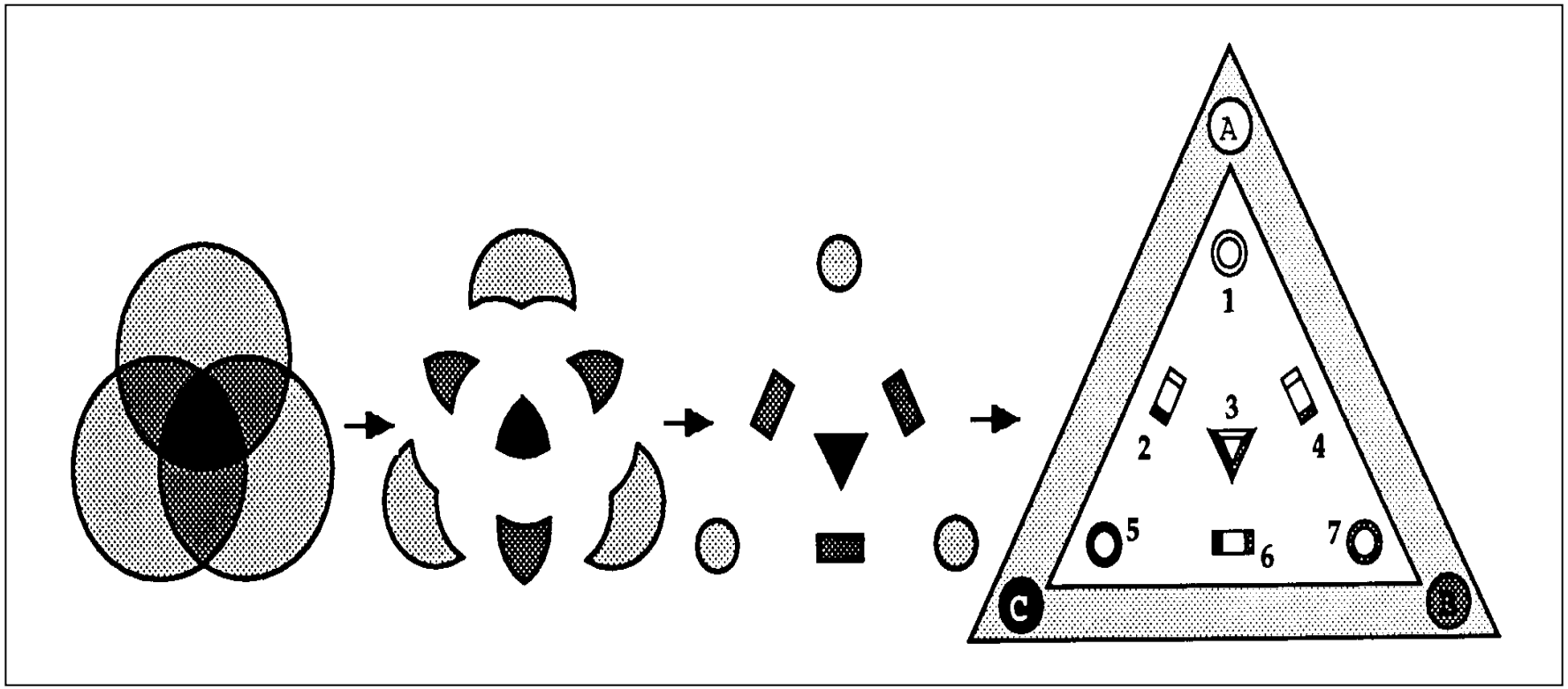
Maes, P. (1994). Agents that reduce work and information overload. *Communications of the ACM*, 30-40.

Interactive Spaces



Pejtersen, A. M. (1989). *The BOOK House: Modeling user needs and search strategies as a basis for system design*. Roskilde, Risø National Laboratory. (Risø report M-2794).

Help with Complex Query Languages



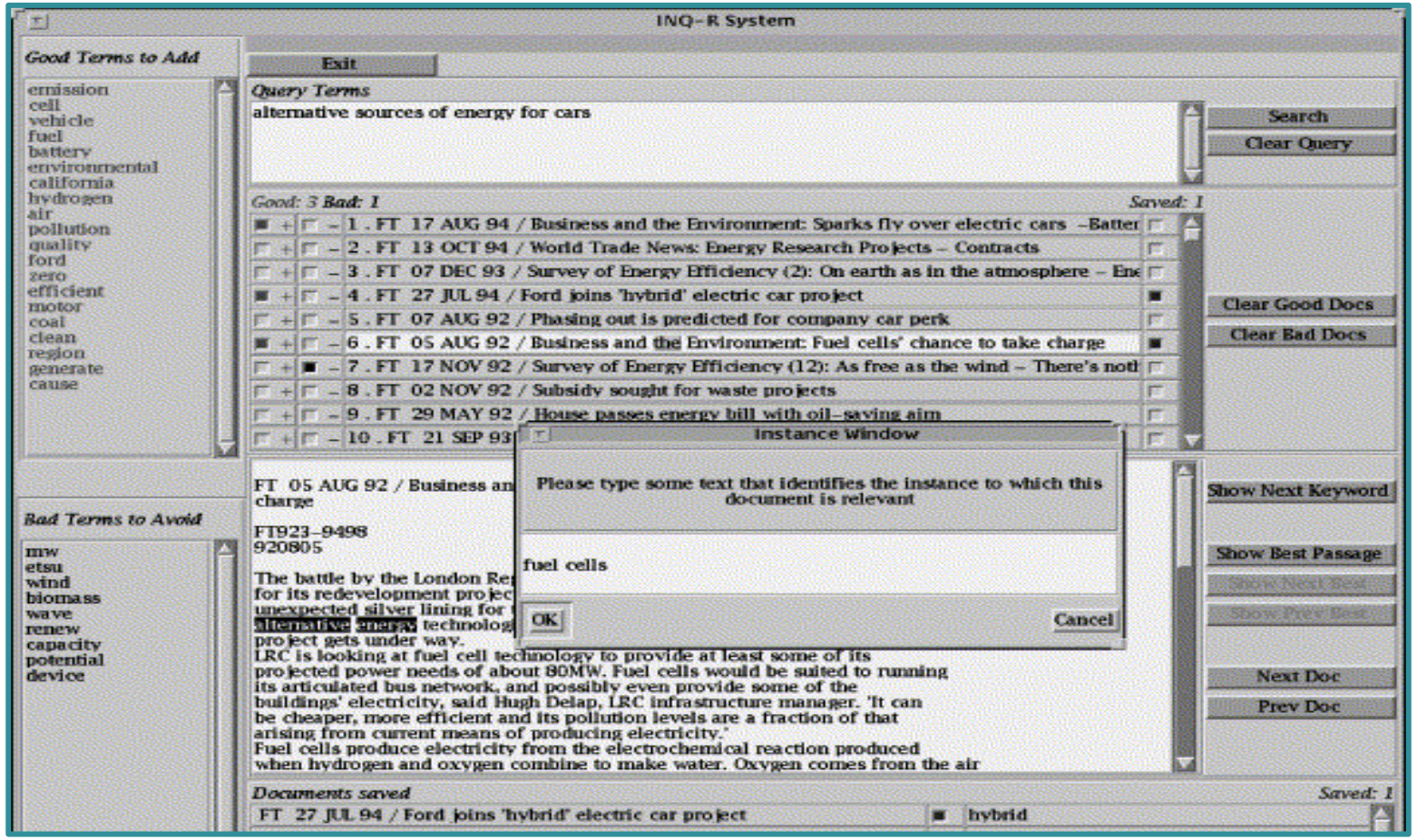
Spoerri, A. (1993). InfoCrystal: A visual tool for information retrieval. *Proceedings of the IEEE Visualization Conference*, 150-157.

TREC Interactive Track

- Ran from TREC 3 to TREC 12
- Explored a variety of tasks including filtering (query writing), ad-hoc, aspectual recall, fact-finding and topic-distillation
- Most noted for establishing the 'model' user study and some guidelines for reporting experiments
- Finding: Difficult to do interactive IR studies in the context of TREC

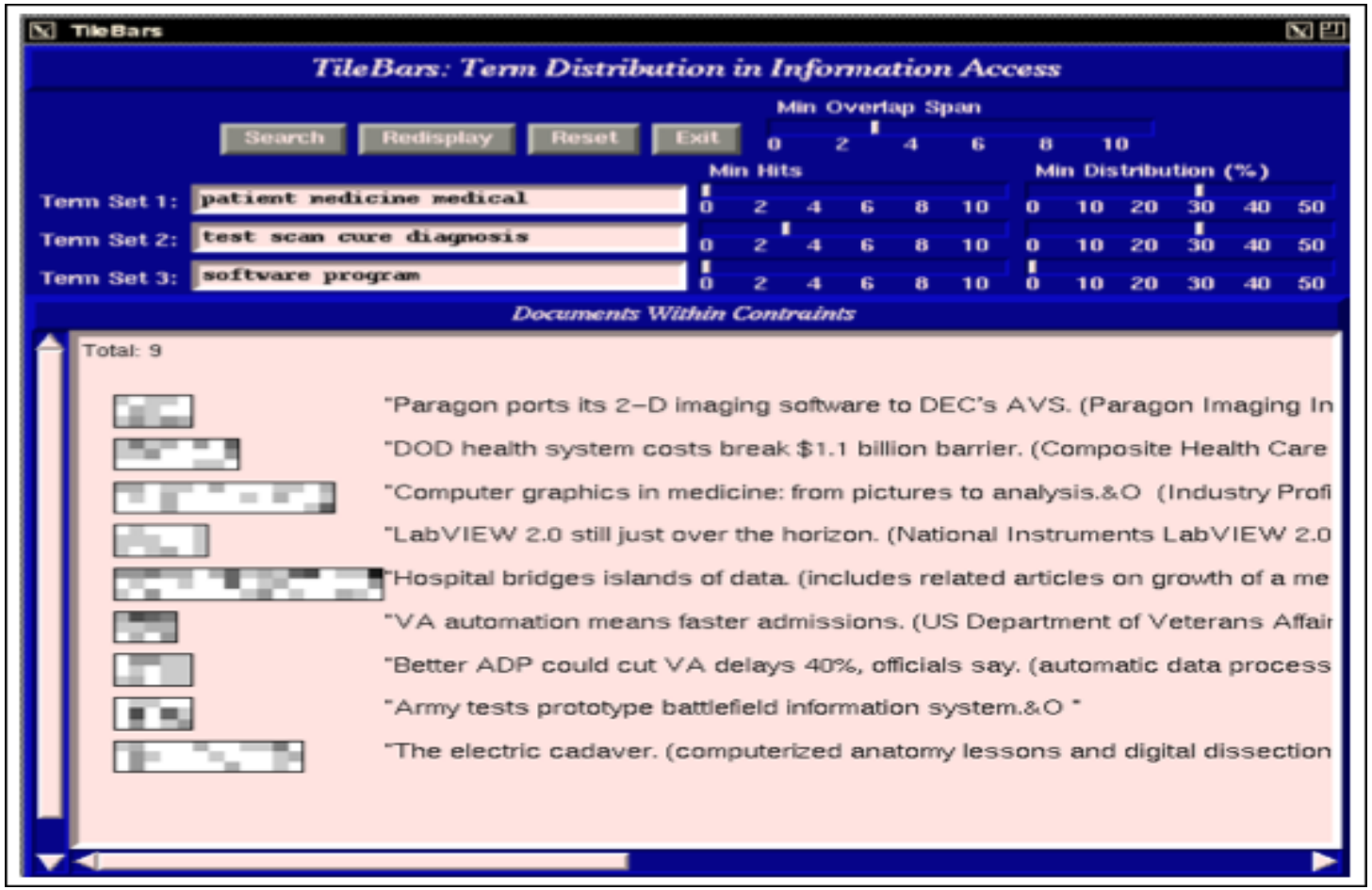
Dumais, S. T. & Belkin, N. J. (2005). The TREC interactive tracks: Putting the user into search. In *TREC: Experiment and Evaluation in Information Retrieval*, (E. M. Voorhees and D. K. Harman, eds.), pp. 123–153, Cambridge, MA: MIT Press, 2005.

Relevance Feedback



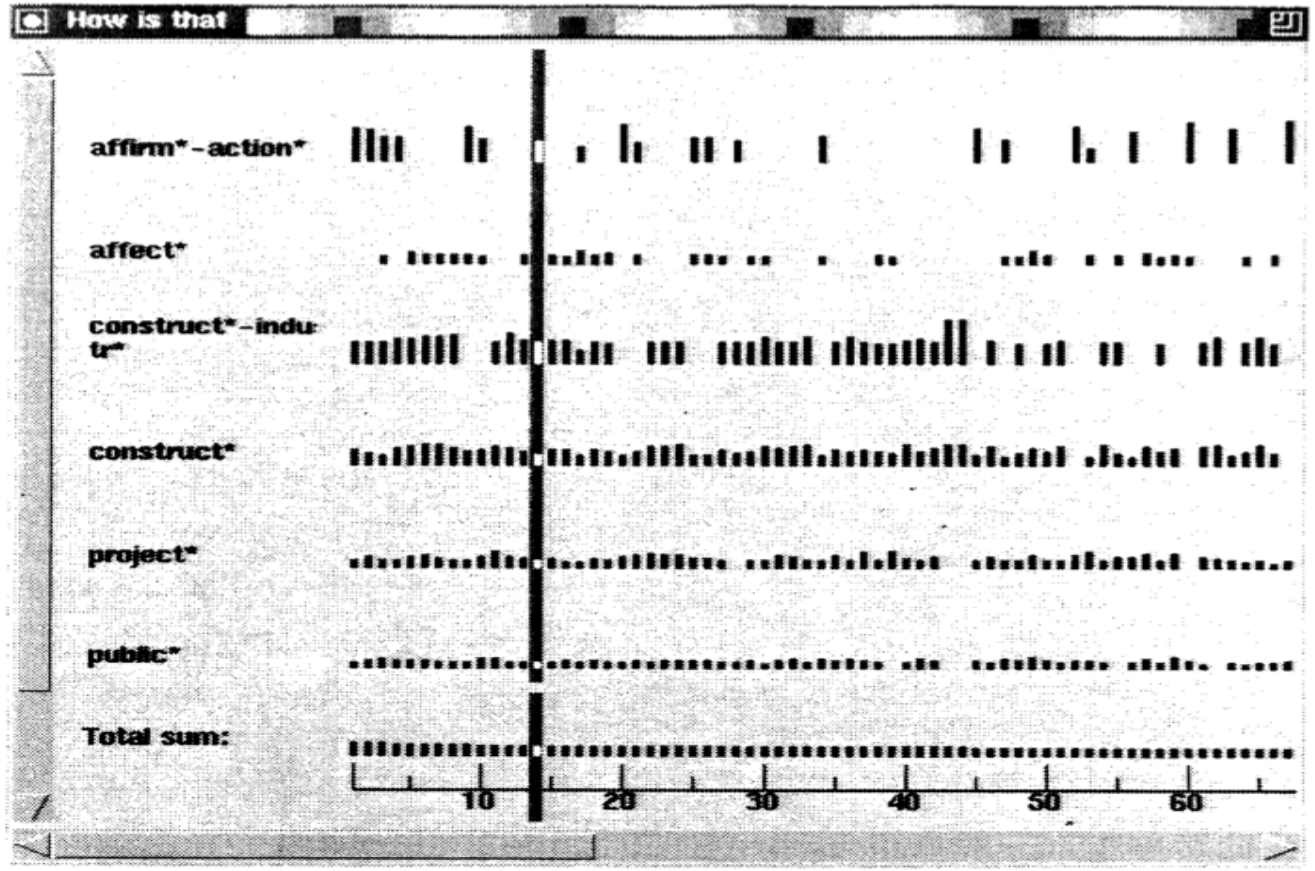
Belkin, N. J., et al. (2001). Iterative exploration, design and evaluation of support for query reformulation in interactive information retrieval. *Information Processing & Management 37*(3), 404-434.

Evaluating Results



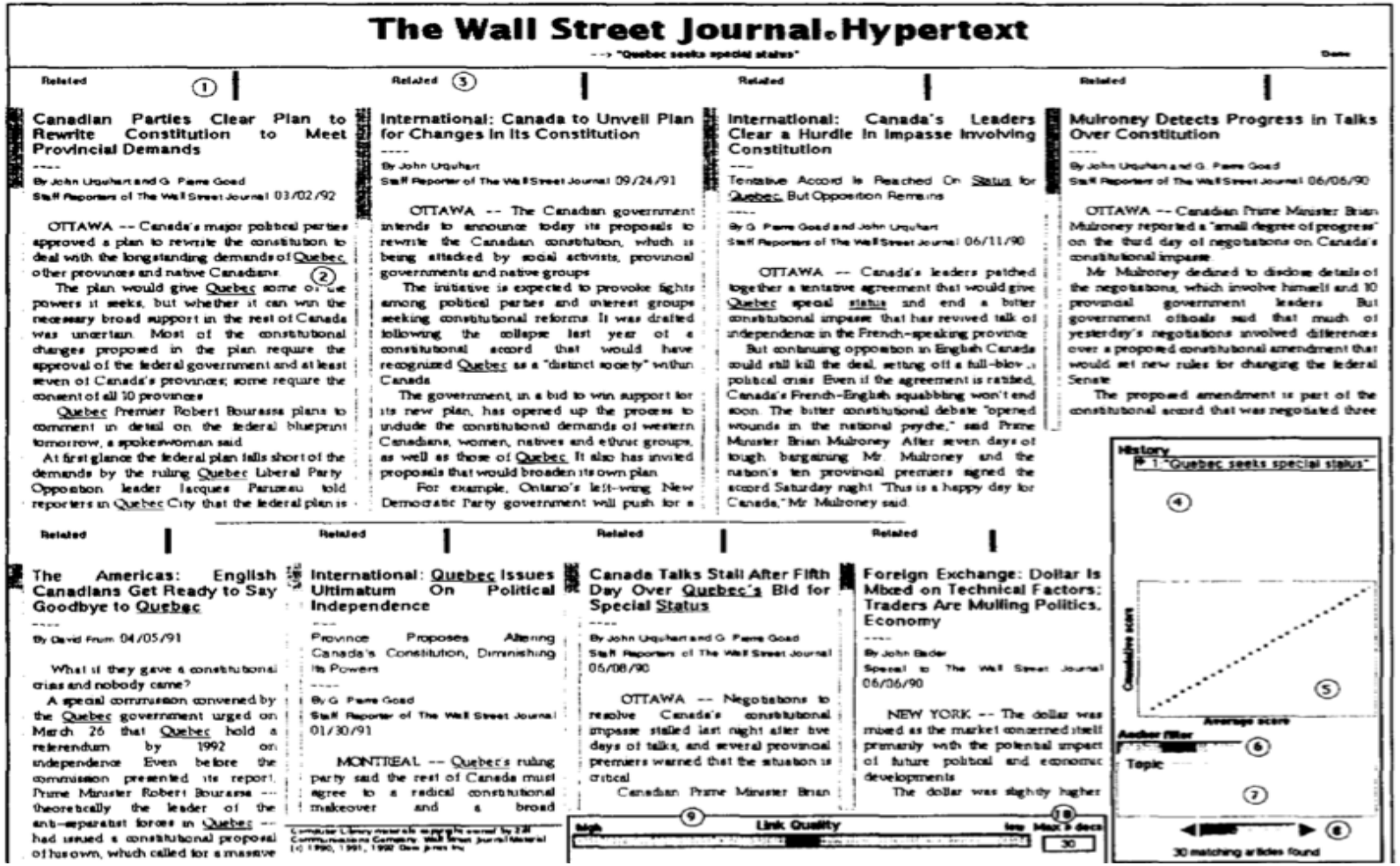
Hearst, M. A. (1995). TileBars: Visualization of term distribution in full text information access. *Proceedings of CHI '95*, 59-66.

Navigating and Comparing Results



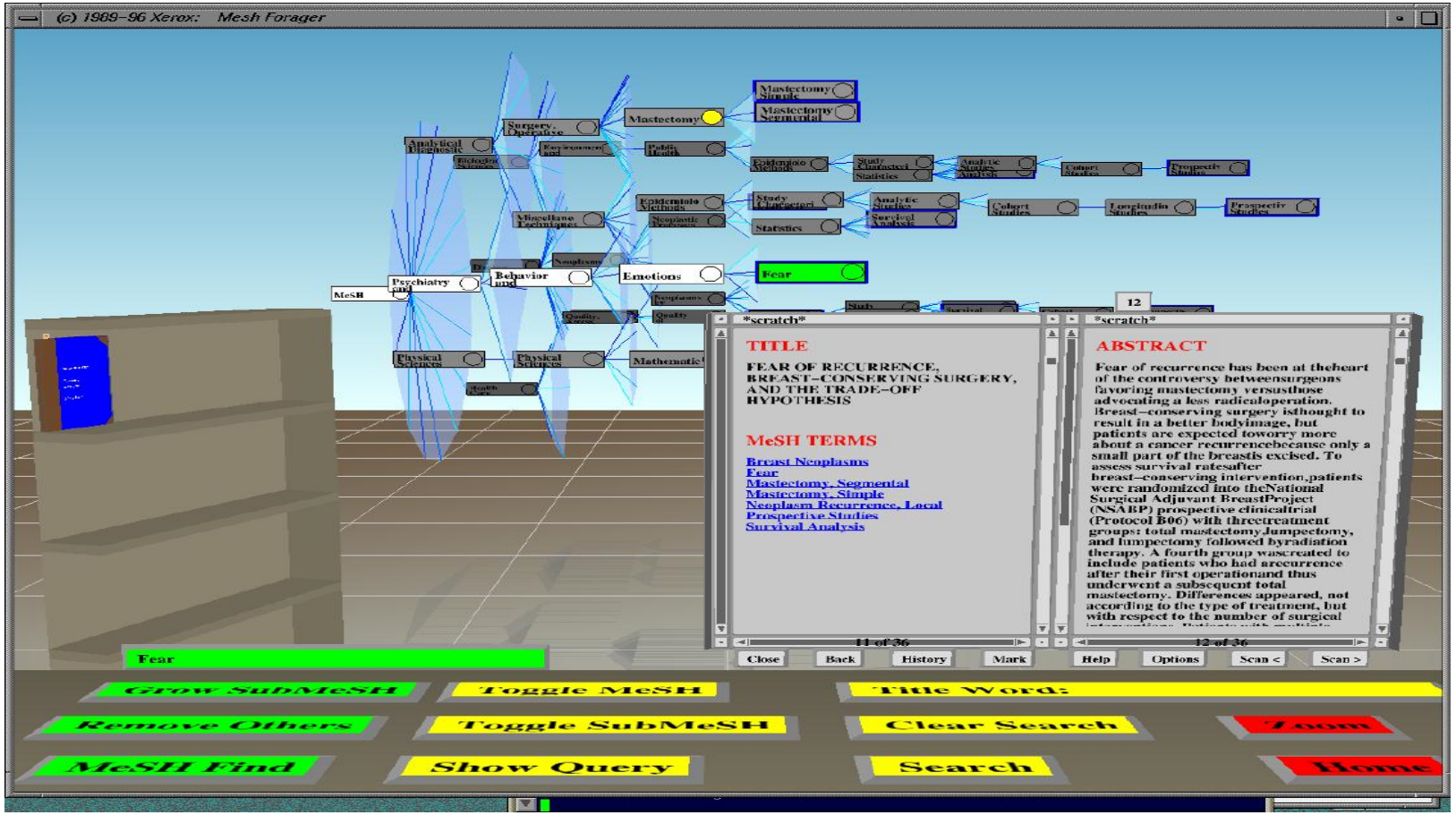
Veerasamy, A. & Belkin, N. J. (1996). Evaluation of a tool for visualization of information retrieval results. *Proceedings of SIGIR '96*, 85-92.

Single View Comparison



Golovchinsky, G. & Chignell, M. H. (1997). The newspaper as an information exploration metaphor. *Information Processing & Management, 33*(5), 663-683.

Interacting with System Components



Hearst, M. A. & Karadi, C. (1997). Cat-a-Cone: An interactive interface for specifying searches and viewing retrieval results using a large category hierarchy. *Proceedings of SIGIR '97*.

Saving and Sorting

Robertson, et al. (1998). Data Mountain: Using spatial memory for document management. *Proceedings of UIST '98*, 153-162.

Google Beta


Google!
BETA
Search the web using Google!
Google Search
I'm feeling lucky
Special Searches
Stanford Search
Linux Search
Help!
About Google!
Company Info
Google! Logos
Get Google!
updates monthly:
your e-mail
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Archive
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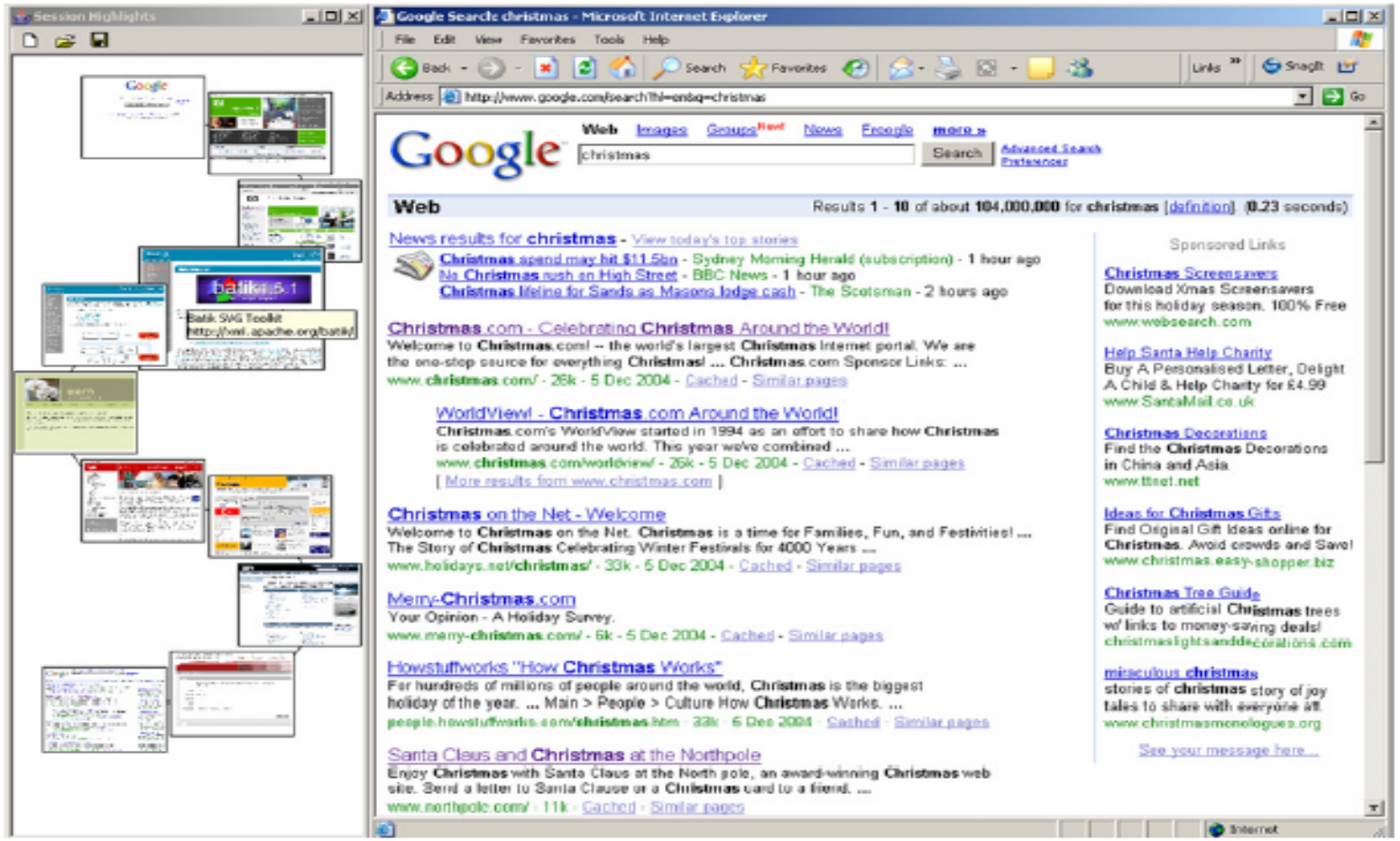
Saving and Sorting



Jhaveri, N. & Raiha, K.-J. (2005). The advantages of a cross-session web workspace. *Proceedings of CHI*.

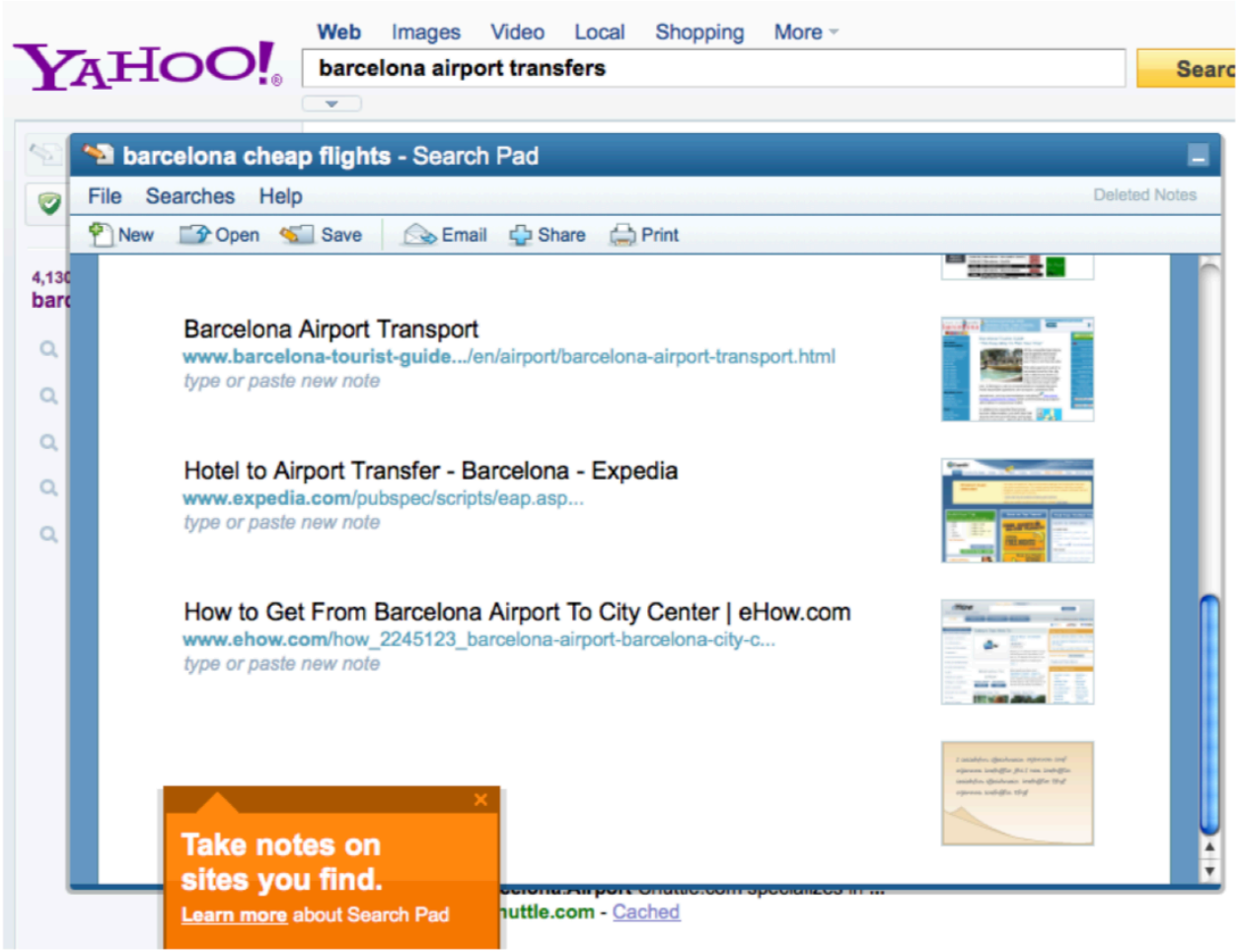
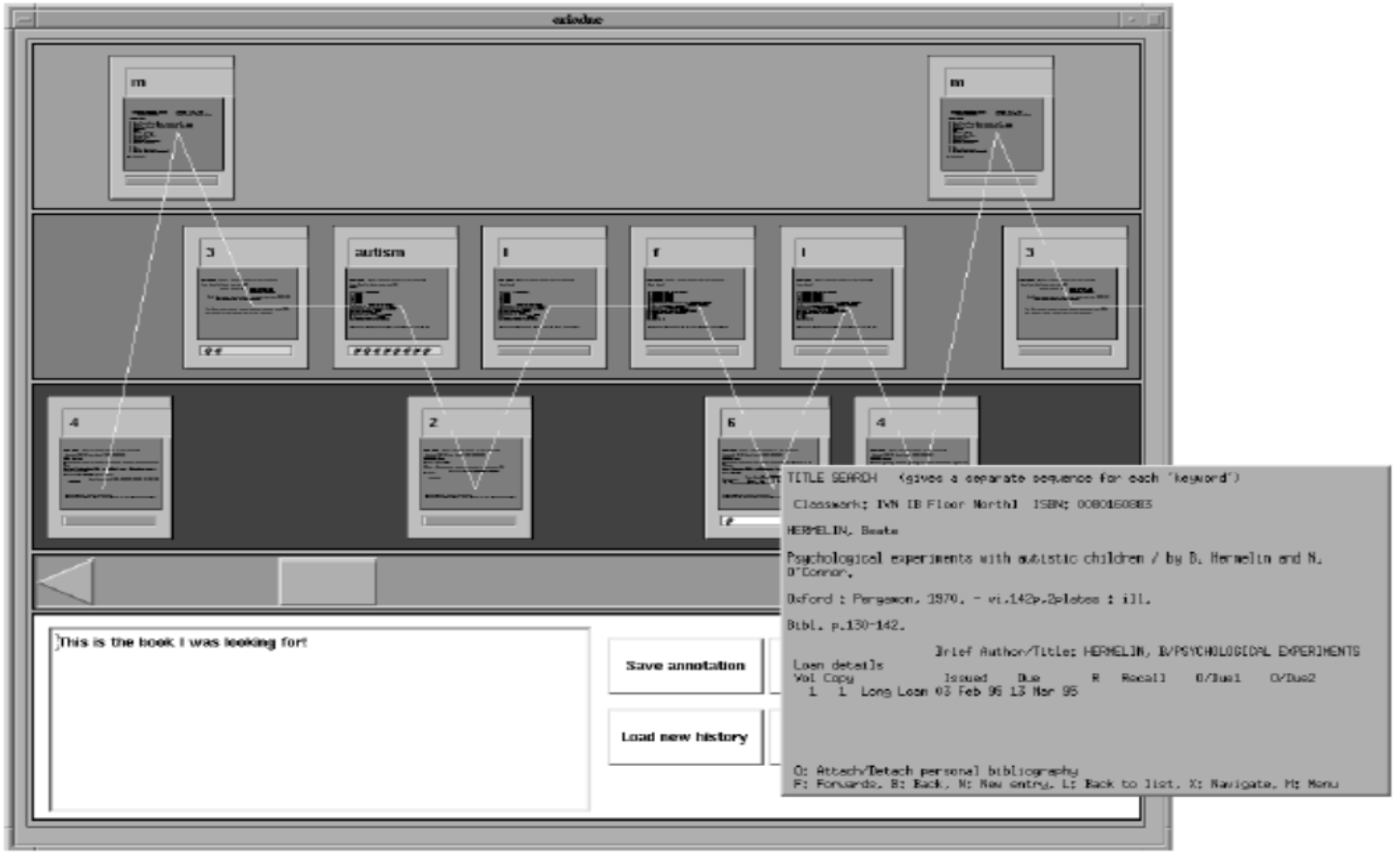


Figure 2: An opened pad object

Donato, D., Bonchi, F., Chi, T., & Maarek, Y. (2010). Do you want to take notes? Identifying research missions in Yahoo! Search Pad. *Proc. WWW Conference*, 321-330.

Collaborative Search

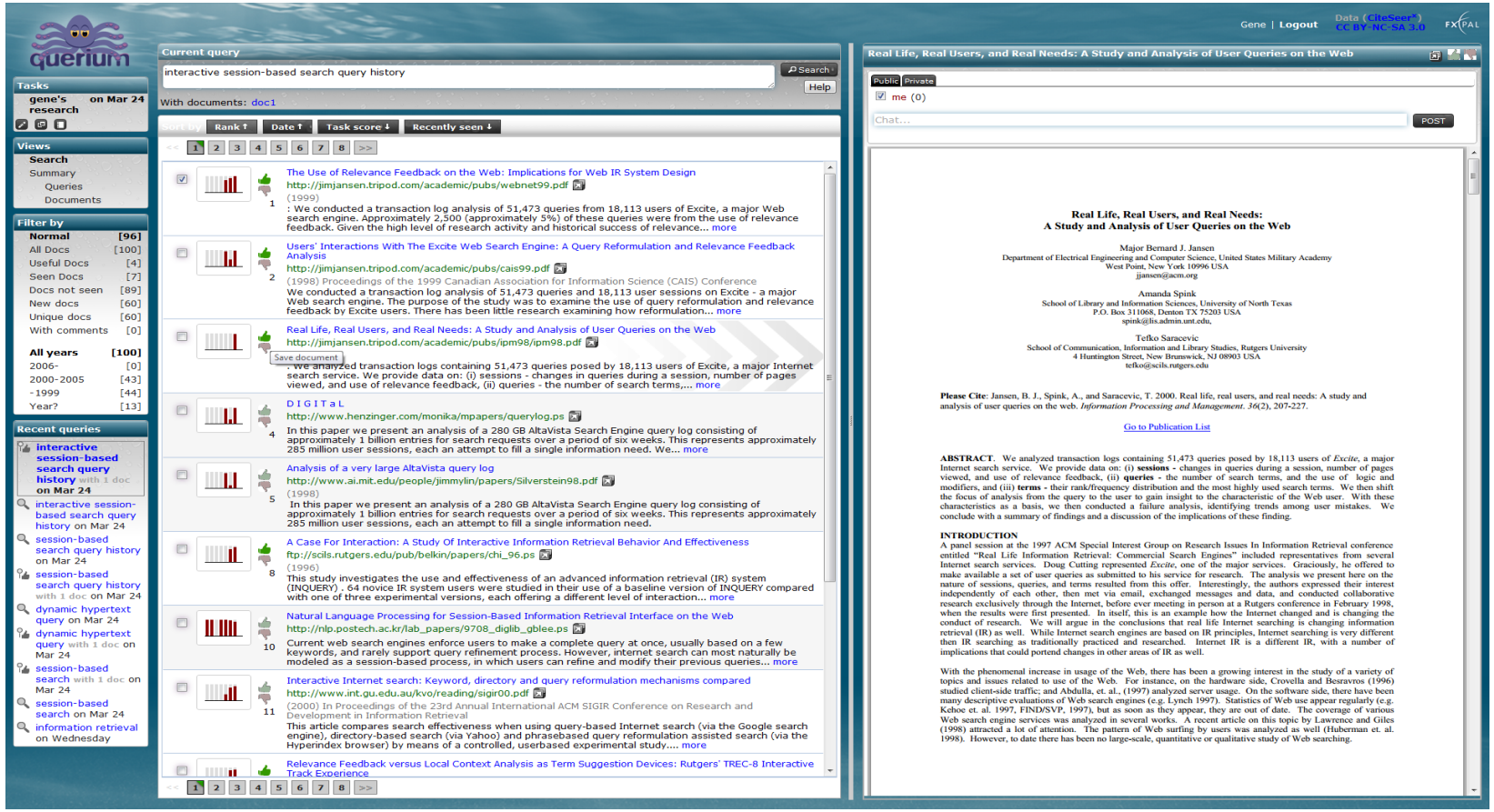


Twidale, M. B. & Nichols, D. M. (1998). Designing interfaces to support collaboration in information retrieval. *Interacting with Computers, 10*(2), 177-193.

Figure 1. The SearchTogether client. (a) integrating messaging, (b) query awareness, (c) current results, (d) recommendation queue, (e)(f)(g) search buttons, (h) page-specific metadata, (i) toolbar, (j) browser

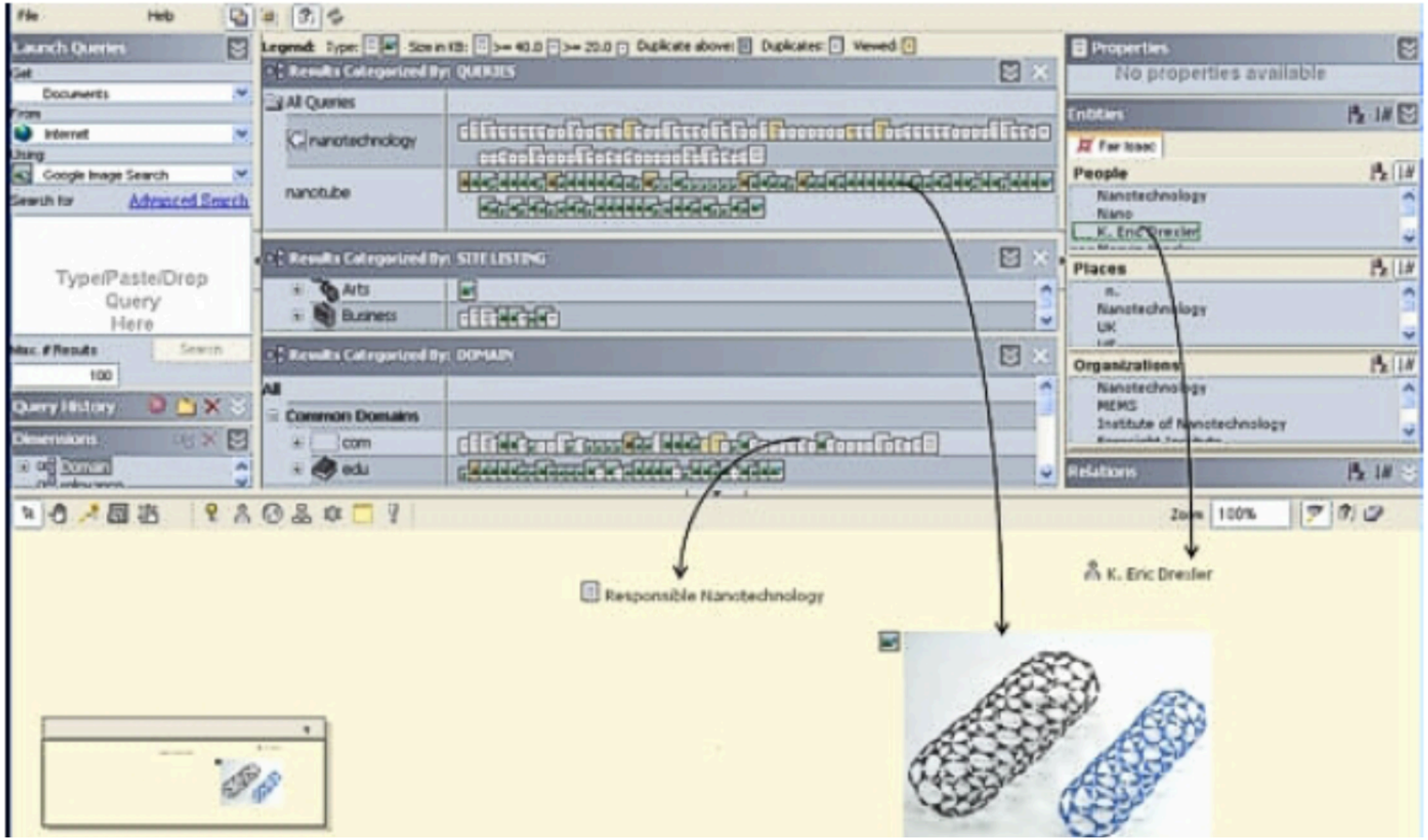
Morris, M. R., & Horvitz, E. (2007). SearchTogether: An interface for collaborative web search. *Proc. of UIST*, 3-12.

Integrated Environments



Golovchinsky, G., Biriye, A., & Dunnigan, T. (2012). The future is in the past: Designing for exploratory search. *Proceedings of IIiX '12*.

Specialized Audiences



Wright, et al. (2006). The Sandbox for analysis-concepts and methods. *Proceedings of SIGCHI Conference*.

Persuading & Nudging People to Change

Figure 1. Empty query box.

Figure 2. As the person starts to type, the halo changes.

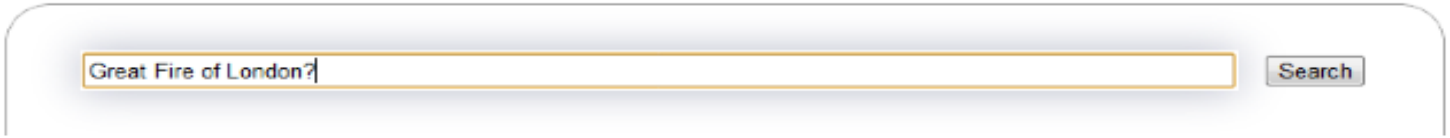


Figure 3. A longer query with a bluer halo.

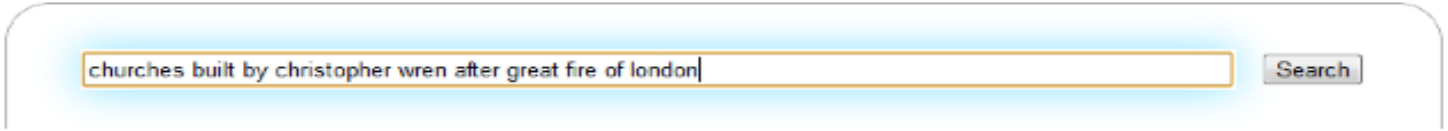
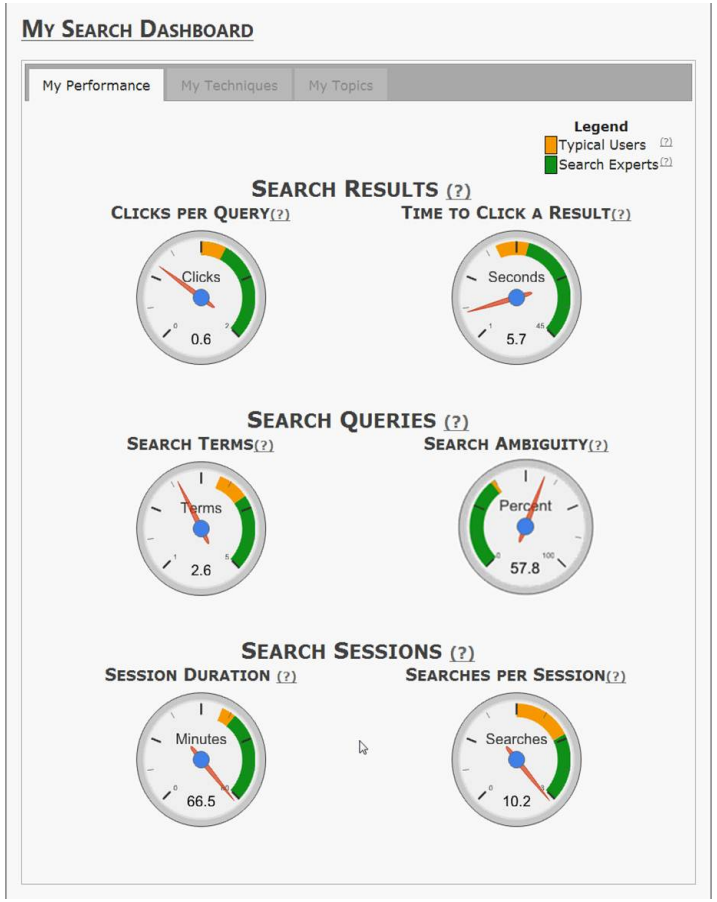


Figure 4. A long query with a bluish halo.

Agapie, E., Golovchinsky, G. & Qvardordt, P. (2012). Encouraging behavior: A foray into persuasive computing. *Proc. of HCIR.*

Reflective Practice & Learning



Bateman, S., Teevan, J., & White, R. W. (2012). The search dashboard: How reflection and comparison impact search behavior. *Proceedings of CHI '12*, Austin, TX, 1785-1794.

Mobile Search

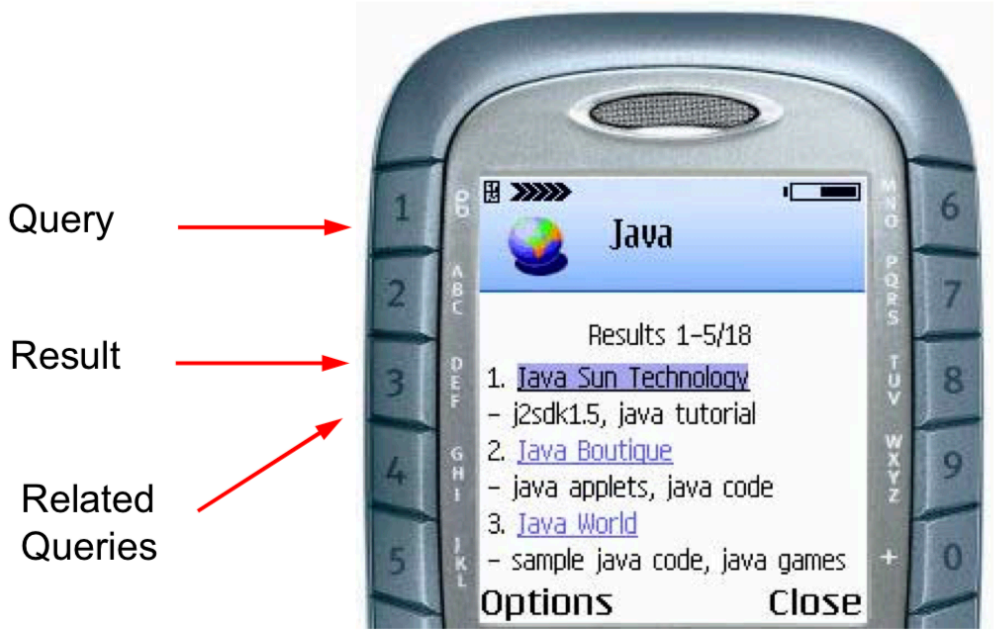
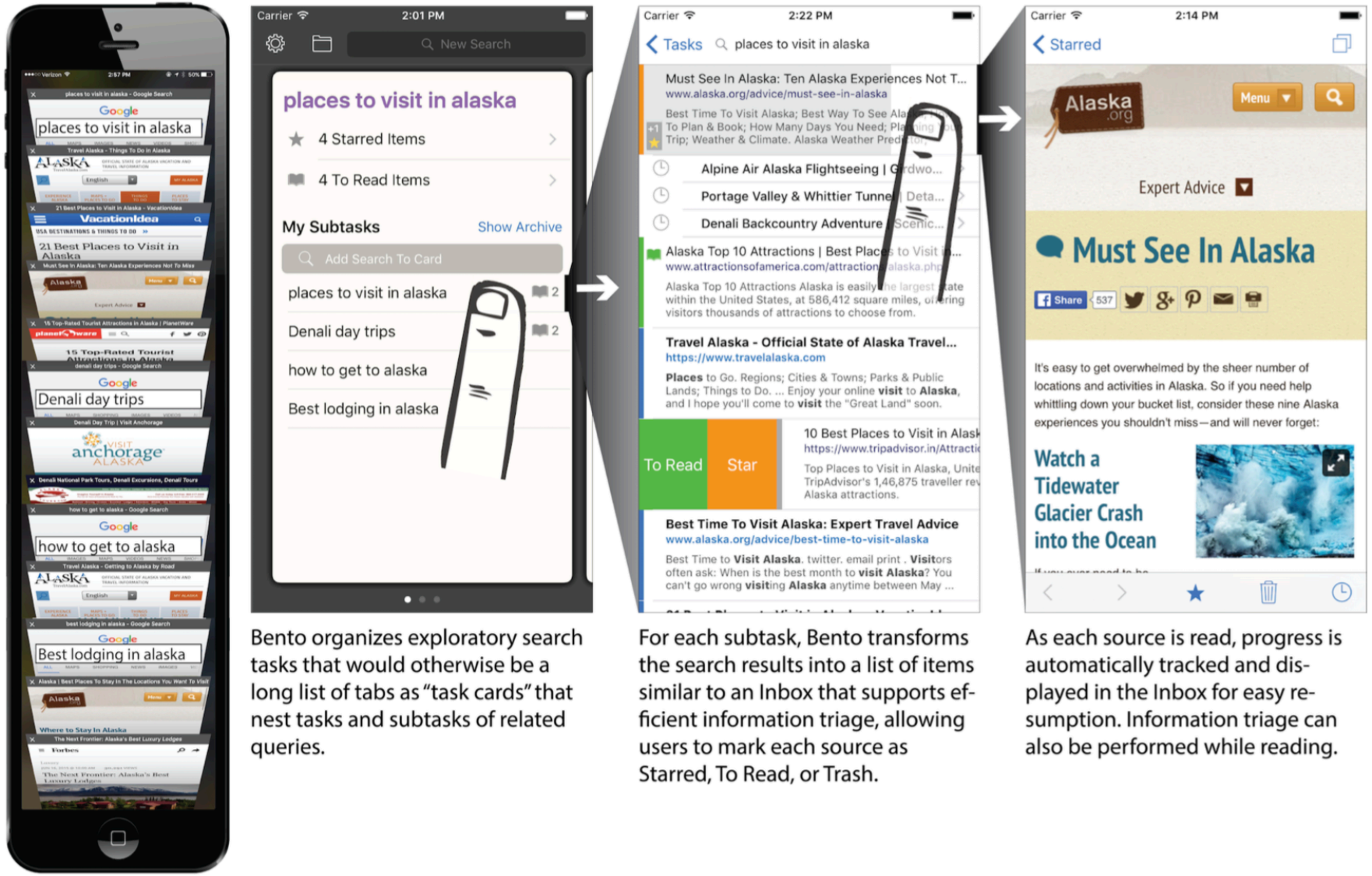


Figure 2: Illustration of the Results and Related Queries Generated for the Query 'Java' on a Mobile Phone

Church, K., Smyth, B., & Keane, M. T. (2006). Evaluating interfaces for intelligent mobile search. *Proc. of the 2006 International Cross-disciplinary workshop on Web accessibility (W4A): Building the mobile web: rediscovering accessibility?* 69-78.



Bento organizes exploratory search tasks that would otherwise be a long list of tabs as "task cards" that nest tasks and subtasks of related queries.

For each subtask, Bento transforms the search results into a list of items similar to an Inbox that supports efficient information triage, allowing users to mark each source as Starred, To Read, or Trash.

As each source is read, progress is automatically tracked and displayed in the Inbox for easy resumption. Information triage can also be performed while reading.

Figure 1. Comparing a typical list of tabs (left) with Bento's search centered navigation from the same exploratory search task.

Hahn, N., Chang, J. C., & Kittur, A. (2018). Bento Browser: Complex mobile search without tabs. *Proc. of ACM CHI*, paper 251.

Proactive Search during Conversations

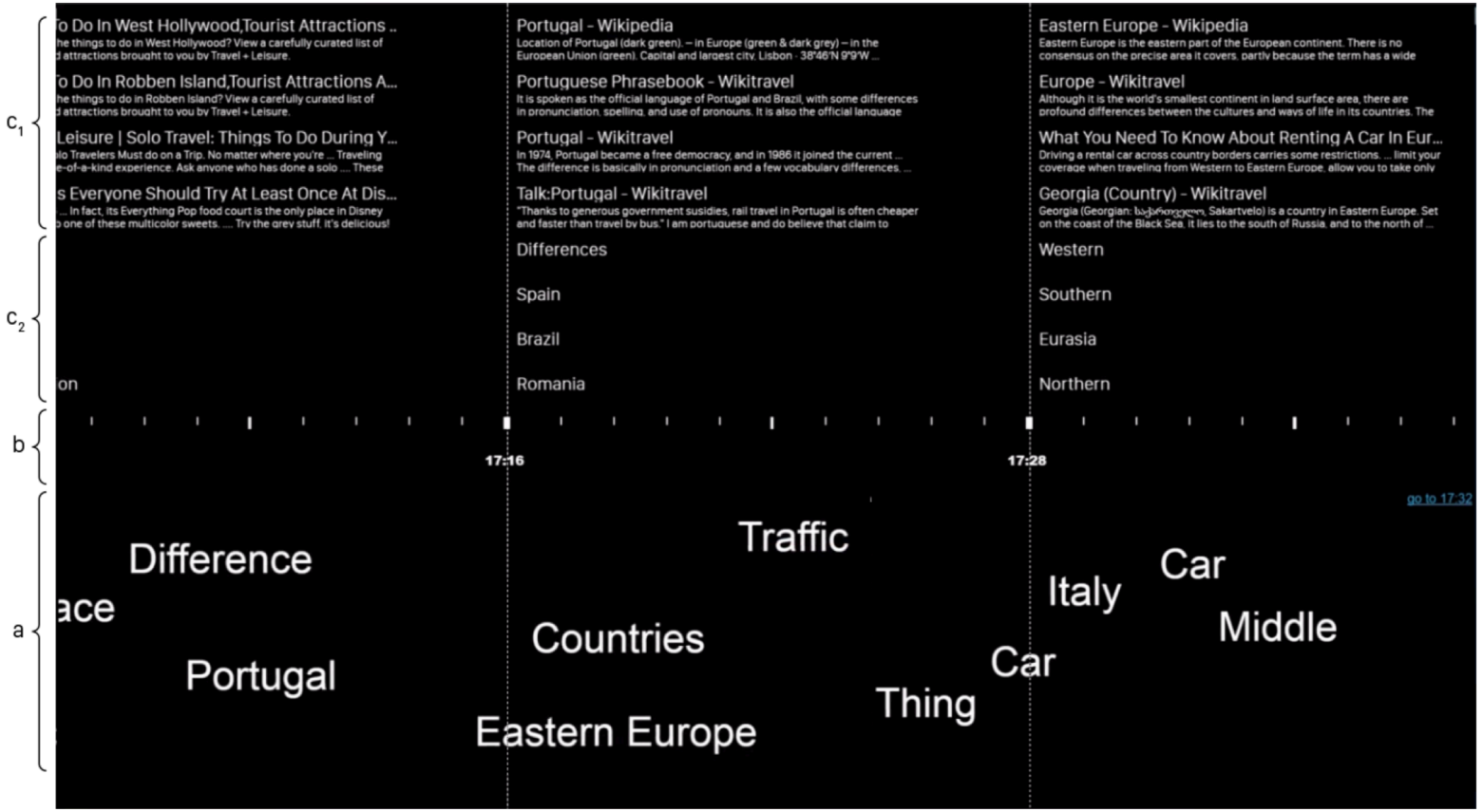
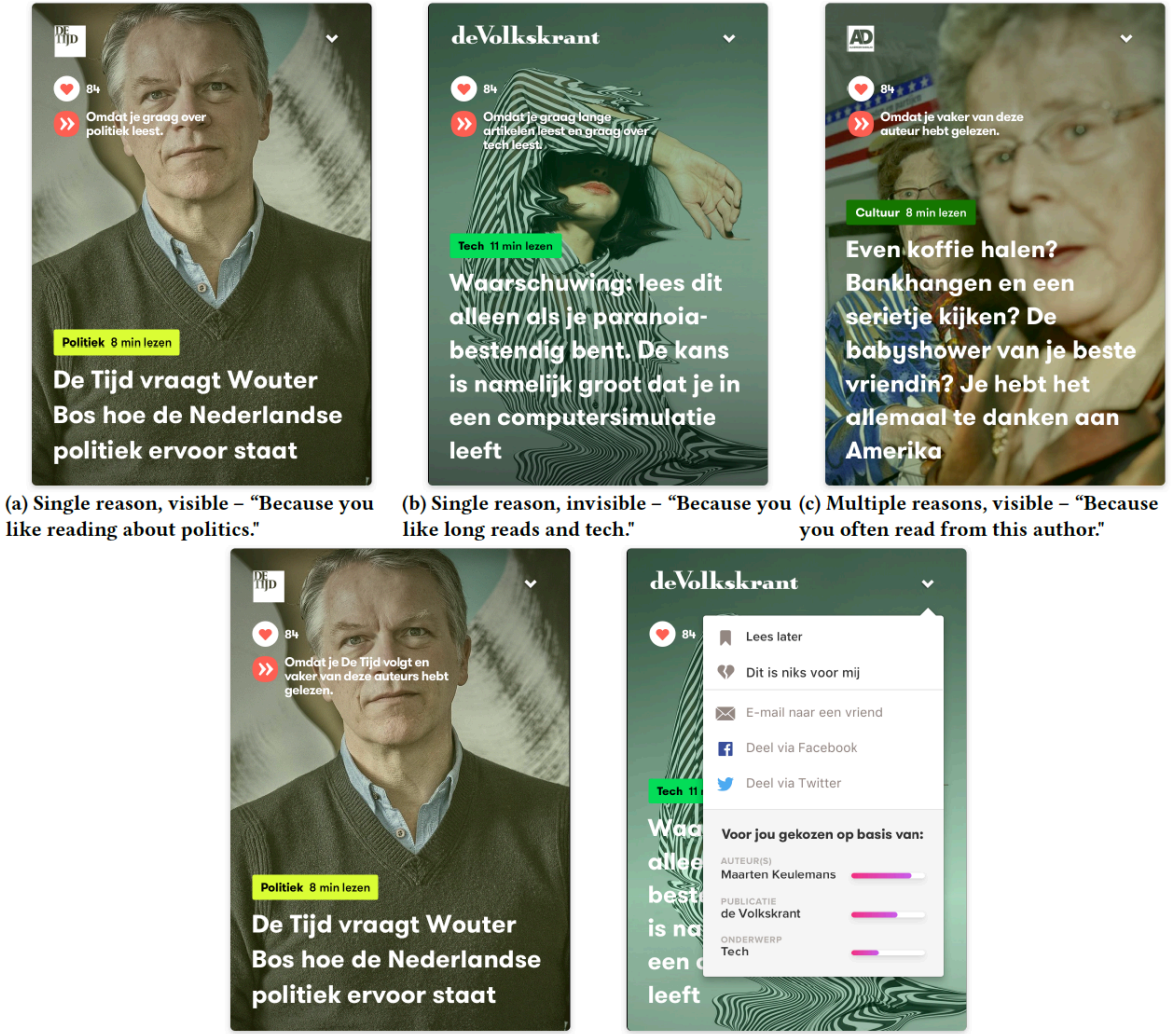


Figure 2. The user interface of the SearchBot system. The system monitors a conversation and provides continuous recommendations of related documents and entities in a non-intrusive way. a) Stream of recognized entities; b) timescale with timecodes; c_1) recommended documents; c_2) recommended entities.

Andolina, S., Orso, V., Schneider, H., et al. (2018). Investigating proactive search support in conversations. *Proc. of the ACM DIS Conference*, 1295-1307.

Explanations



(a) Single reason, visible – "Because you like reading about politics."

(b) Single reason, invisible – "Because you like long reads and tech."

(c) Multiple reasons, visible – "Because you often read from this author."

(d) Multiple reasons, combined – "Because you follow De Tijd and read from these authors more often."

(e) Bar chart – "Selected for you based on: Author(s): Maarten Keulemans; Publication: De Volkskrant; Topic: Tech"

Figure 1: Examples of reason types as shown to users in our user study. Textual reasons are in the lines that start with "Omdat" (*because*). For the bar chart layout the reasons starts with "Voor jou gekozen" (*selected for you*). Translations are given below each article.

Maartje Ter Hoeve, Mathieu Heruer, Daan Odijk, Anne Schuth, Martijn Spitters, and Maarten de Rijke. Do News Consumers Want Explanations for Personalized News Rankings?. In *FATREC Workshop on Responsible Recommendation*, August 2017.

User-Centered Evaluation

Different Types of Methods

	Observational	Experimental
Lab Studies *Controlled interpretation of behavior with detailed instrumentation*	In-lab behavior observations	In-lab controlled tasks, comparison of systems
Field Studies *In the wild, ability to probe for detail*	Ethnography, case studies, panels (e.g., Nielsen)	Clinical trials and field tests
Log Studies *In the wild, little explicit feedback but lots of implicit signals*	Logs from a single system	A/B testing of alternative systems or algorithms

Table 1. Different types of user data in HCI research.

Dumais, S., Jeffries, R., Russell, D. M., Tang, D. & Teevan, J. (2014). Understanding user behavior through log data and analysis. J.S. Olson and W. Kellogg (Eds.), *Human Computer Interaction Ways of Knowing*. New York: Springer.

User Studies in Controlled Settings

- Allows the researcher to interact with users to better understand their experiences.
- Allows for the use of a wider-variety of data collection techniques, including:
  - Logs, scales, questionnaires
  - Interviews, think-aloud
  - Eye-tracking, physiological data, EEG, fMRI
- Enables manipulation, control and isolation of effects

What is an experiment?

> "By experiment we refer to that portion of research in which variables are manipulated and their effects upon other variables are observed."
>
> (Campbell & Stanley, 1963, p. 1)

- Manipulated variables: independent variables.
- Observed variables: dependent variables.

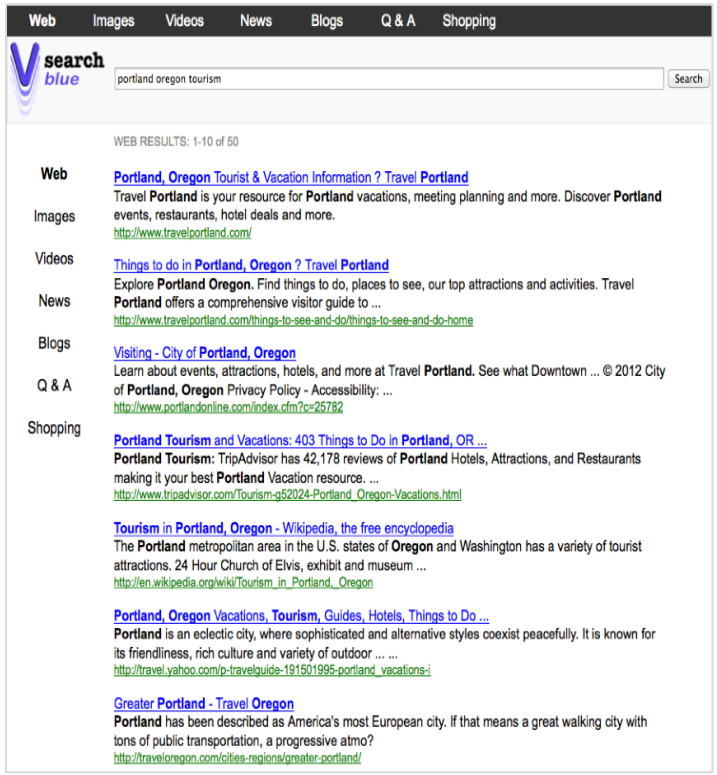
What is an experiment?

> "By experiment we refer to that portion of research in which variables are manipulated and their effects upon other variables are observed."
>
> (Campbell & Stanley, 1963, p. 1)

- Experiments are conducted to evaluate causal relationships.

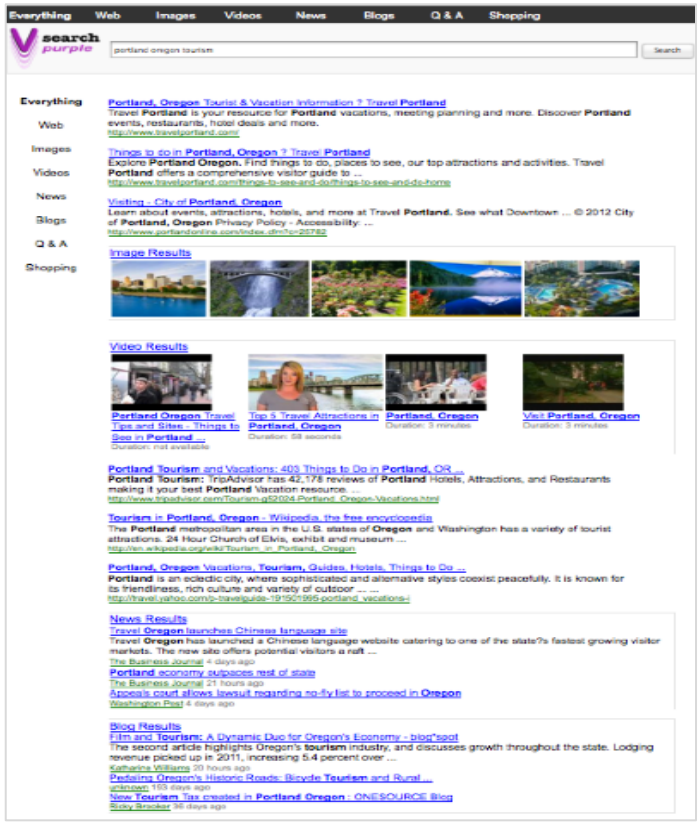
Simplest Case: Interface Evaluation

Non-blended Interface



Vs.

Blended Interface



Arguello, J., Wu, W.C., Kelly, D., & Edwards, A. (2012). Task complexity, vertical display and user interaction in aggregated search. *Proceedings SIGIR '12*, 435-444.

Simplest Case: Interface Evaluation

How does vertical display impact the workload experienced by people during search?

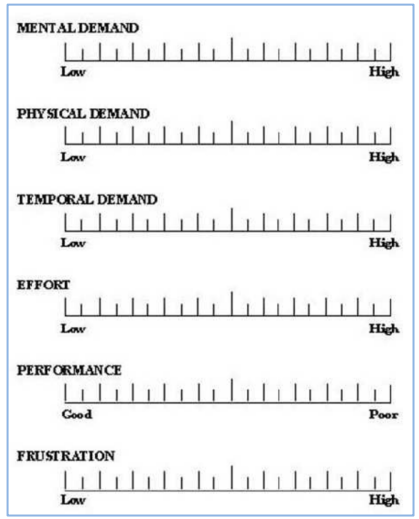
Independent variable

Vertical Display

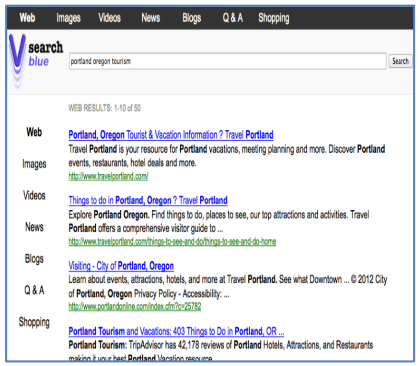
Dependent variable

Workload

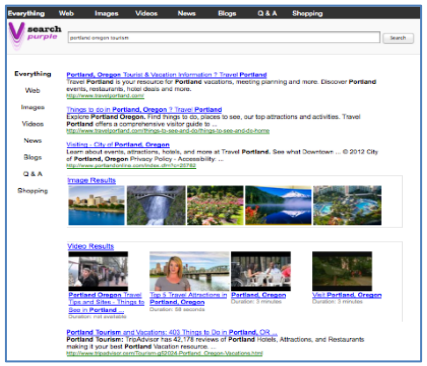
NASA-TLX



Non-blended



Blended



Field and Lab Experiments

- In a field experiment, researchers conduct a live experiment ‘in-the-wild’ and participants often do not know they are participating.
  - Example: AB Test
  - Note: Using Mechanical Turk is not a field experiment
- Field experiments often have better ecological validity than laboratory experiments, but the researcher has far less control, which makes it harder to isolate cause and effect.

Lab Experiments are Useful For …

- Examining search behavior and user differences
  - How does task complexity impact search behavior?
  - How does time pressure impact search behavior?
- Examining the relevance judgment process
  - How does the presentation order of documents impact a person's relevance assessments?
- Evaluating interfaces and systems
  - Is my new interface any good?
  - Is my query suggestion technique any good?
- Testing theory
  - To what extent does Information Foraging Theory explain people's stopping behaviors during search?

Example: Interface Evaluation

Experimental Treatment

Baseline; Control Condition

Qvarfordt, P., Golovchinsky, G., Dunnigan, T. & *Agapie, E. (2013). Looking ahead: Query preview in exploratory search. Proc. of ACM SIGIR Conference*, 243-252.

Example: Interface Evaluation

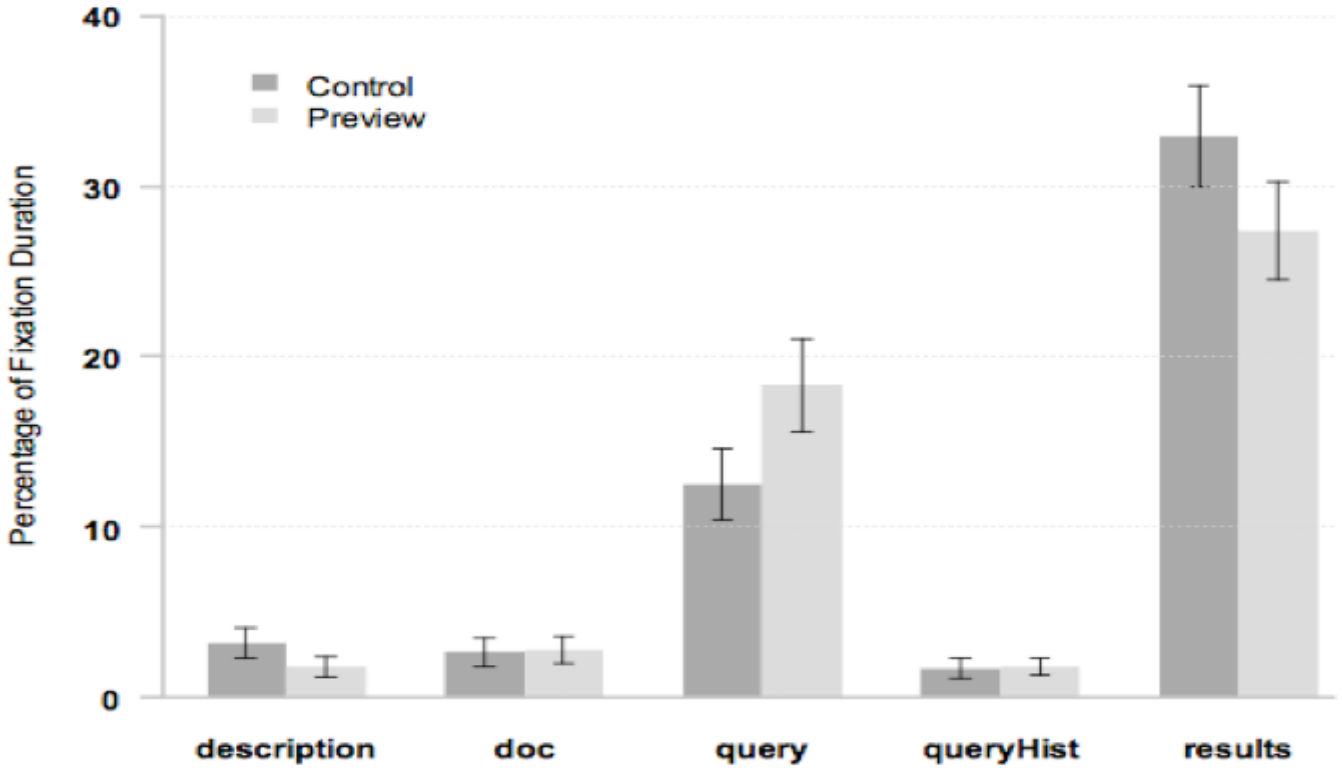


Figure 6. Percentage of attention on UI elements *during* query formulation (total fixation duration on UI element).

Example: Individual Differences Research

- The basic premise is that people differ along many characteristics; researchers in this area seek to explain variations in behaviors by variations in characteristics.
- Some of the earliest work in interactive IR research focused on investigating how search success was related to individual differences.
- Example differences that have been studied include: age, biological sex, undergraduate major, learning styles, and cognitive abilities.
  - Cognitive Abilities
    - Perceptual speed
    - Associative memory
    - Visualization ability

Example: Cognitive Ability

Do people with different levels of perceptual speed exhibit different search behaviors when solving the same information search tasks?

	Low Perceptual Speed	High Perceptual Speed
Session length (min)	6.85 (3.71)	6.43 (3.73)
Query length	4.62 (2.24)	5.85 (1.98)
SERP clicks	1.91 (1.78)	3.52 (2.68)
URLs viewed	2.38 (1.96)	4.63 (3.81)
URLs per query	1.26 (0.88)	1.84 (1.58)
All differences significant at $p<0.01$		

Brennan, K., Kelly, D., & Arguello, J. (2014). The effect of cognitive abilities on information search for tasks of varying levels of complexity. *Proceedings of the Information Interaction in Context Conference (IIiX)*, Regensburg, Germany, 165-174.

What is an experiment?

- In an experiment, we deliberately manipulate the environment to isolate the effect of one variable on another.
- This can be contrasted with correlational research, where we take a snapshot of several variables at a time and investigate how they co-relate (often in natural settings).
  - Example: retrospective log analysis
- Correlation is a necessary condition for establishing causality, but is not sufficient.

Components of a User-Centered Study

Kelly, D. (2009). Methods for evaluating interactive information retrieval systems with users. *Foundations and Trends in Information Retrieval, 3(1-2)*.

Components of a User-Centered Study

- Participants
- Experimental “Conditions”
  - Systems/Algorithms
  - Interfaces
  - Instructions
  - …
- Search Tasks (sometimes called topics; can be used as independent variables)
- Collection/Corpus of Information Objects
- Measures
- Data Collection Techniques
- Data Analysis Procedures

Participants

- Participants should be *target* users.
  - E.g., Asking undergraduate students to evaluate an enterprise search system is unlikely to be meaningful.
- Studying computers scientists isn't always bad.
- Important to describe recruitment methods and characteristics of participants.
- Sample sizing is not magic or ad-hoc, although it often appears this way.

Digression: Sample Sizing

- There are statistical methods to help you understanding *risks* associated with sample sizes
  - The goal of *statistical power analysis* is to identify a sufficient number of participants to keep the risk of Type I errors and risk of Type II errors at acceptably low levels given a particular effect size without making the study unnecessarily expensive or difficult.
- Bigger ≠ Better
  - i.e., don't confuse sample size with sample representativeness

Type I and Type II Errors

- A Type I error (α) occurs when the researcher rejects a null hypothesis that is actually 'true.' (False positive)
- A Type II error (β) occurs when the researcher fails to reject the null hypothesis that is actually 'false.' (False negative)

Type I and Type II Errors

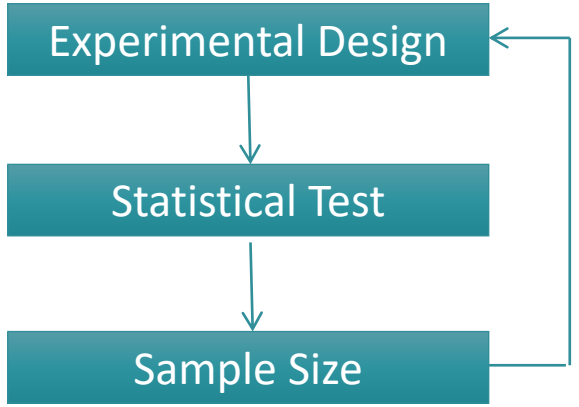
- The amount of risk a researcher is willing to tolerate with respect to making Type I or Type II errors can be quantified.
- In fact, researchers already state their risk for Type I errors when they set α= 0.05 as the threshold for statistical significance (α is the *p*-value before the statistic is computed).
  - When α= 0.05, you are risking a 5% chance of a Type I error.
- Side note: The more tests you do, the greater the likelihood of Type I errors.
- Tip: probability theory says to try something 20 times and then you'll find at least one significant result!

Type I and Type II Errors

- Most people are less familiar with when and how to declare tolerance for Type II errors (β).
- Works the same way in that risks are expressed as decimals (i.e, 0.05, or 5% risk).
- β is not used as an input to most statistical tests, but it is used during power analysis.
- Statistical power is expressed as 1 – β

What is Statistical Power?

- Statistical significance testing is computed after a study is completed.
- Statistical power is computed before a study is conducted. It involves two major steps:
  - Hypothesizing an effect size
  - Estimating risks associated with Type I and Type II errors
- It is also a function of the type of statistical test one wants to perform (which is a function of the experimental design).



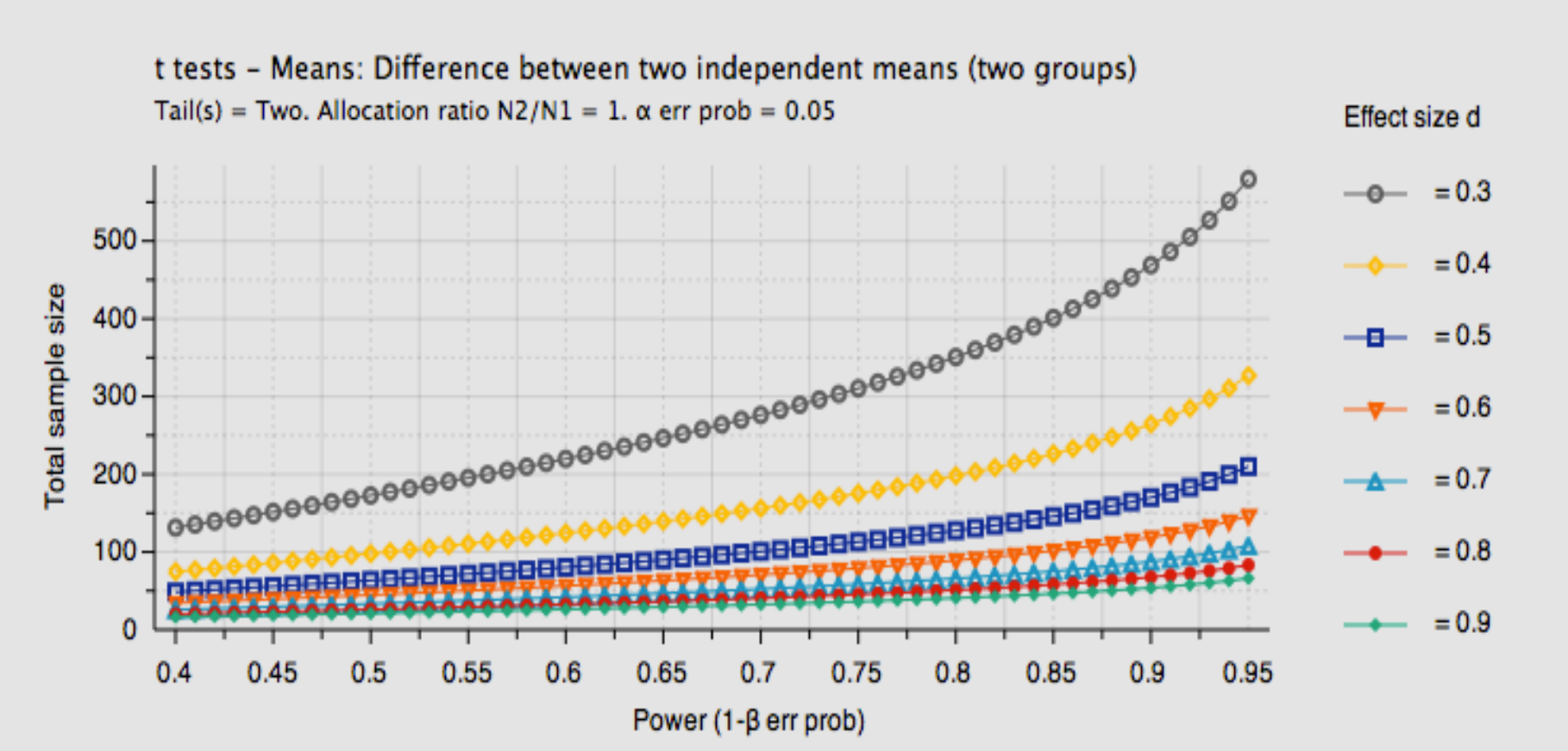
What is Effect Size?

- Effect Size is the strength of a statistically significant finding. The *actual value* is computed after one runs a statistical test, but its *estimate* is used in power analysis.
- Effect size is a standardized measure of the magnitude of the association between the treatment and outcome variables.
  - Does task complexity lead to a (10%? 20%? 70%?) increase in number of queries entered?
  - Does Interface A lead to a (10%? 20% 70%) increase in the performance over Interface B?
- Most uncertain aspect of sample size planning
  - Requires a hypothesis of the expected effect size

Repeat

- Statistical power analysis allows a researcher to estimate sample size given:
  - Specific type of statistical test (e.g., independent samples t-test) (which is a function of the research design)
  - Anticipated effect size
  - Alpha value (risk of Type I errors)
  - Desired power (risk of Type II errors)
    - Reminder: Power = 1 – β
- Demo of G*Power

Power Analysis of Independent Sample T-Test



Summary

- Statistical power analysis and G*Power are analytical tools to help you better understand the risks (mostly Type II) associated with your experiment given a particular sample size.
- You can pick any sample size you want (there are no correct answers!), but you should understand the risks associated with Type II errors.
- An underpowered study mostly affects you … and potentially what we know as a community.

Experimental Designs

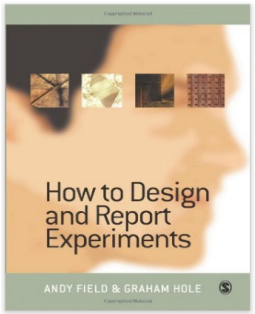
Note to ESSIR Students: We weren't able to cover the next set of slides, but I leave them in here for your reference if they are useful.

Types of Experimental Designs

- Between subjects factor (or variable)
  - Participants are only exposed to one level of the factor.
  - Example: You are testing two interfaces and each participant only uses one interface.
  - Also called between groups design.
- Within subjects factor (or variable)
  - Participants are exposed to more than one level of the factor.
  - Example: You are testing two interfaces and participants use both interfaces.
  - Also called *repeated measure(s)* design.

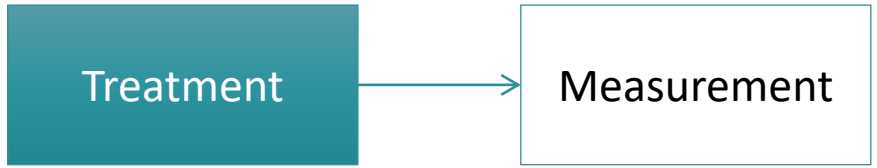
Between Subjects Designs

- Advantages
  - Simplicity
  - Less chance of practice and fatigue effects.
  - Useful when it is impossible for an individual to participate in all experimental conditions.
- Disadvantages
  - More expensive in terms of time, effort and number of participants.
  - Insensitive to experimental manipulations.



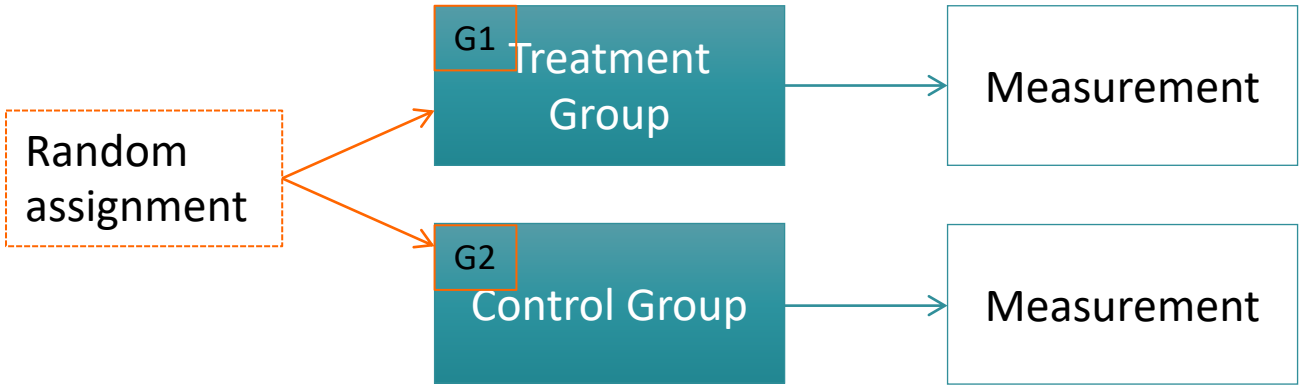
(Not) an Experimental Design

Classic Usability Test



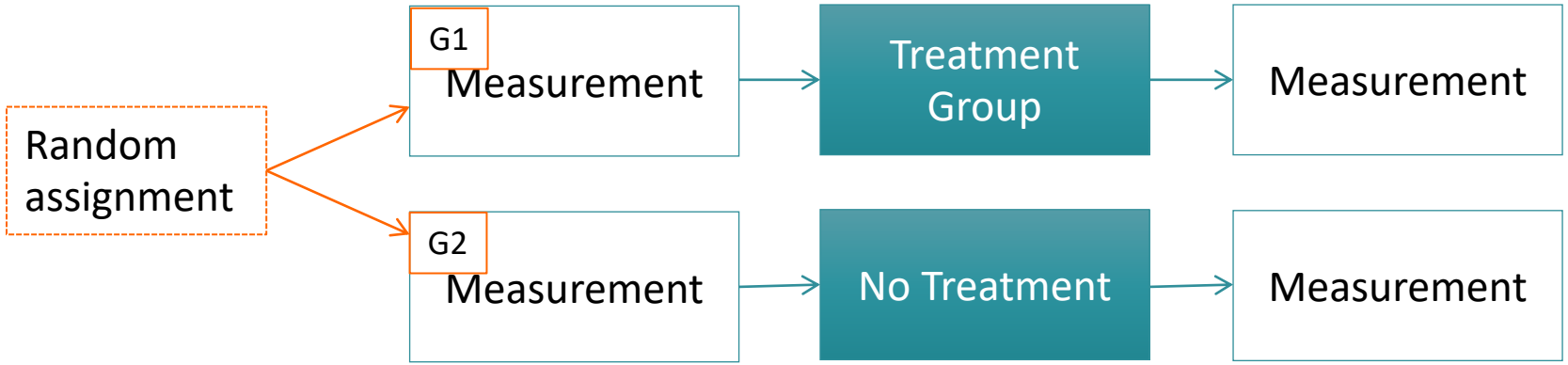
Between Subject Designs

Post-test only/control group design



Between Subject Designs

Pre-test/Post-test control group design



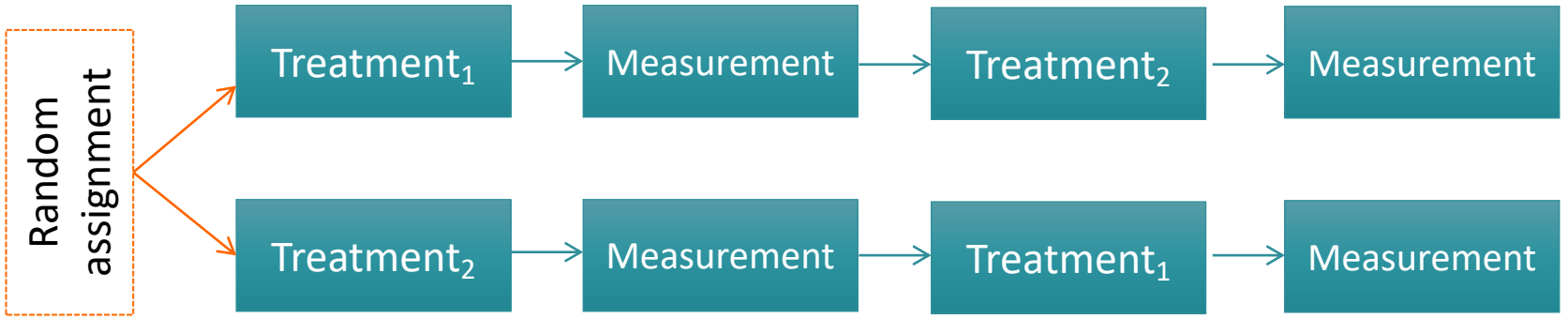
Within Subject Design

- All things being equal, a repeated-measure (within subject design) is more sensitive than a between subjects design because there are fewer sources of random variation in our outcome measures.
  - Participants act as their own controls.
- More economical with respect to time and effort, but …

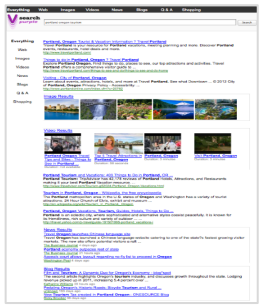
Within Subject Designs

- Disadvantages
  - ‘Carry-over’ effects from one condition to another.
    - These designs take more time for the participant and so ‘systematic’ variations like fatigue, boredom, practice, learning can become more of an issue.
  - The need for conditions to be reversible.
    - Example: Time pressure

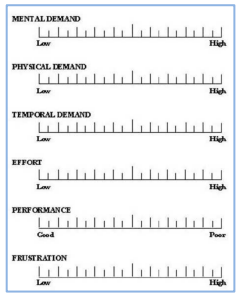
Within Subject Designs



Treatment 1



Treatment 2



Measurement

[Treatments are *Counterbalanced*]

Mixed Between/Within Design: Example

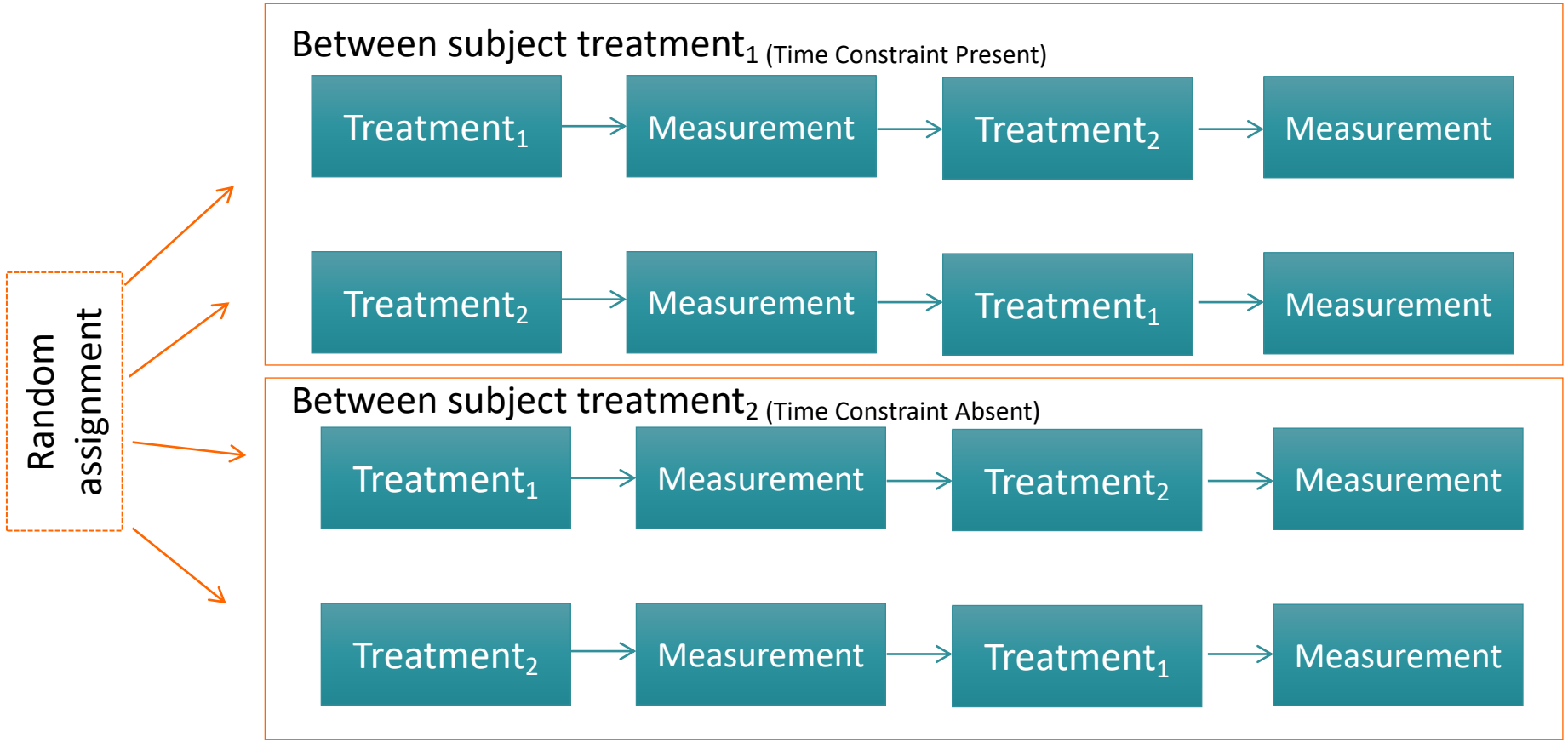
- **Time constraint** (between-subjects):
  - none vs. 5 min to complete each task
- **Delay** (within-subjects):
  - none vs. 5 sec. added to each query and SERP click
  - Every other task (delay order counterbalanced)

- 4 search tasks

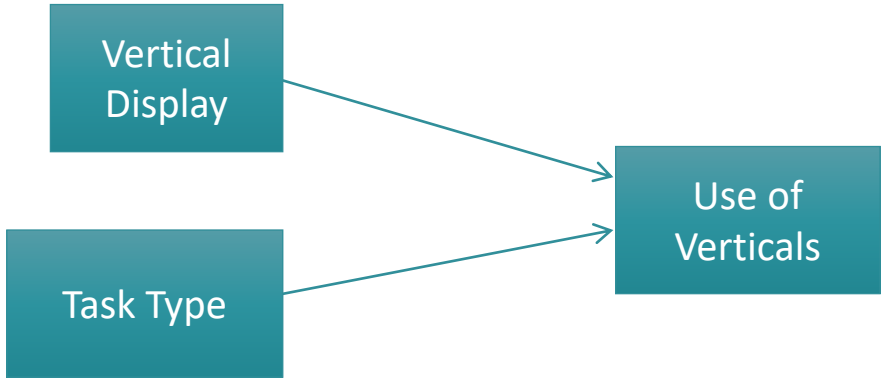
Crescenzi, A., Kelly, D. and Azzopardi, L. 2016. Impacts of Time Constraints and System Delays on User Experience. In *Proceedings of the 2016 ACM on Conference on Human Information Interaction and Retrieval, CHIIR 2016*, ACM. New York. 141-150.

Mixed Between/Within Design

Between: Time constraint (present or absent)
Within: Time delay (present or absent)

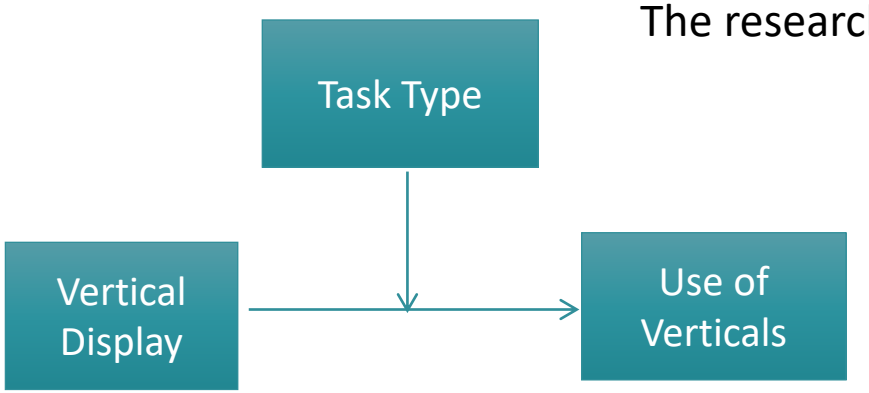


Other Ways to View Research Designs



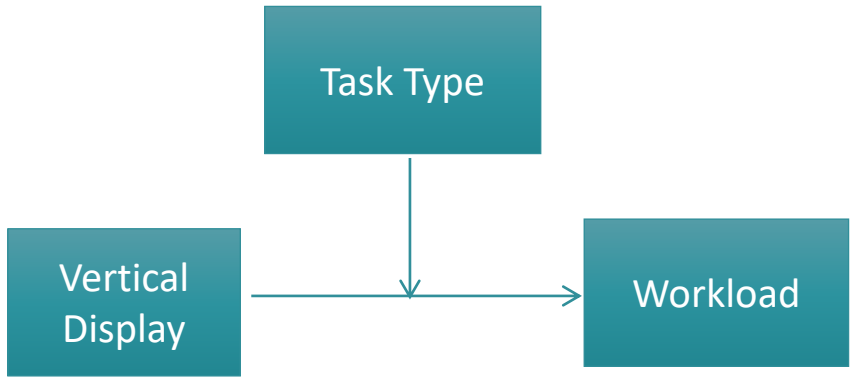
- Two independent variables
- One dependent variable

The research MODEL matters.



- One independent variable
- One moderating variable
- One dependent variable

Research Designs



- One independent variable
- One moderating variable
- One dependent variable

- Factorial Design (new concept)
- 2X2 Factorial Design
- Main Effects
- Interaction Effects

		Vertical Display		
Task Type		Blended	Non-Blended	**Total**
	Fact Finding	18.1	6.3	11.7
	Exploratory	5.2	16.8	11.6
	Total	12.25	11.05	11.65

Workload:
1 … 20

What is a Task?

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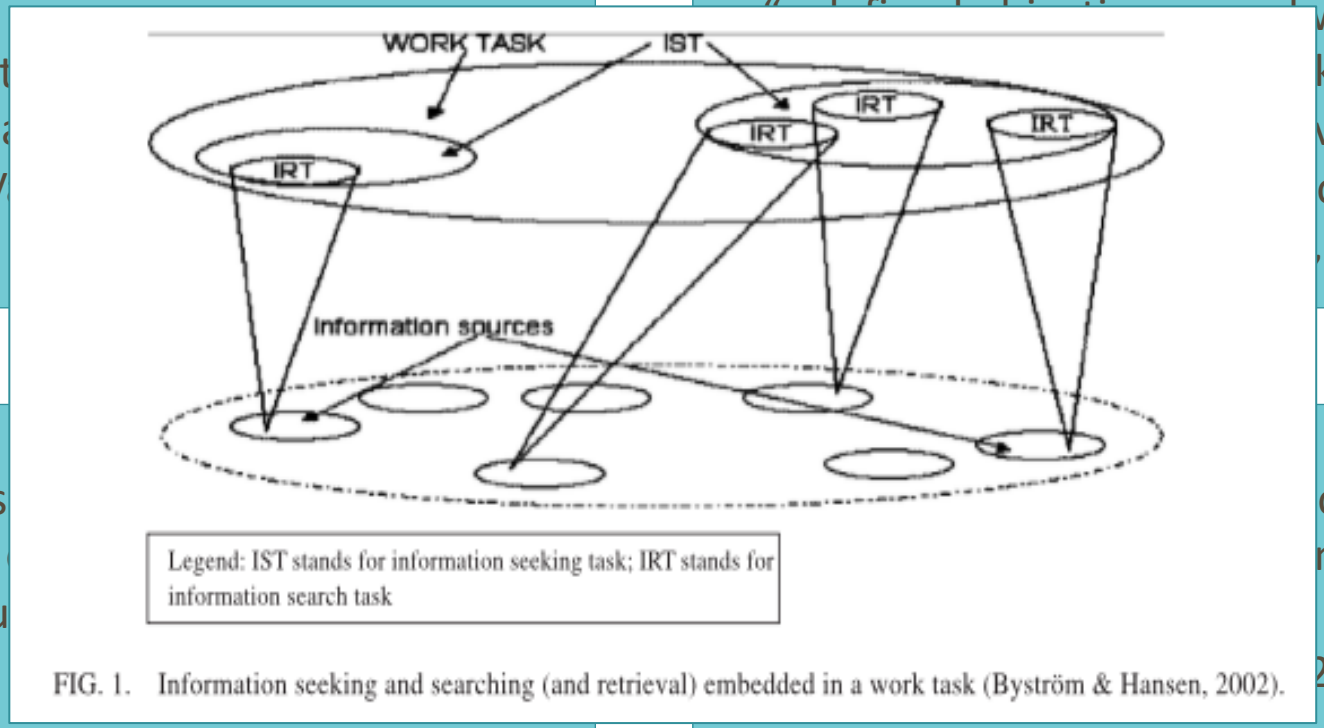


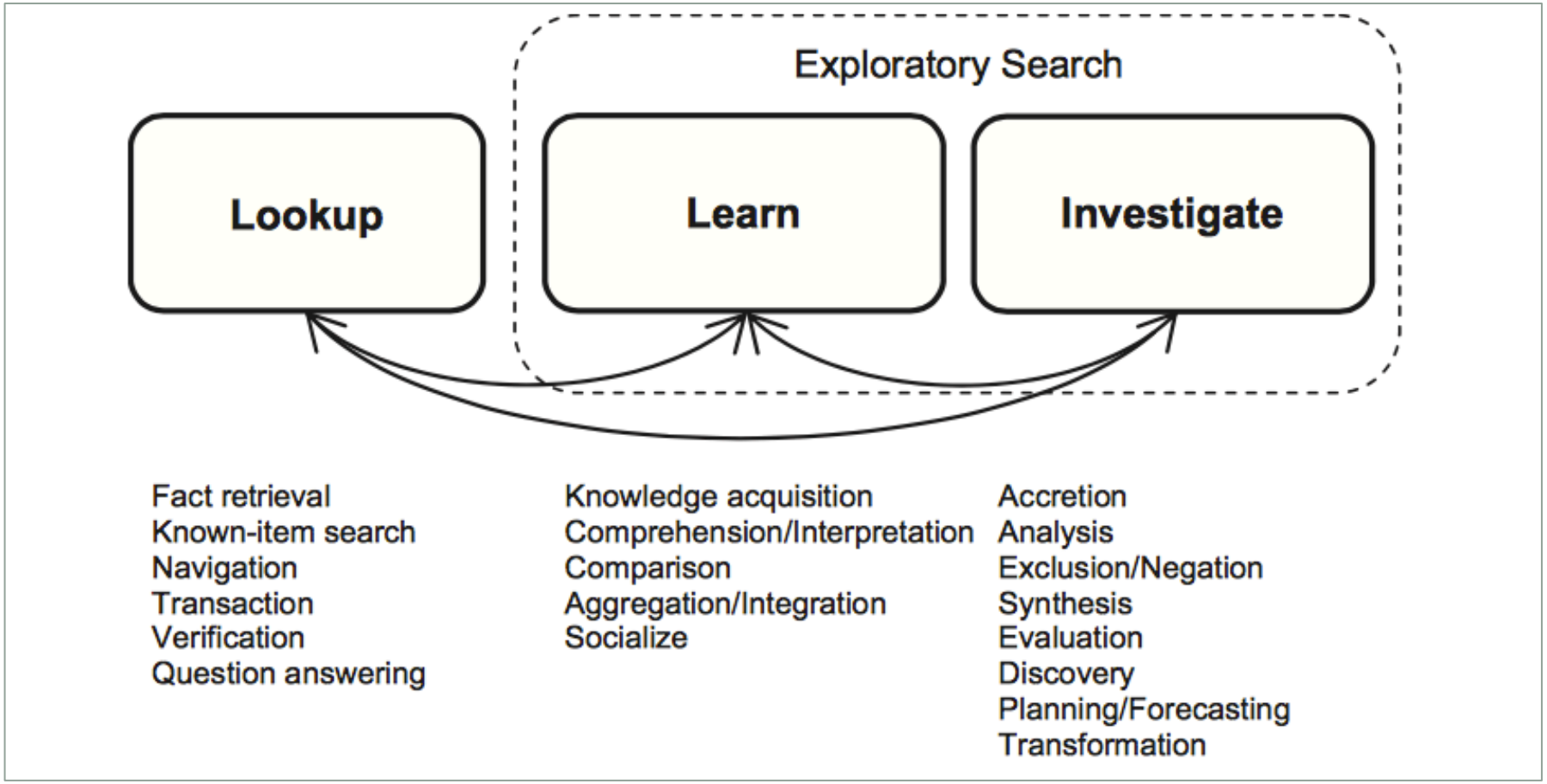
FIG. 1. Information seeking and searching (and retrieval) embedded in a work task (Byström & Hansen, 2002).

What is a Task?

- soft surroundings
- belly dancing music
- christian dior large bag
- best western airport sea tac
- www.bajawedding.com
- marie selby botanical gardens
- big chill down coats

Planning to attend a wedding?

Task Types



White, R. W. & Roth, R.A. (2009). *Exploratory search: Beyond the query-response paradigm*. Morgan & Claypool. modified from Marchionini (1995)

Example Search Task

You recently heard a story on National Public Radio about the use of biomass as fuel. Biomass refers to material created from living organisms. What are different types of biomasses that are used as fuels and how are they created? How do biomass fuels compare with fossil fuels when it comes to environmental impact? Which do you think is better? Why?

Edwards, A. & Kelly, D. (2016). How does interest in a work task impact search behavior and engagement? *Proceedings of CHIIR.*

Task Have Lots of Attributes …

- Type (Fact-finding, decision-making, etc.)
- Complexity (objective)
- Difficulty (subjective)
- Saliency
- Urgency
- Importance
- …

Li, Y. & Belkin, N. J. (2008). A faceted approach to conceptualizing tasks in information seeking. *IP&M*, *44*, 1822-1837.

… Which Makes Task Design Difficult

- Task type, task complexity, and task difficulty are all variables which can quickly pile-up into a complicated, experimental mess.
- Complicated experiments are often difficult to understand and analyze.
- Some task attributes are experiential, which make them hard to predict, model and control.

Tasks as Experimental Infrastructure

- The IR community has a strong culture of creating experimental infrastructures.
- Tasks are experimental infrastructure for IIR experiments.
- The development of search tasks can be difficult and time consuming, and often requires specialized knowledge and expertise.
- Clear guidelines for creating tasks do not exist.
- No reference models and few sets of shared search tasks.

Why Task Design Matters

- Poor task design can:
  - Confound results
  - Generate undesirable search behaviors
  - Result in wasted time and money

Genuine vs. Assigned Tasks

- Previous work on genuine and assigned tasks has shown that participants generally indicate greater interest in genuine tasks than assigned tasks.
  - Borlund, Dreier and Byström's (2012) participants rated their genuine tasks more interesting, spent more time searching, and generally found genuine tasks more difficult than simulated work tasks.
  - Poddar and Ruthven (2010) found participants had greater positive emotions, made more use of various search strategies, and had more confidence in their ability to succeed on their own tasks versus assigned tasks.
- So, why would we want to assign tasks?

Creating Interesting Tasks

1. How can we assign tasks to participants that will interest them?
2. To what extent with search behaviors and experiences differ for participants when searching for tasks that interest them versus tasks that do not interest them?

Edwards, A. & Kelly, D. (2016). How does interest in a work task impact search behavior and engagement? *Proceedings of CHIIR.*

Example Task and Procedure

You recently heard a story on National Public Radio about the use of biomass as fuel. Biomass refers to material created from living organisms. What are different types of biomasses that are used as fuels and how are they created? How do biomass fuels compare with fossil fuels when it comes to environmental impact? Which do you think is better? Why?

- Eight “evaluate” tasks were created using four domains.
- Day before experimental session, participants were asked to rank tasks from 1-8, with 1=most interesting and 8=least interesting.
- Task order randomized for each participant.
- Participants assigned two most interesting and two least interesting tasks to complete during the study.

Participants' Task Rankings

Task	Interesting (1 or 2)	Uninteresting (7 or 8)
Online Communication	25	3
Energy Sources	11	6
Lupus	9	10
Endurance Sports	10	8
Vehicle Purchase	8	15
Tattoo Removal	7	13
Video Game Violence	4	12
Biomass Fuel	6	13
Total	80	80

Edwards, A. & Kelly, D. (2016). How does interest in a work task impact search behavior and engagement? *Proceedings of CHIIR.*

Manipulation Check

Table 2. Means, standard deviations, and t-test results of pre-search questionnaire, df=79, ***p<.001

	Interesting Tasks	Uninteresting Tasks	*t*-values
Interest	4.01 (0.96)	2.77 (1.15)	7.39***
Prior Knowledge	3.00 (1.13)	2.20 (1.80)	5.27***
Relevance	3.61 (1.23)	2.24 (1.23)	7.06***
Search Frequency	2.44 (1.20)	1.64 (0.94)	4.69***
Difficulty	3.35 (1.15)	3.81 (0.93)	2.72***

Edwards, A. & Kelly, D. (2016). How does interest in a work task impact search behavior and engagement? *Proceedings of CHIIR.*

Were people's search experiences different?

Table 3. Means, standard deviations and *t*-test results for post-search questionnaire (all non-sig), df = 79

	Interesting Tasks	Uninteresting Tasks	*t*-values
Difficulty	3.61 (0.83)	3.38 (0.89)	1.35
Skill	3.85 (0.70)	3.62 (0.85)	1.57
System Ability	3.40 (0.86)	3.35 (1.04)	0.27
Success	3.77 (0.69)	3.80 (0.77)	-0.17
Frustration	2.45 (0.56)	2.52 (0.84)	-0.65

Edwards, A. & Kelly, D. (2016). How does interest in a work task impact search behavior and engagement? *Proceedings of CHIIR.*

Were people's search experiences different?

Table 4. Means, standard deviations and t-test results for User Engagement Scale, df = 79, **p<.01, ***p<.001

	Interesting Tasks	Uninteresting Tasks	t-values
Perceived Usability	3.63 (0.60)	3.56 (0.79)	0.50
Focused Attention	2.87 (0.79)	2.64 (0.66)	2.70**
Felt Involvement	3.61 (0.50)	3.27 (0.72)	3.00***
Endurability	3.41 (0.58)	3.20 (0.76)	1.60
Novelty	3.72 (0.67)	3.09 (0.90)	4.43***
Total Engagement	3.45 (0.42)	3.15 (0.64)	3.04***

Edwards, A. & Kelly, D. (2016). How does interest in a work task impact search behavior and engagement? *Proceedings of CHIIR.*

Did people behave differently?

Table 5. Means, standard deviations, and t-test results of search behaviors, df = 79, *p<.05

	Interesting Tasks	Uninteresting Tasks	t-values
Total Time (in minutes)	6.86 (3.84)	5.88 (3.06)	2.06*
Time on SERP	2.04 (1.80)	1.74 (1.30)	1.40
Time on Docs	2.72 (2.25)	2.33 (1.79)	1.45
Queries	5.65 (4.45)	5.06 (4.13)	1.01
Query Length (in words)	2.56 (1.77)	2.55 (1.78)	0.94
Clicks Per Query	7.77 (4.77)	6.79 (3.97)	1.66
SERPs viewed	13.80 (9.16)	12.29 (7.88)	1.42
Bookmarks	3.60 (2.06)	3.42 (1.83)	0.63

Edwards, A. & Kelly, D. (2016). How does interest in a work task impact search behavior and engagement? *Proceedings of CHIIR.*

Simulated Work Task

- Borlund proposed the use of simulated work tasks, which provide a short "cover story that describes an IR requiring situation."
- These tasks are tailored to target participants.
- Allows participants to direct their own searches, while providing a common scenario to anchor experimental comparisons and relevance judgments.
- Better motivates people to search by providing them with tasks that interest them.

Borlund, P. (2003). The IIR evaluation model: a framework for evaluation of interactive information retrieval systems. *Information Research*, *8*.

Simulated Work Task

Simulated situation:

Simulated work task situation: After your graduation you will be looking for a job in industry. You want information to help you focus your future job seeking. You know it pays to know the market. You would like to find some information about employment patterns in industry and what kind of qualifications employers will be looking for from future employees.

Indicative request: Find, for instance, something about future employment trends in industry, i.e., areas of growth and decline.

Figure 1. Example of a simulated situation/simulated work task situation (Borlund, 2000a; 2000b).

Borlund, P. (2003). The IIR evaluation model: a framework for evaluation of interactive information retrieval systems. *Information Research*, *8*.

Data Collection Techniques & Measurement

Data Collection Techniques

- Logging & Observation
- Self-report
  - Questionnaires (many types)
  - **Scales (standardized)**
  - Relevance measures
- Think-aloud & Stimulated Recall
- Interviews & Open-ended Questions
- Evaluation of End Products
- Learning

Morae

Data Collection Techniques

- Eye-tracking
- Physiological Signals
- EEG
- Brain Scans (fMRI)

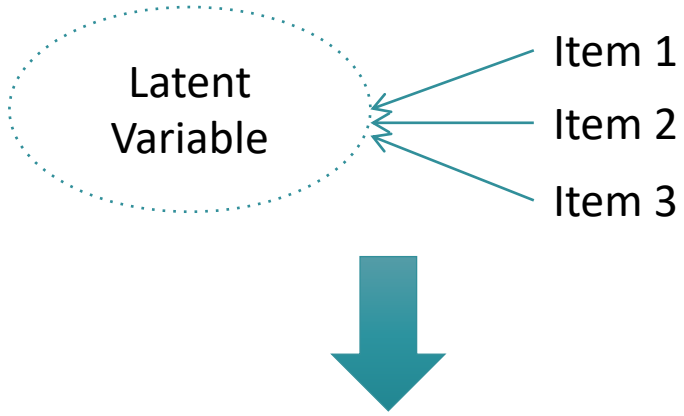
But … What does this tell us?

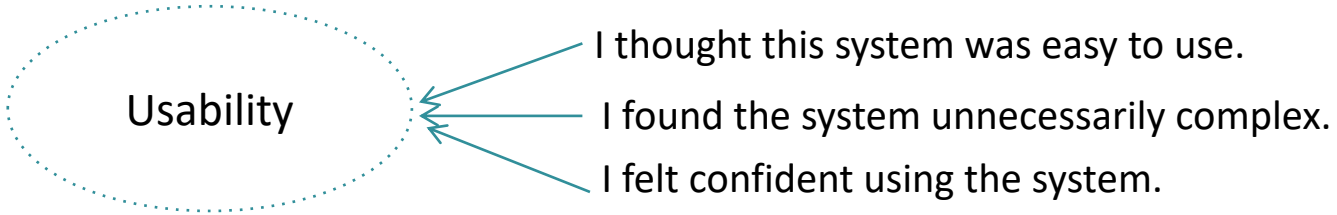
Measures

- Contextual
  - Individual Differences
    - Cognitive Ability
    - Need for Cognition
    - …
  - Tasks
    - Type
    - Difficulty
    - …
- Interaction
  - Queries issued
  - SERP clicks
  - Time spent
  - …
- Performance
  - Number saved
  - Query diversity
  - …
- User Experience
  - Usability
  - Preferences
  - Mental Effort, Workload
  - Flow and Engagement
  - Emotion
  - …

Digression: Self-Report Measures and Scales

Are you assuming some latent construct (psychometric theory)?





Or just want to ask a question?

How would you rate this system's response time?

Slow				Fast
1	2	3	4	5

Example: Workload

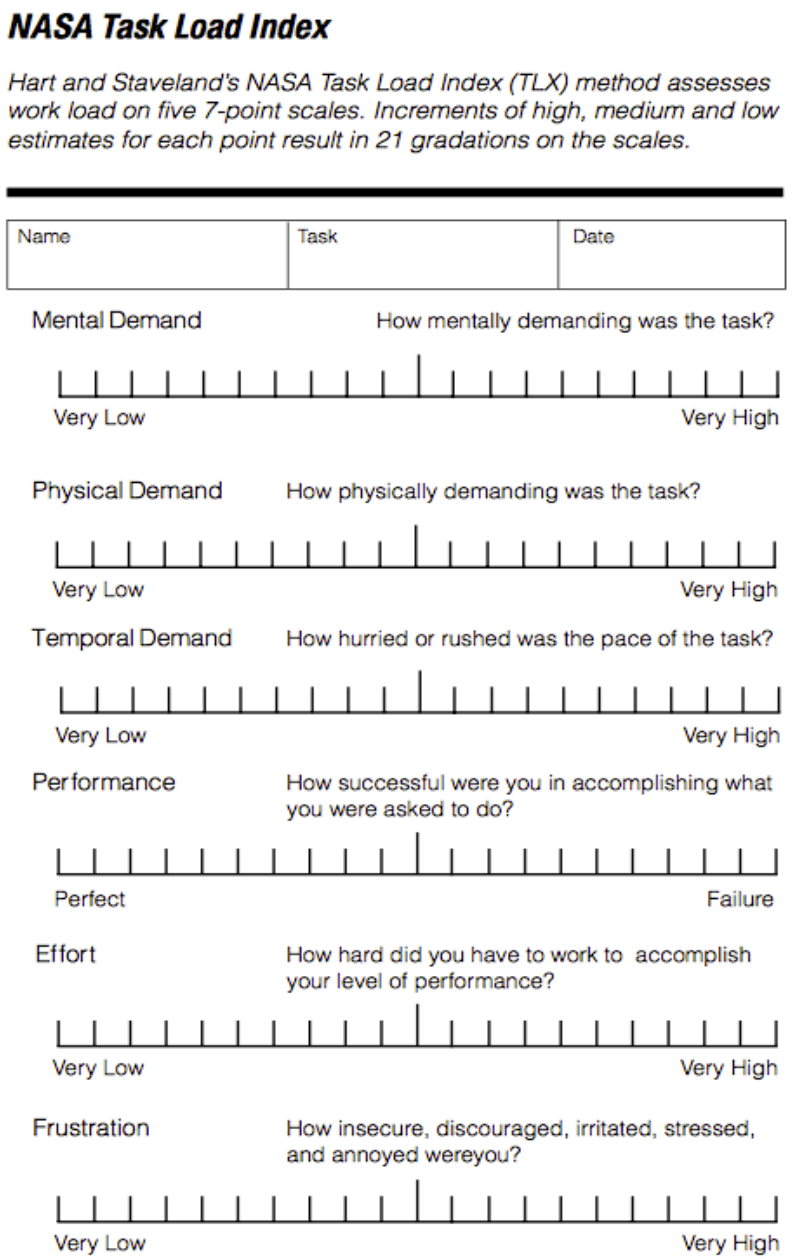
Operationalization links a conceptual definition to a specific set of measurement techniques or procedures.

An operational definition could be:

- A scale (NASA TLX)
- One or more survey questions
- A method of observing events in a field setting

A conceptual definition of workload is:

- "Workload is a term that represents the cost of accomplishing mission requirements for the human operator."



NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Name	Task	Date

Mental Demand — How mentally demanding was the task?
Very Low — Very High

Physical Demand — How physically demanding was the task?
Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?
Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?
Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?
Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?
Very Low — Very High

Hart, S. G. (2006). NASA-Task Load Index (NASA-TLX); 20 Years Later. Proceedings of the Human Factors and Ergonomics Society 50th Annual Meeting, 904-908. Santa Monica: HFES.

Psychometrics

- Psychometrics is a field of study concerned with the theory and technique of psychological measurement.
- The field is concerned with the objective measurement of skills and knowledge, abilities, attitudes, personality traits and educational achievement.
- Two major tasks:
  - Construction of instruments
  - Development of procedures for measurement

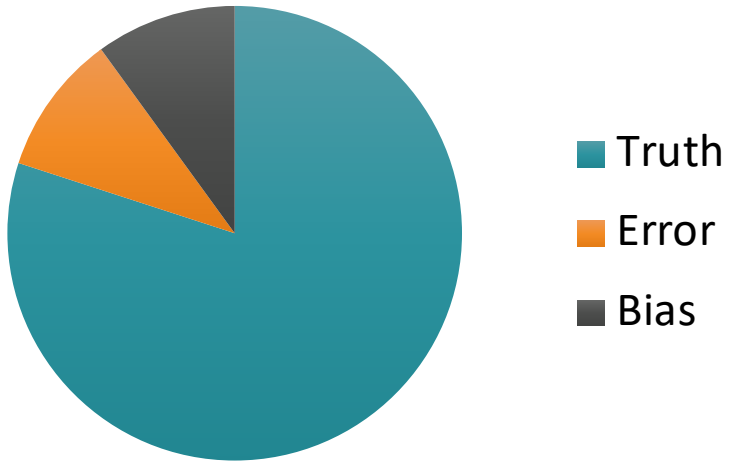
From Wikipedia

Psychometrics

- Measurement is, “the assignment of numerals to objects or events according to some rule.”
  - Stevens (1946)
- “Measurement in psychology and physics are in no sense different. Physicists can measure when they can find the operations by which they use to measure meet the necessary criteria; psychologists have but to do the same. They need not worry about the mysterious differences in meaning of measurement in the two sciences.”
  - Reese (1943)

Psychometrics Model

$$O = T + E + B$$



(From Spector, 1992)

Example: Error

- Which option to you prefer?
  - Option A
  - Option B
  - Option C
  - Option D

It’s not just how you ask questions; the format of the question can also introduce error.

Example: Error

The system provided results quickly.

Strongly Disagree	Disagree	Neither Agree or Disagree	Agree	Strongly Agree
○	○	○	○	○

Example: Bias

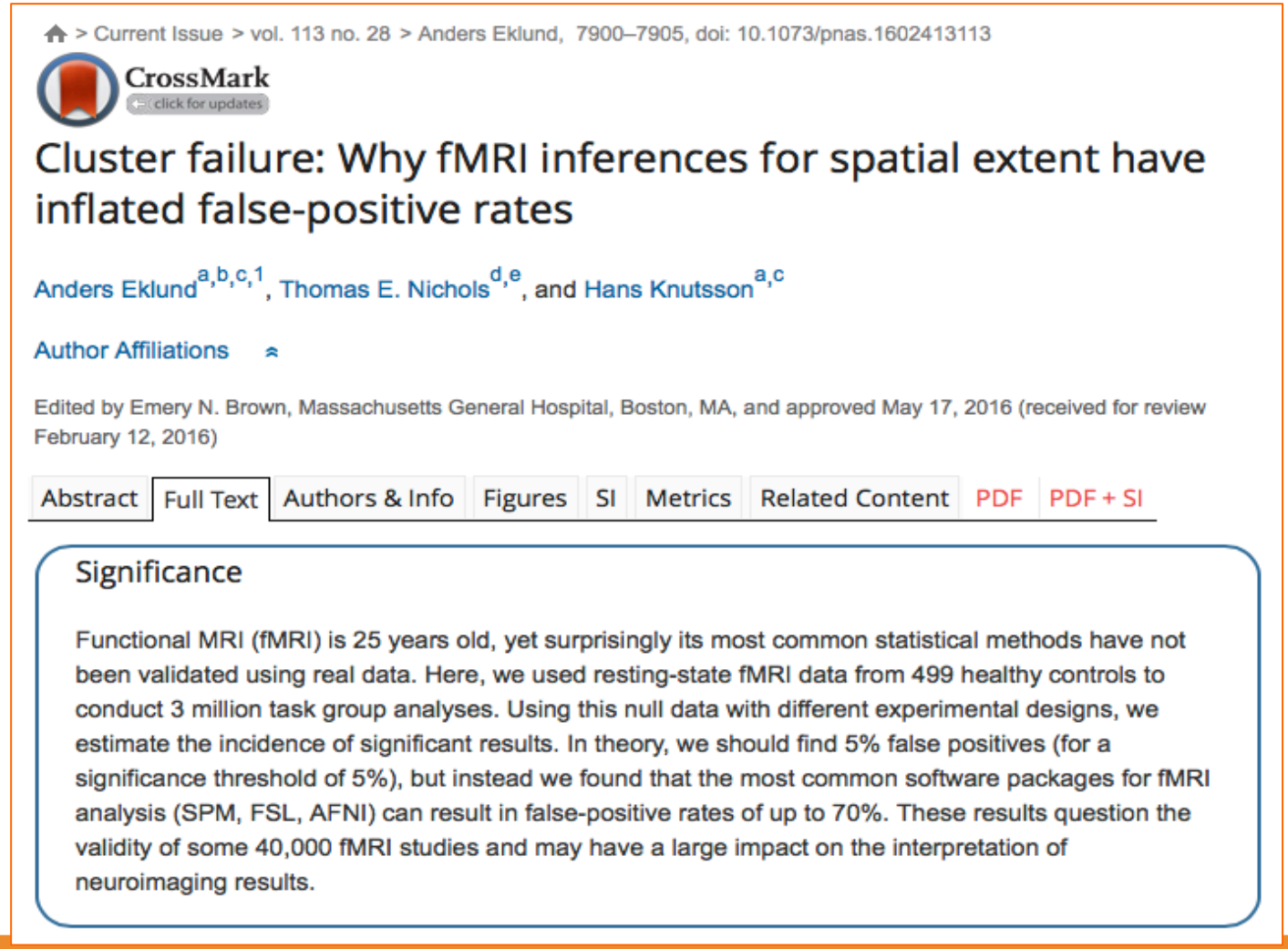
- How much time did you spend preparing for ESSIR?
  - 0 hours
  - 1 hour
  - 2 hours
  - 3 hours
  - 4 hours
  - 5 hours
  - More than 5 hours

Note: All measurement is manmade.

Stanford-Binet Fifth Edition (SB5) classification	
IQ Range ("deviation IQ")	**IQ Classification**
145–160	Very gifted or highly advanced
130–144	Gifted or very advanced
120–129	Superior
110–119	High average
90–109	Average
80–89	Low average
70–79	Borderline impaired or delayed
55–69	Mildly impaired or delayed
40–54	Moderately impaired or delayed

Levine and Marks 1928 IQ classification	
IQ Range ("ratio IQ")	**IQ Classification**
175 of above	Precocious
150–174	Very superior
125–149	Superior
115–124	Very bright
105–114	Bright
95–104	Average
85–94	Dull
75–84	Borderline
50–74	Morons
25–49	Imbeciles
0–24	Idiots

Be Aware of “Objective” Instruments



> Current Issue > vol. 113 no. 28 > Anders Eklund, 7900–7905, doi: 10.1073/pnas.1602413113

CrossMark click for updates

Cluster failure: Why fMRI inferences for spatial extent have inflated false-positive rates

Anders Eklund[a,b,c,1], Thomas E. Nichols[d,e], and Hans Knutsson[a,c]

Author Affiliations

Edited by Emery N. Brown, Massachusetts General Hospital, Boston, MA, and approved May 17, 2016 (received for review February 12, 2016)

Significance

Functional MRI (fMRI) is 25 years old, yet surprisingly its most common statistical methods have not been validated using real data. Here, we used resting-state fMRI data from 499 healthy controls to conduct 3 million task group analyses. Using this null data with different experimental designs, we estimate the incidence of significant results. In theory, we should find 5% false positives (for a significance threshold of 5%), but instead we found that the most common software packages for fMRI analysis (SPM, FSL, AFNI) can result in false-positive rates of up to 70%. These results question the validity of some 40,000 fMRI studies and may have a large impact on the interpretation of neuroimaging results.

Measurement Variability

- No standardized measures for most concepts.
  - Everyone creates their own measures.
- Different studies measure the same concept in different ways.
  - For example, task complexity.
- The same measure (or observation) is used to represent different concepts, which are oftentimes completely opposite of one another.
  - For example,
    - # clicks = engagement
    - # clicks = frustration
    - Long display time = interest, engagement
    - Long display time = difficulty, failure
- Observations often not mapped to concepts.

Method Variance & Measurement Error

- Method variance refers to variance that is attributable to the measurement method rather than to the construct of interest.
  - For example,
    - A protocol that primes participants to behave in a particular way.
    - Variation in how the study is delivered (e.g., researcher effects).
    - An instrument that introduces error (a poorly designed Likert scale).
    - A researcher who doesn't randomly assign participants to conditions.
- Crowdsourced and naturalistic studies necessarily contain a lot of method variance, which usually cannot be measured. Moreover, the sources of variance are not well-understood, or even known in most cases.

Method Variance & Measurement Error

- Use of outdated test collections that are mismatched to target participants
- Use of unrealistic tasks that are mismatched to target participants

Data Analysis

Data Analysis

- Analytical methods are closely tied to experimental design.
- Techniques that model relationships, such as structural equation modeling, have not been used very much, but are starting to get more attention.
- Qualitative data analysis is often used:
  - Superficially
  - Rigorously

Kelly, D. & Sugimoto, C. R. (2013). A systematic review of interactive information retrieval evaluation studies, 1967-2006. *Journal of the American Society for Information Science and Technology, 64*(4), 745-770.

Statistical (Un)Reliability

- Several practices are of concern:
  - Undirected search for patterns (“fishing expedition”) (“p-hacking”)
  - Multiple-tests with no correction (increases risks of Type I error)
    - Limited use of data reduction techniques
    - Tests conducted using highly correlated measures
  - Inadequate number of study participants (under-powered studies) (increases risk of Type II error)
    - Lack of understanding of how to conduct formal, a priori power analysis
    - Don’t like results of power analys☹
    - Resource constraints (e.g., time, money)

Statistical (Un)Reliability

- More concerning practices:
  - Use of statistical methods designed for ”little” data on ”big” data produce many significant (and often meaningless) differences
  - Lack of evidence about the strength of findings (i.e., not computing, or publishing effect size measures)

Close: Contemporary Problems

Contemporary Problems

- User Interfaces
  - Conversational
  - Proactive
  - Explanations
  - Decision-making

Judgment and Decision Making, Vol. 10, No. 6, November 2015, pp. 549–563

On the reception and detection of pseudo-profound bullshit

Gordon Pennycook* James Allan Cheyne† Nathaniel Barr‡ Derek J. Koehler†
Jonathan A. Fugelsang†

Abstract

Although bullshit is common in everyday life and has attracted attention from philosophers, its reception (critical or ingenuous) has not, to our knowledge, been subject to empirical investigation. Here we focus on pseudo-profound bullshit, which consists of seemingly impressive assertions that are presented as true and meaningful but are actually vacuous. We presented participants with bullshit statements consisting of buzzwords randomly organized into statements with syntactic structure but no discernible meaning (e.g., "Wholeness quiets infinite phenomena"). Across multiple studies, the propensity to judge bullshit statements as profound was associated with a variety of conceptually relevant variables (e.g., intuitive cognitive style, supernatural belief). Parallel associations were less evident among profundity judgments for more conventionally profound (e.g., "A wet person does not fear the rain") or mundane (e.g., "Newborn babies require constant attention") statements. These results support the idea that some people are more receptive to this type of bullshit and that detecting it is not merely a matter of indiscriminate skepticism but rather a discernment of deceptive vagueness in otherwise impressive sounding claims. Our results also suggest that a bias toward accepting statements as true may be an important component of pseudo-profound bullshit receptivity.

Keywords: bullshit, bullshit detection, dual-process theories, analytic thinking, supernatural beliefs, religiosity, conspiratorial ideation, complementary and alternative medicine.

Contemporary Problems

- Many problems and challenges to tackle in user-centered evaluation including:
  - Development of research infrastructure including standardized measures and tasks
  - Analysis of issues related to statistical power, validity, reliability and reproducibility.
- Development and evaluation of theoretical explanations for information interactions with information systems.