A STUDY OF INFORMATION SEEKING BEHAVIOR: INVESTIGATING EXPLORATORY BEHAVIOR IN PHYSICAL & ONLINE SPACES

by

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ABSTRACT OF THE DISSERTATION

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An individual has their own behavioral patterns that exhibit commonalities over different contexts and situations. Several studies have shown (1) dichotomic human mobility patterns in everyday life such as returner vs. explorer, (2) the analogy of the "Explorer" and the "Web Explorer," and (3) the same brain structure used during both physical and online navigation. Meanwhile, modern technologies such as smart phones and wearable devices have allowed researchers to collect users' personal, contextual, and cognitive information and to create behavioral models from different perspectives. Based on the analogy between the physical and online searching, this dissertation investigates individuals' behaviors during online and physical search tasks to identify their behavioral patterns. To observe the behaviors, during web search task and physical search games, 31 participants' data was collected via eye-tracker, web browser, and wearable video recorder. Analysis of the behavioral data suggests individuals have preferred searching strategy that they adopt in different tasks and environments. The behavioral pattern, however, was found to be affected by the task type and the way information is structured in the environments.

Preface

Parts of this dissertation are based on work previously published by the author in Choi et al. (2016) and Choi et al. (2017).

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First, I would like to thank my advisor, Dr. Chirag Shah for his guidance, advice and support for my dissertation. I would not be able to finish my work without his support and encouragement at every stage of the dissertation process. I am very grateful to him for being a great mentor during my research journey during my PhD program that enabled me to successfully face all the obstacles.

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Chapter 1

Introduction

You have brains in your head.
You have feet in your shoes.
You can steer yourself in any direction
you choose.

Dr. Seuss (Theodor Seuss GeiselSeuss (1990))

1.1 Background

Picture an infant in her crib. Perhaps crying, she uses on only her eyes to find her mom resting on a nearby bed. Seeing is one of the most important and basic ways to perceive surroundings, understand environments, and gather information. At least for the baby, seeing is the most primitive way to obtain information from her surroundings. In this regard, when considering the intention of this behavior, *seeing*, it is not surprising that ancient people thought the visual perception of a human being is accomplished by rays of light emitted by the eyes; Plato held a theory named “extramission theory,” related to visual perception (Wong and Kwen, 2005). This theory has been replaced by “intromission theory,” in which the visual perception comes from “something representative of the object entering the eye,” which later turned out to be rays of light reflected from the object (Wong and Kwen, 2005). What matters in both theories, regardless of truth, is the intentionality and related decision-making concerning what and why people *see*.

Another behavior that has the same purpose is *visiting* places - perceiving surroundings, understanding environments, and seeking information. From the perspective of human information interaction (HII), we can argue that information is all over the place and some part of it is captured by our cognitive system, just as rays of light fill our eyes regardless of whether we actually see the full potential of what they reveal. In this regard, *seeing* and *visiting* are the primary ways of exploration in information space, both in physical and online settings.

Meanwhile, human information behavior (HIB) refers to several types of information-related behavior in different levels and contexts. While Wilson (1999) explains human information behavior with an integrated model of *information behavior, information seeking behavior,* and *information search behavior,* several behavioral models have been suggested to understand and explain people's information seeking/searching behavior. Kuhlthau's information search process (ISP) model (Kuhlthau, 1991, 1993, 2004) defines the stages of information seeking that include the *exploration* stage in which the person seeks and investigates information regarding their information needs. In her *berrypicking* model, Bates (1989) conceptualizes information searchers as explorers in an information space. Information foraging theory (IFT) (Pirolli and Card, 1995; Pirolli, 2007) considers searching to be a series of visits to different information patches that reside in a sub-hierarchy of an information space and allow searchers to obtain fruits, or found information. Exploratory behavior, as one aspect of human behavior, spans various types of action, as shown in Figure 1.1.

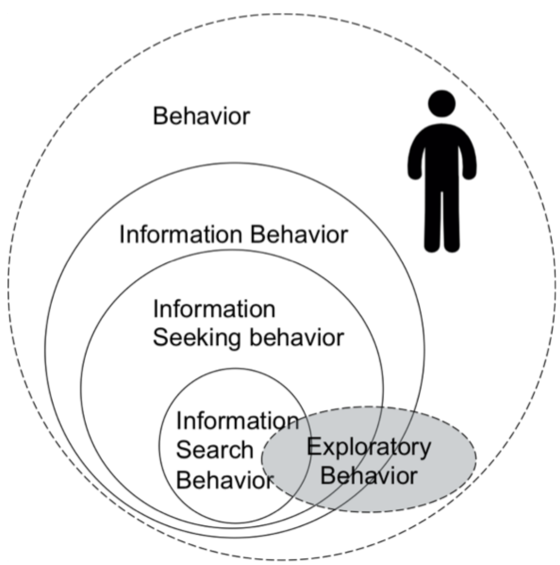


Figure 1.1: Exploratory behavior in human behavior as well as in information behavior. The outer circle that presents human behavior and the oval of exploratory behavior are added onto Wilson's nested model (Wilson, 1999).

Regarding the exploration behavior, people show unique, distinct, but habitual behavioral patterns in different contexts. For instance, Pappalardo et al. (2015b) examine people's geographical exploration data to find a dichotomy in human mobility: returners vs. explorers. Along the same line, Web browsing behavior also presents similar patterns in users' online exploration (Barbosa et al., 2016). An fMRI study (Benn et al., 2015) that shows people use similar brain structures throughout both physical and online contexts (see Figure 1.2) provides some hints to understand the similar human navigating behavior that occurs in both types of space.

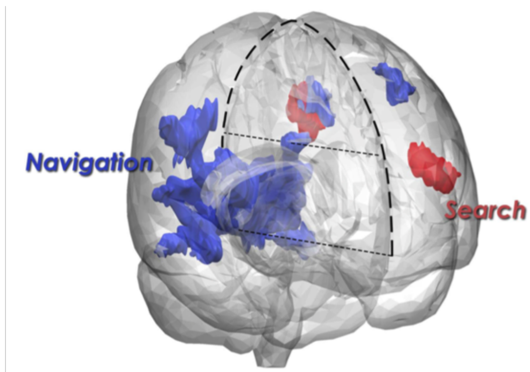


Figure 1.2: Brain structure used for digital folder navigation and real world navigation. Copied from Benn et al. (2015).

1.2 Problem Statement

As increasingly diverse facets of human life are mediated by information technology, our general behavior and corresponding experience is manifested in mingled reality of various contexts and environments we are interacting with. In the meantime, human behaviors that are captured by multimodal sensors have been studied from different perspectives. Previous studies utilized people's daily life signals, building human behavioral models to predict outcomes in different contexts, such as social patterns (Eagle and Pentland, 2006), spending behavior (Singh et al., 2013), and personality (de Montjoye et al., 2013).

Regarding information seeking contexts, Barbosa et al. (2016) investigated people's Web browsing history to find out similar visitation patterns - returners and explorers - to that revealed in mobility patterns (Pappalardo et al., 2015b). However, their work did not examine behavior of the same individuals, comparing exploratory behavior in web searching and geographical exploration. Choi et al. (2016) discovered relationships between geographical exploration and information seeking behavior of the same population, but their work still lacked ways to (1) connect people's exploratory behavior in online and physical space, and (2) understand the contexts and purposes of visitations that have specific goals. There has been little research, to the best of my knowledge, on investigating searching behavior in goal-driven tasks, comparing the ways of interacting with online and physical environment.

In this regard, the main goals of the dissertation are: (1) to examine people's searching behavior in online and physical space, (2) to identify behavioral patterns of searching and exploration in different information spaces, and (3) to find interconnections between those behaviors.

1.3 Significance of the Study

In this section, I present the significance of the study: (1) methodology that captures different aspects of information search behavior in different information spaces and (2) finding out the interconnections between online search and physical search.

1.3.1 Methodology

One contribution of my dissertation is to develop new methods through which we observe individuals' information seeking behavior in online and physical information spaces. The newly proposed method in this research, a treasure hunt game, is designed to understand individuals' searching activities in a building, simulating similar search tasks in web environment. Inspired by the concept of *information patches*, which is suggested in *information foraging theory* (Pirolli and Card, 1997), the game consists of (1) different types of information patches that we encounter in ordinary places in our daily life and (2) tasks that require participants to search and navigate the clues and information to accomplish them. To monitor searching behavior happening in both spaces, this dissertation utilized unobtrusive, passive sensors such as plugin installed in Web browser and portable video recorder that participants wear during the experiment. The methodology can be applied to other studies of how people interact with information in onilne, virtual, and physical environments in general.

1.3.2 Searching in Online and Physical Space

When it comes to the applications of this kind of research that examines personal behavioral traits using passive sensors, Shmueli et al. (2014) mention three directions of research: sensing, understanding, and shaping (social) behavior. In this sense, the results of this research can be used in three ways: (1) understanding individuals' distinct search patterns and (2) helping them feel satisfied when interacting with information interfaces, and (3) supporting individuals to achieve better outcomes.

The interrelationship between searching behavior in online and physical space found in this dissertation can be applied for *personalization* of user experience or interface design. For instance, identifying that a user tends to under-explore during search tasks could be used to customize the way in which the person interacts with information in a virtual reality (VR) environment. When a user's Web search behavior indicates that they are an 'under-explorer,' a VR interface can adjust to their preference to see and visit *fewer* places, or areas of interest. As opposed to other users, the 'under-explorer' is presented with simpler filters and a shorter menu if the task is suited to a rough investigation. However, if said user needs more serious examination to accomplish a task, the system may intervene and force them to focus on necessary material in the information space and spend much less time looking at extraneous things (see Figure 1.3).

1.4 Summary

This chapter presented the background of this dissertation, identified a lack of knowledge regarding searching behavior in different domains, and then followed the motivations of why pursuing further research on this specific research problem is of importance. The problem I am addressing is the lack of understanding of whether a person presents a similar behavior seeking information in online and physical space.

The next chapter will discuss the related work and past research conducted in the relevant areas important to addressing the research problem in detail.

Figure 1.3: Exploration in Virtual Reality (VR) Environment. (1) In case of some fun activities in VR (e.g., tour), a user may want to see and visit fewer places. (2-4) For a task that requires thorough examination and investigation (e.g., problem-solving tasks like games, professional practices, and military training), the system may nudge the user to explore more. It could highlight a specific relevant area (2), advise which particular spaces to examine (3), or suggest where to spend more time (4). Pictures are copied from Microsoft Hololens site (https://www.microsoft.com/microsoft-hololens/en-us) and the blue graph (1), square (2), and speech balloons (3,4) are added by the author for illustration.

Chapter 2

Literature Review

The current literature review attempts to understand information behavior related to exploration and searching behavior. Previous studies reveal behavioral traits and different factors that have been examined to explain these phenomena. Since the concept of information behavior in this dissertation is focused on investigating how people interact with information and the environment in different contexts, an introduction to a general overview of theories and models about information behavior will first be provided.

Next, there will be a review of behavioral models and styles in physical and online explorations. Following this, the next sections discuss previous studies on searching behavior in different domains.

Finally, I will present preliminary work that inspired this dissertation.

2.1 Interacting with Information

This section reviews several models that describe human information behavior, the human processor model that focuses on a cognitive aspect of a human when interacting with information, information seeking/searching process frameworks, and information foraging theory.

2.1.1 Human Information Behavior (HIB) Models

Ingwersen (1996) proposed that each act of information processing is influenced by a system of categories and concepts that constitutes a world model with a cognitive point of view based on the concept of *polyrepresentation* (See Figure 2.1). The concept of polyrepresentation refers to an individual's cognitive space and methods of representation of the information objects in the information space. The model consists of three main components: information object (e.g., text, pictures, and models), the intermediary (cognitive space and social environment around the person), and the information space (information resources) of the IR system. Ingwersen argues that the functions of each of these components are the results of cognitive models of the domain of interest.

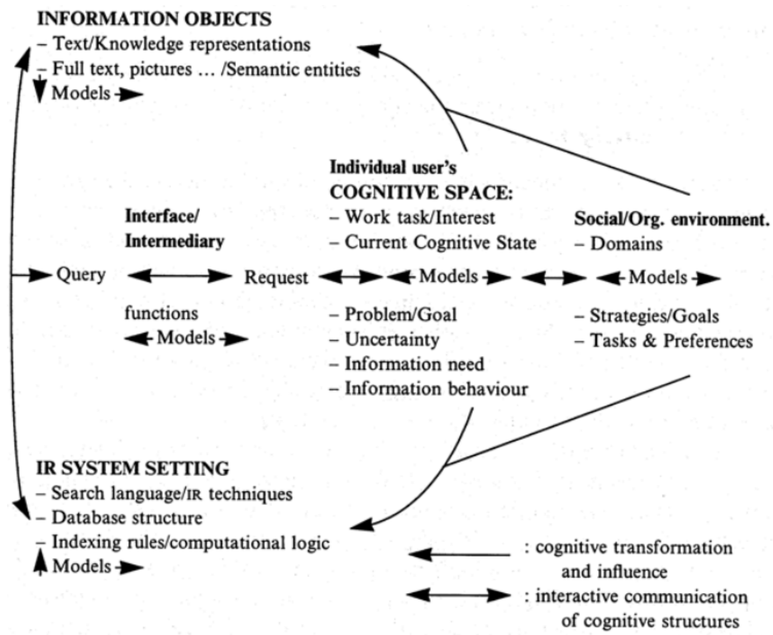


Figure 2.1: Cognitive model of IR interaction. Copied from Ingwersen (1996).

While Ingwersen (1996) considered the information process from the cognitive perspective on information retrieval (IR) theory, Savolainen (1995) proposed the concept of the everyday life information seeking (ELIS), regarding information seeking behavior in "nonwork" environments. The framework mainly consists of *way of life* and *mastery of life* (See Figure 2.2). The 'way of life' concept was inspired by Bourdieu's idea of habitus (Bourdieu, 1984), or individuals' "socially and culturally" determined systems of thinking, perception, and evaluation. In this sense, while *way of life* describes the internalized 'order of things,' *mastery of life* represents the actions - or activities - that 'keep things in order' during tumultuous or threatening times. These two elements interact with each other to (re)form individuals' information behavior patterns.

Wilson (1997) suggested a revised version of the information behavior model, incorporating theories from a variety of disciplines such as decision-making, psychology, innovation, health communication, and consumer research. The model attempted to include several factors, or mechanisms, that explain whether particular needs invoke information seeking behavior and

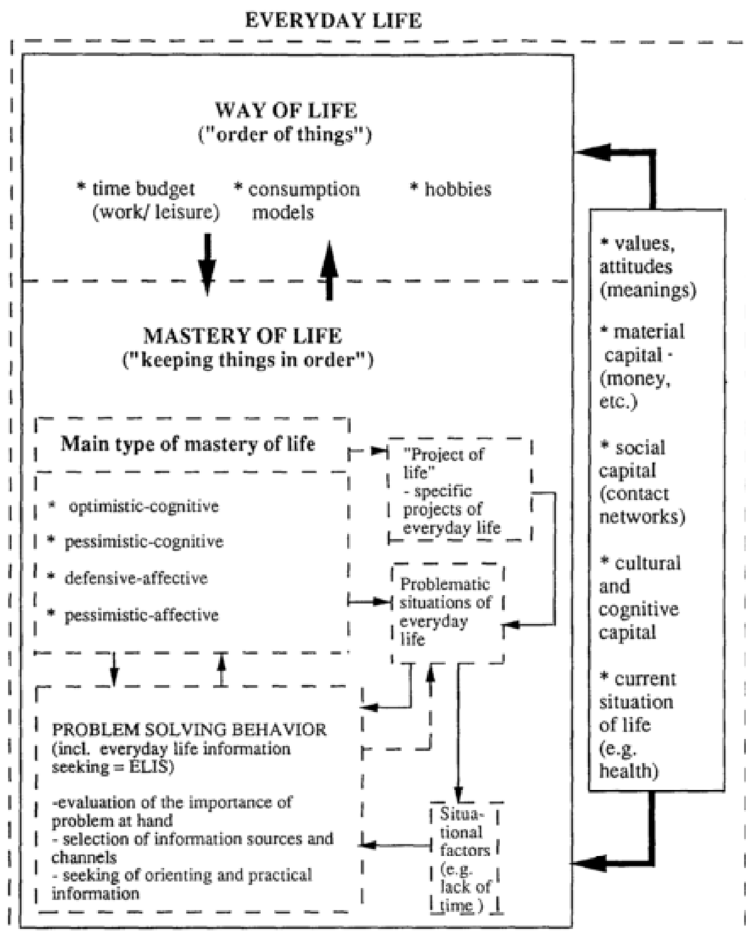


Figure 2.2: The basic components of the study of ELIS. Copied from Savolainen (1995).

why an individual prefers specific information sources as well as certain intervening variables. Showing the relations between information behavior models, Wilson (1999) proposed to integrate the models into a more general framework (see Figure 2.3).

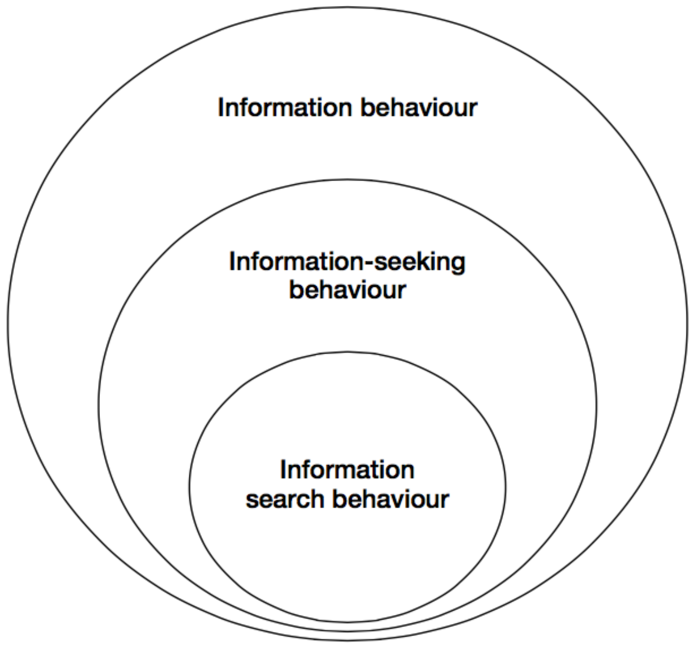


Figure 2.3: Wilson's nested model. Copied from Wilson (1999).

When it comes to user modeling in IR, Sutcliffe and Ennis (1998) suggested a user model of information searching activities and knowledge sources with query formulations and reformulations as the core components. They realized that query formulation/reformulation is one of the main activities in an IR process, and the complexity of query formulation is affected by the complexity of the IR system and the user's query generating skills.

2.1.2 Model Human Processor

Regarding the cognitive system that governs and decides human behaviors, Card et al. (1983) proposed a cognitive model of the user - named the *model human processor* (Figure 2.4) - that provides a framework from which to predict user performance and to evaluate different kinds of interfaces for information tasks.

The *model human processor* comprised three interacting systems - perceptual, cognitive, and motor systems - each of which has its own memory and processor. As a very simplified

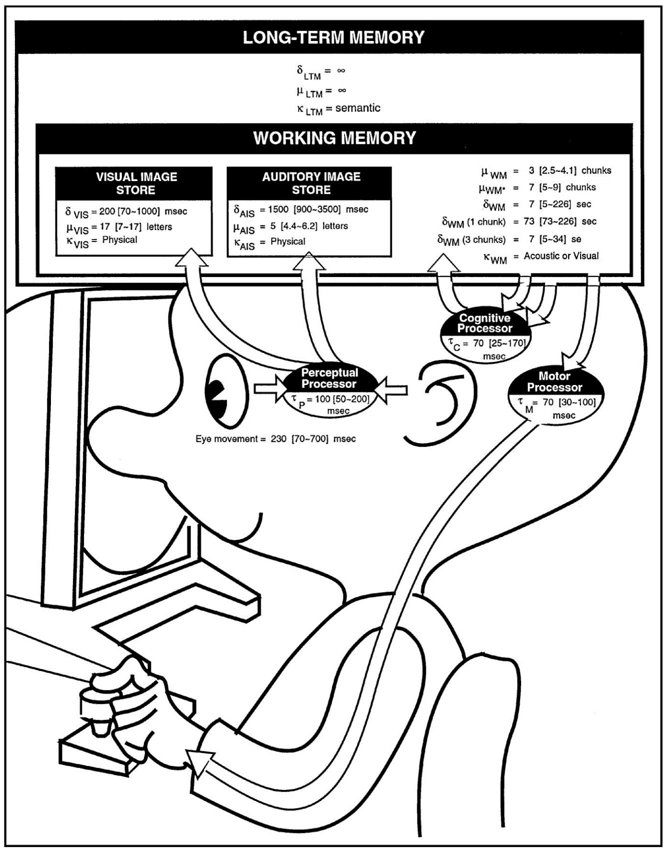


Figure 2.4: The Model Human Processor. Copied from Card et al. (1983).

model that shows how the system is evaluated, Card et al. (1983) developed a set of predictive models, collectively referred to as GOMS (Goals, Operators, Methods, and Selection rules), that focused on designing and analyzing interactive systems.

2.1.3 Seeking/Searching Process

Ellis and colleagues proposed a set of eight features that form a framework for information seeking behavior (Ellis, 1989; Ellis et al., 1993; Ellis and Haugan, 1997). Differentiating the information seeking patterns of scientists and engineers in regard to their information environments, Ellis and Haugan (1997) introduced the eight features as follows: (1) *starting*: initial activities such as conducting a literature overview or locating key people working in the field; (2) *chaining*: following footnotes and references in known material or proceeding in personal networks; (3) *browsing*: variably directed and structured scanning of information sources; (4) *differentiating*: filtering the information obtained using known differences in information sources; (5) *monitoring*: regularly following developments in a field via formal and informal channels and sources; (6) *extracting*: selectively identifying relevant material in an information source; (7) *verifying*: checking the accuracy of information; and (8) *finding*: activities finishing the information seeking process.

While most information seeking situations can be characterized by the Ellis model, the model does not capture undirected processes such as browsing (Bates, 2002). Choo et al. (2000) proposed a model of online information seeking that includes browsing and searching. The model showed that much of Ellis's model and feature sets can be implemented as Web browser components, and thus explains the information seeking processes in Web environments. Searchers begin at a Web site (starting), follow links to information sources (chaining), bookmark pages (differentiating), subscribe to services that provide electronic mail alerts (monitoring), and search for information within sites and information sources (extracting).

Kuhlthau's information search process (ISP) model (Kuhlthau, 1991, 1993, 2004) featured the differences in feelings, thoughts, and actions that people experience during the search process (See Figure 2.5). Ingwersen and Järvelin (2006) interpreted the stages as follows: (1) *initiation*: being aware of the information need; (2) *selection*: the general topic for seeking information is identified and selected; (3) *exploration*: seeking and investigating information on the general topic; (4) *focus formulation*: fixing and structuring the problem to be solved; (5) *collection*: gathering pertinent information for the focused topic; and (6) *presentation*: completing seeking, reporting, and using the result of the task. The ISP model has its advantage in that it considers the psychological aspect of search in information seeking.

	Initiation	Selection	Exploration	Formulation	Collection	Presentation	Assessment
Feelings (Affective)	Uncertainty	Optimism	Confusion Frustration Doubt	Clarity	Sense of direction / Confidence	Satisfaction or Disappointment	Sense of accomplish-ment
Thoughts (Cognitive)	vague →			focused →	increased	interest	Increased self-awareness
Actions (Physical)	seeking	relevant Exploring →	information	seeking	pertinent Documenting	information	

Figure 2.5: Kuhlthau's information search process (1991).

With the analogy of a person picking berries in a forest, Bates (1989) proposed the "berrypicking" approach to information seeking behavior (See Figure 2.6). The approach envisioned an information seeker moving through an information space, gathering chunks of information and seeking cues that help to navigate them through a decision. This model highlighted the *dynamism of needs* during the search, not the actual activities.

2.1.4 Information Exploration Model

Waterworth and Chignell (1991) suggested the information exploration model with three dimensions: (1) structural responsibility (navigation vs. mediated search), (2) target orientation (browsing vs. querying), and (3) interaction methods (descriptive vs. referential), as shown in Figure 2.7.

Considering the difference between exploratory behavior in terms of querying and browsing, Waterworth and Chignell (1991) came up with a visual description of information exploration behaviors in Figure 2.8.

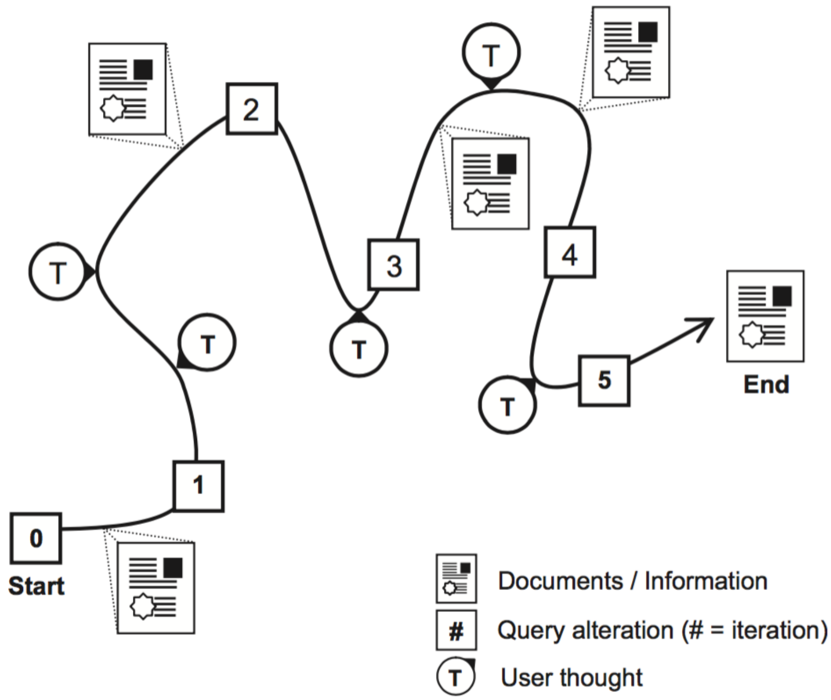


Figure 2.6: Berrypicking search (1989). Figure copied from White & Roth (2009).

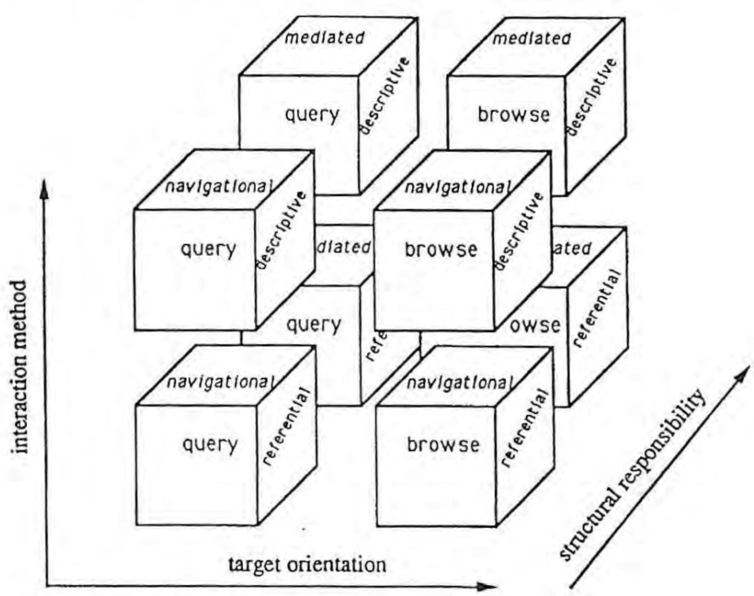


Figure 2.7: 3D Model of Information Exploration. Copied from Waterworth (1991).

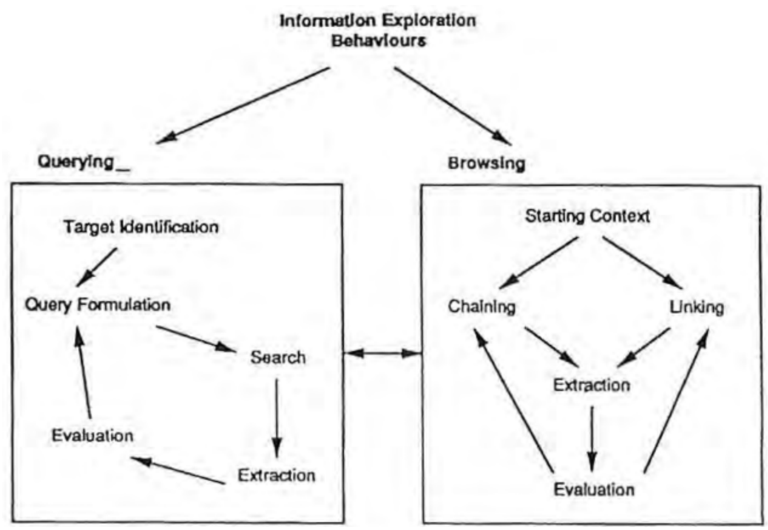


Figure 2.8: A Characterization of Information Exploration Behaviors. Copied from Waterworth and Chignell (1991).

2.1.5 Information Foraging Theory (IFT)

Following the berrypicking approach, Pirolli and Card (1997) proposed *information foraging theory* (IFT) that adopts an evolutionary ecology approach. It pursued explanations that take environmental structure and variation as an essential element in the explanation of the observed behavioral structure and variation. Applying foraging theory (Stephens and Krebs, 1986) and the algorithm for *optimal selection policy*, Pirolli and Card (1997, p.33) suggested a person as an “information predator” whose aim is to select “information prey,” maximizing the rate of information gain relevant to her task. Optimization of the model predicts that people somehow rank the probabilities of the information prey’s relevance. IFT believes the information foraging adaptations are *exaptions* (i.e., an application to one purpose that becomes adapted to another) of the behavioral plasticity that humans developed for food-foraging. The theory also highlighted that people adapt to the constraints and problems they face in complex, dynamic, technology-based environments where they conduct tasks that require processing external information-bearing resources. The problems and constraints of such environments can be seen as forming abstract landscapes of information value and costs, such as the costs of accessing, rendering, and interpreting information.

The *marginal value theorem* (Charnov, 1976) was suggested to handle the analysis of the optimal amount of time spent in a patch. The theorem dealt with situations where foraging

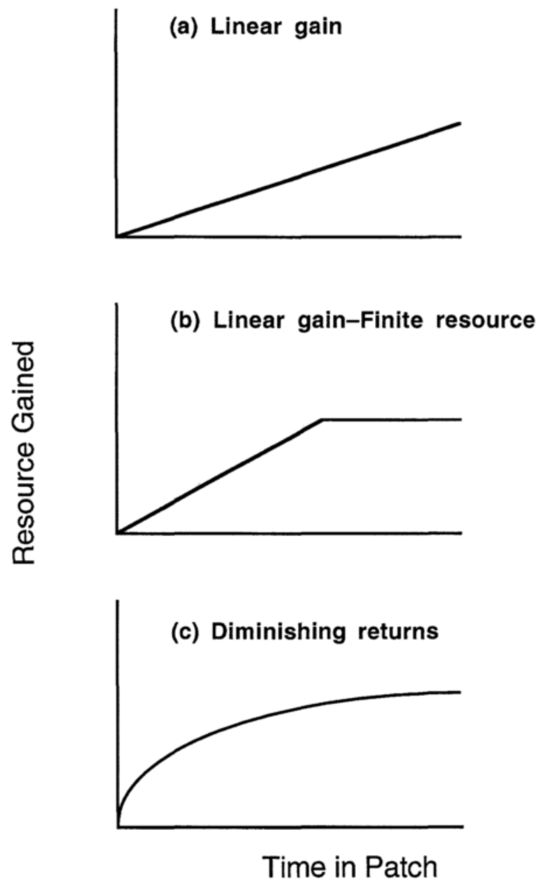


Figure 2.9: Some possible within-patch cumulative gain functions (adapted from (Kaplan and Hill, 1992))

within a patch has decelerating cumulative gain function, as shown in Figure 2.9. The theorem states that a forager would stay in a patch as long as the marginal rate of gain within the patch is greater than the overall rate of gain for the environment when averaged across navigation time and within-patch time. Figure 2.10 represents Charnov's marginal value theorem capturing the basic relations for the situation in which there is only one kind of patch-gain function, $g_i(t)$. The prevalence of patches in the environment (assuming random distribution) can be captured by λ, the average rate of patch encounters while the forager is searching. The average inter-patch navigation time will be $1/\lambda$. In Figure 2.10 (a), navigation time between patches is plotted on the horizontal axis, starting at the origin and moving to the left. To draw a line tangent to the gain function $g_1(t)$ and passing through $1/\lambda_1$ to the left of the origin determines the overall maximum rate of gain R_1, the slope of the tangent. The point of tangency also provides the optimal maximum foraging time $\hat{t}_1^*$.

Figure 2.10 (a) shows that as inter-patch navigation time decreases, from $1/\lambda_1$ to $1/\lambda_2$, the optimal residence time decreases from t_1^* to t_2^*. Figure 2.10 (2) suggests that as the quality of a patch increases, from the gain function g_2 to g_1, the optimal residence time decreases.

2.2 Interaction with Environment: General Behavior

This section generally reviews behavioral models and styles observed in physical & online spaces and examines previous works that study the factors found to be associated with the revealed behaviors.

2.2.1 Behavioral Models

People have their own typical behaviors in spatial, social, and temporal contexts and situations. They live day-to-day and tend to have generalized and habitual behavior patterns regarding particular routines. For instance, a student who studies at a university has a periodic cycle in a regular semester, such as class schedule, social events among friends and family, and a series of assignments, exams, and research projects. Multiple studies have acknowledged the role of individual personalities, demographic variables, and personal contexts in such behaviors. However, earlier studies had to focus on traits that can be easily observed - such as gender

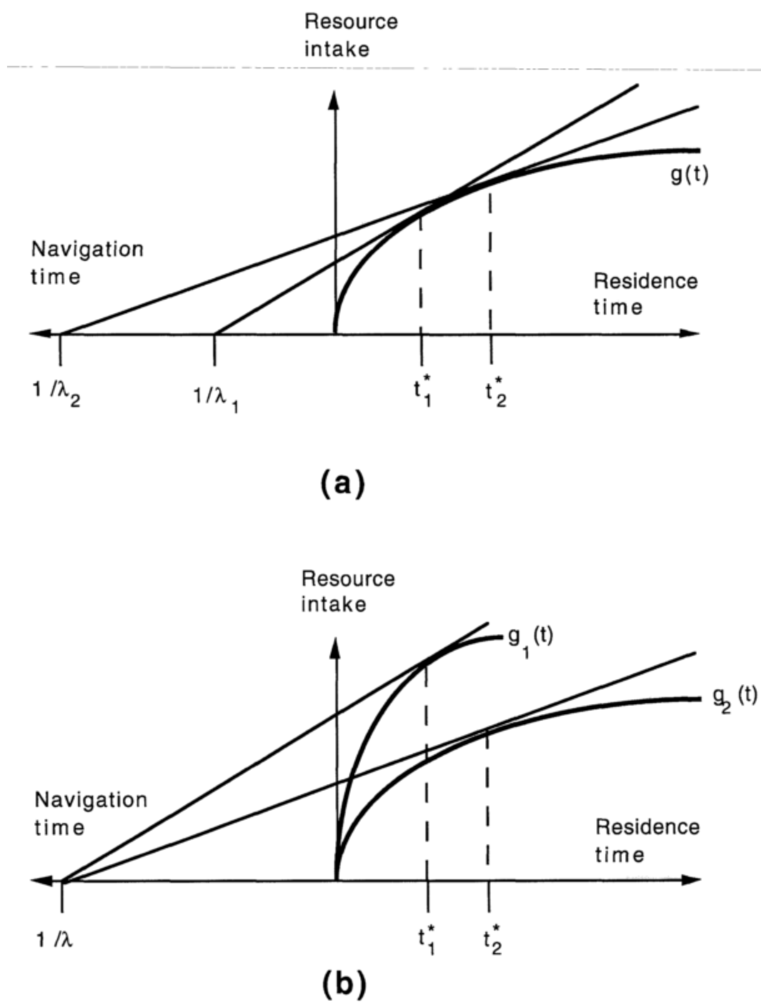


Figure 2.10: Charnov's marginal value theorem (from (Pirolli and Card, 1997))

and ethnicity - or examined in a short time in a controlled environment such as in a lab experiment. While the behaviors observed in a constrained setting might not accurately represent the person's natural and innate actions, data recorded or reported by a participant also has several limitations, including subjectivity in observation, recall/cognitive/socio-cognitive biases, and limited observation opportunities (Eagle and Pentland, 2006; Giles, 2012; Podsakoff et al., 2003).

Meanwhile, the emergence of smartphones and passive sensors in various devices has allowed the gathering of rich, personalized data as well as the creation of human behavioral models in daily life, connecting them to various outcomes. Singh et al. (2013) collect individuals' social behavior such as face-to-face interactions, phone calls, and SMS. They use logs to predict spending behaviors that include visiting diverse businesses or overspending. Individuals' spatio-temporal behavior has been studied regarding their financial outcomes (Singh et al., 2015). Contextual signals from device sensors have encouraged researchers to build systems that are able to detect depression (Burns et al., 2011) , emotion and affect (Rachuri et al., 2010; Yano et al., 2012), student life (Wang et al., 2014), personality traits (de Montjoye et al., 2013), and social networks (Stopczynski et al., 2014).

2.2.2 Mobility Behavior

Past research investigates individuals' trajectories with different perspectives: mobile trajectory with temporal spatial regularity (González et al., 2008), mobility patterns and social networks (Wang et al., 2011; Cho et al., 2011), location with context (Eagle and Pentland, 2006), and spending over various places (Shmueli et al., 2014; Singh et al., 2015). Pappalardo et al. (2015b) find two distinct types of people based on geographic movement - *returners* and *explorers* - through the analysis of large-scale real life mobility datasets; *returners* limit their mobility to a few locations, while the mobility of *explorers* cannot be reduced to few locations. Barbosa et al. (2016) discover similar patterns in human mobility and Web browsing behaviors based on four years of historical data. Along this line, regarding the similarity of human navigating behavior over both physical space and digital space, Benn et al. (2015) use fMRI experiments to find that people use similar brain structures in both environments: limbic (including the retrosplenial cortex) and parahippocampal regions.

2.2.3 Personality Traits

Multiple studies have defined individuals' personalities into particular traits and one example of these looks at five aspects of personality - Big Five Traits - such as *Neuroticism*, *Extroversion*, *Openness*, *Agreeableness*, and *Conscientiousness* (John and Srivastava, 1999). While the detailed factors and measures regarding five facets of personality have been discussed and developed by scholars, one example description for the five dimensions is presented in Table 2.1.

Tidwell and Sias (2005) investigated information seeking behavior of organizational newcomers, who are proactively seeking new information to reduce uncertainty whilst adapting to the new working environment. The results indicated that conscientious newcomers were more likely to overtly seek information, being motivated toward success.

Amichai-Hamburger and Ben-Artzi (2003) discovered that for men the use of Internet services is not related either to the extent of feeling loneliness, neuroticism or extraversion but for women, loneliness is related both to neuroticism and the use of social services in the Internet.

Heinström (2003) studied the extent to which information behavior can be predicted by personality. They conducted correlation analysis between personality measured by NEO Five-Factor Inventory (NEO FFI) (Costa and MacCrae, 1992) and information seeking traits such as *critical information judgment*, *time pressure*, etc. The results are presented in Table 2.11. For instance, neuroticism - the vulnerability to negative emotions - was found to be related to preference for confirming information, feeling that time pressure was a barrier to information searching and retrieval. These connections indicate that negative affection may hinder successful information retrieval, supporting the relationship between temporary states of anxiety and levels of persistence in searching (Ford et al., 2001).

2.2.4 Cognitive Styles

Cognitive style can be defined as "an individual's preferred and habitual approach to organize and represent information" (Felder and Spurlin, 2005; Riding and Rayner, 2013) and has been studied in various domains. For instance, regarding students' learning patterns and performance in online instructions, individual's cognitive style was found to be affecting the ways in which

Table 2.1: Example of Five Facets: NEO PI-R Facets copied from Costa and MacCrae (1992).

Big Five dimensions	**Facet (and correlated trait adjective)**
Extraversion versus introversion	Gregariousness (sociable)
	Assertiveness (forceful)
	Activity (energetic)
	Excitement-seeking (adventurous)
	Positive emotions (enthusiastic)
	Warmth (outgoing)
Agreeableness versus antagonism	Trust (forgiving)
	Straightforwardness (not demanding)
	Altruism (warm)
	Compliance (not stubborn)
	Modesty (not show-off)
	Tender-mindedness (sympathetic)
Conscientiousness versus lack of direction	Competence (efficient)
	Order (organized)
	Dutifulness (not careless)
	Achievement striving (thorough)
	Self-discipline (not lazy)
	Deliberation (not impulsive)
Neuroticism versus emotional stability	Anxiety (tense)
	Angry hostility (irritable)
	Depression (not contented)
	Self-consciousness (shy)
	Impulsiveness (moody)
	Vulnerability (not self-confident)
Openness versus closedness to experience	Ideas (curious)
	Fantasy (imaginative)
	Aesthetics (artistic)
	Actions (wide interests)
	Feelings (excitable)
	Values (unconventional)

	Personality				
Information seeking behaviour	**Neuroticism**	**Extraversion**	**Openness**	**Agreeableness**	**Conscientiousness**
Relevance difficulties	r=.16 p=.008	—	r=-.13 p=.03	r=-.18 p=.002	r=-.20 p=.001
Time pressure as a barrier to information	r=.14 p=.02	r=-.12 p=.04	—	r=-.18 p=.002	r=-.15 p=.01
Confirmation of previous knowledge	—	r=-.13 p=.02	r=-.11 p=.07	—	r=-.14 p=.01
Critical information judgement	—	—	r=.23 p=.0001	r=-.24 p=.0001	—
Aiming to acquire new ideas from retrieved information	—	r=.17 p=.007	r=.11 p=.07	—	r=.14 p=.01
Effort	—	—	r=.19 p=.002	—	r=.18 p=.003

Figure 2.11: Pearson correlation analysis of information seeking behavior and personality traits. Copied from Heinström (2003).

they view ideas, think, react to and represent situations, make decisions, conduct information seeking tasks, and retrieve information (Chen and Liu, 2011).

Past studies have examined people's cognitive styles and defined cognitive style with different terms, as shown in Table 2.2: field-dependent vs. field-independent (Witkin et al., 1975); divergent vs. convergent (Hudson, 1967); holist vs. serialist (Pask, 1976); verbalizer vs. visualizer (Richardson, 1977); and wholist-analytic/verbal-imagery (Riding and Cheema, 1991).

To investigate and assess individual cognitive styles, several instruments have been developed such as the Revised Approaches to Studying Inventory (Tait et al., 1998), Group Embedded Figures Test (Witkin, 1971), Cognitive Style Index (Allinson and Hayes, 1996), Verbal-Imagery Code Test (Riding and Calvey, 1981), and Cognitive Styles Analysis Test (Riding, 1991).

Regarding the cognitive styles in information seeking, Ford et al. (2002) tested several

Table 2.2: Cognitive styles suggested by scholars.

Reference	Style	Description
Witkin et al. (1975)	field-dependent	Field-dependent people are relatively unable to distinguish detail from other information around it
	field-independent	Field-independent people have a tendency to separate details from the surrounding context.
Hudson (1967)	divergent	Divergent people see new combinations of ideas and to examine the possibilities of more than one way of doing things, leading to several outcomes.
	convergent	Convergent people are ones who tend to look for unique methods and unique solutions. Such thinkers are noted for creativity or lateral thinking.
Pask (1976)	holist	Holists build up an overview of the learning situation and later fill in the details of the learning schema.
	serialist	Serialists prefer to concentrate on particular features of the data and build up a conception of the situation from these details.
Richardson (1977)	verbalizer	Verbalizers prefer verbal information that can be read or listened to.
	visualizer	Visualizers prefer visual information such as diagrams, pictures, and graphs.
Riding and Cheema (1991)	wholist-analytic	The W-A dimension reflects how individuals organise and structure information: Wholists retain a global or overal view of information, while analysts deconstruct information into its component parts.
	verbal-imagery	Verbalizers represent information in words or verbal associations, while imagers represent information in mental pictures.

hypotheses linking global/analytic cognitive styles and perspectives of researchers' problem-solving and information seeking behavior. Their results showed that field-independent researchers are more analytic and active than field-dependent scholars, and holists are more engaged in exploratory and serendipitous search behavior than serialists.

2.2.5 Hierarchy of Behaviors

One significant claim that Information Foraging Theory (Pirolli and Card, 1997; Pirolli et al., 2003) employed from Newell (1994) and Anderson (2002) is that the behaviors related to human cognition can be viewed and modeled at many different levels, or time scales. Newell (1994) and Card et al. (1983) viewed human behavior as a hierarchically organized system in which the basic time scale of operation of each system level increases by a factor of 10 as one moves up the hierarchy (see Figure 2.12).

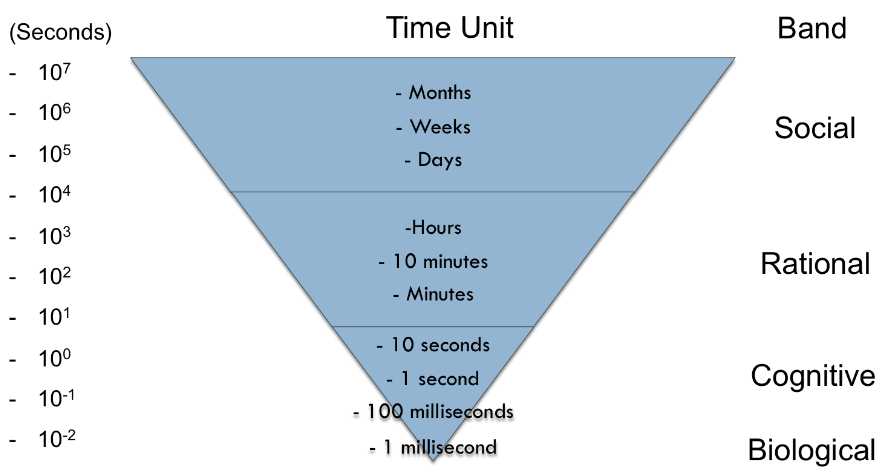


Figure 2.12: Time scales of different bands of behavior. (Adapted from (Newell, 1994))

For instance, behavioral analysis at the *biological* band level (approximately milliseconds to tens of milliseconds) is governed by biochemical, biophysical, and especially neural processes. At the level of *cognitive*, or *psychological* band, the typical unit of analysis is a single response function, which involves a perceptual input stage, a cognitive stage, and a stage of output action. As the time scale of activity increases, at the *rational* band, the behavior is analyzed based on *task*, which is defined by a *goal*. It is assumed that a person has *preferences* for *actions* that they *perceive* to be applicable to their *environment* and that they *know* will move the current situation toward the goal, goals, knowledge, perceptions, actions, and preferences that shape their behavior. On the other hand, the structure, constraints, and resources given in the environment where the task occurs (*task environment*) will also shape behavior. Behavioral analysis at the rational band is dominated by rational principles that are shaped by the structure and constraints of the task environment.

2.2.6 Domain-General Search Process

An ongoing debate in the cognitive literature concerns the process for search, problem solving, and decision making in a variety of domains. One argument is that the mind incorporates numerous autonomous and domain-specific neural modules (Barrett and Kurzban, 2006; Cosmides and Tooby, 1994), each of which is designed to manage a specific class of problems. On the other hand, evidence is accumulating that supports the existence of domain-general cognitive processes, specifically, the search process as the means for problem solving.

Hills et al. (2008) discovered behavioral tendencies over different search spaces - a spatial search and a lexical search task - to suggest the priming effect on the domain-general search process. Participants were first asked to find as many resource tokens as possible, searching in a virtual world on the PC screen. The resource was distributed in various ways - diffusely or in clusters - and participants chose to give up on a given area and move on or to stay on local resource patches. After finishing the spatial search, participants were asked to find a total of 30 words over a series of letter sets, with one letter set at a time. They could move to another letter set when they felt they had sufficiently exhausted another. Participants who conducted the spatial search in a clustered space tended to continue searching longer in each letter set, which indicates they transferred their behavior for one task to a superficially dissimilar task.

2.3 Searching Behavior

2.3.1 Animal Foraging

In animal ecological study, searching behavior has been investigated regarding animals' behavior seeking food, nest, and other resources for their need. Animal foraging literature has shown that different animals exhibit individualistic patterns of foraging (e.g. Hawkes and O'Connell (1985)). When presented with a spatial distribution of "patches" with different utility, animals face a trade-off between the conflicting demands of sampling a variable environment and the exploitation of the most profitable resources (e.g. Clark and Ehlinger (1987)). The response of different animals to this trade-off varies, and while some animals demonstrate higher degrees of "exploration" across patches, others tend to show higher degrees of "exploitation" of the known patches (Smith and Sweatman, 1974a; Sih et al., 2004; Wilson et al., 1994; Groothuis and Carere, 2005). Further, while certain animals tend to show very similar patterns of behavior over time even with the changes in the environment, others demonstrate behavioral "plasticity" and change their behavior promptly (Réale et al., 2000; Dall et al., 2004). A combination of these behavioral traits - exploration, exploitation, and plasticity - has been demonstrated to have significant predictive power on an animal's social stature, survivability, metabolism rates, reproductive success, well being, and other life outcomes (Smith and Sweatman, 1974b; Sih et al., 2004; Wilson et al., 1994; Groothuis and Carere, 2005).

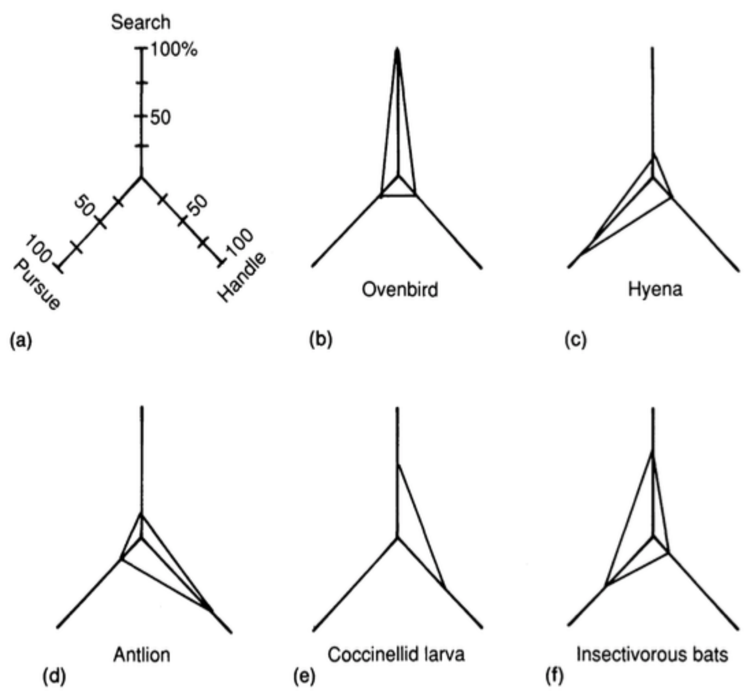


Figure 2.13: Proportion of time spent searching for resources compared to time spent handling (opening, subduing, swallowing) and pursuing (or chasing down) food resources. Copied from Bell (2012).

More specifically, the behavior can be categorized into three behaviors: (1) searching, (2) pursuing, and (3) handling. Whereas searching is the process of finding resources, pursuing includes stalking and chasing down prey, and handling means the process of subduing, swallowing, and digestive pauses. Bell (2012) presented the proportion of time allocated to search, pursuit, and handling for a number of species (see Figure 2.13).

2.3.2 Web Search Behavior

In general (online) search tasks, search interactions consist of search queries and content page selections from the search engine results page (SERP). The search queries that users pose to search engines or systems are explicit, usually short presentations of search intent. Users reveal their interests and intentions and include information to retrieve relevant content through the queries. Thus, query formulation can be a challenging task with mental, cognitive, and temporal efforts, especially concerning topics for which the searcher may lack domain knowledge (Stanton et al., 2014; Zuccon et al., 2015). Aula (2003) studied the factors that affect query formulation in web search, and the questionnaire responses suggest that experience in using computers, web, and web search engines affect the query formulation process; more specifically, (1) media expertise, (2) domain expertise, and (3) type of search are significant. Generally, experienced searchers generate longer and more specific queries.

Users click on hyperlinks on the SERP to either navigate to another location or perform some other actions, for example, following a query suggestion or going through the available search results. Searchers evaluate the relevance or usefulness of information, examining particular pages. Dwell time, or viewing time, on a retrieved document is a useful signal of document relevance. In this regard, dwell time is used to identify individual and task differences in implicit feedback performance (Kelly and Belkin, 2004; White and Kelly, 2006).

As in the interactive processes between the user and the search environment, search trails - a timely ordered sequence of items visited by searchers (Bilenko and White, 2008) - represent the dynamics between user and system/environment. However, when behaviors revealed in the trails are not static, visualization and search trail analysis are not straight forward. In this regard, inspired by the problem behavior graphs (Newell and Simon, 1972), Card et al. (2001) suggested the web behavior graph (WBG) to analyze people's activity during information foraging experiments, and White and Drucker (2007) investigated the behaviors from different classes of searchers.

Broder (2002) differentiated and introduced a taxonomy of web searches, categorizing 'queries' according to their intent into three classes: (1) *navigational,* the intent is to reach a particular site; (2) *informational,* the intent is to acquire some information presented on one or more web pages; and (3) *transactional,* the intent is to perform some web-mediated activities such as purchasing a product on an online shopping site. Based on Broder's taxonomy, Kang and Kim (2004) showed that optimizing search engines with regard to different intent of informational and navigational search improved the performance. There are several studies that employed eye tracking methods to investigate search behaviors. Several key variables can be used as significant indicators of ocular behaviors, including fixations, saccades, pupil dilation, and scan paths (Rayner, 1998). A fixation refers to a spatially stable gaze that lasts for approximately 200 to 300 ms, indicating that the person has a visual attention directed to a specific area of the visual display, for the most information acquisition and processing. Saccades are the continuous and rapid eye movements between fixation points, while scanpaths define the sequences of fixations that represent eye movements and sequential behavior.

Granka et al. (2004) analyzed eye-tracking data to discover that (1) before making an initial click (not the first ranked link), users fixate on abstracts presented for links ranked first and second, and (2) users who selected the lower ranked links tend to view more abstracts overall, indicating that users scan the list and abstracts from top to bottom.

Klöckner et al. (2004) looked into both breadth-first and depth-first sequence patterns revealed by Google usage records. While depth-first searches mean that a user visits the page described by an abstract on the Google SERP before reading the next abstract, breadth-first searches refer to reading each abstract in the Google result list before visiting the page(s) of interest.

Teevan et al. (2004) interviewed fifteen Computer Science graduates twice a day over five days, grouping them into *filers* (people who organized information using fixed structures) and *pilers* (people who maintained unstructured information organization). They observed that filers and pilers relied on two different search strategies. Filers relied more on keyword searches, while pilers were more likely to use site search engines (such as eBay site search) rather than generic search engines.

Aula et al. (2005) defined two kinds of search strategy - "economic" and "exhaustive" -

based on whether a user scanned less than or more than half of the visible results before making a decision to click. Figure 2.14 presents examples of both evaluation styles. The *y* axis refers to the vertical position in the search result page and the *x* axis shows the order in which different area of interests (AOIs) were visited. The size of each circle presents the time spent on each AOI, the largest circle meaning approximately 3 seconds.

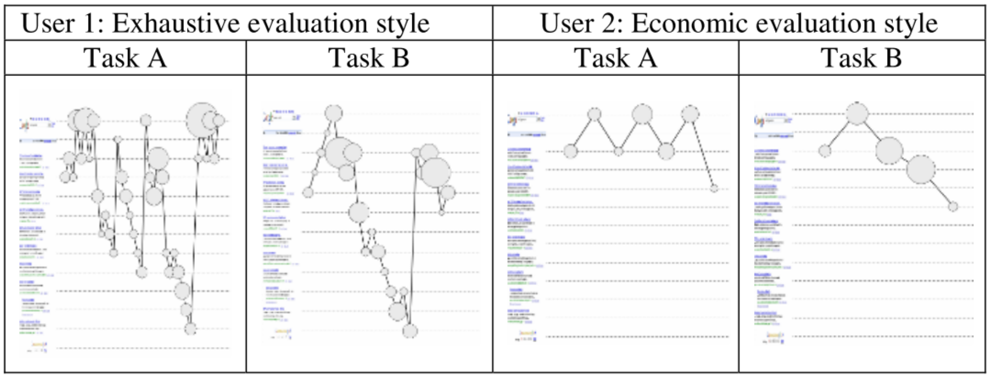


Figure 2.14: Examples of evaluation styles: exhaustive and economic style. In task A, the results shown to participants were irrelevant, thus both users reformulated the query. Task B shows the case in which most of the results were relevant. Copied from Aula et al. (2005).

Lorigo et al. (2006) examined the effect of gender and task on information seeking behavior on the web, analyzing users' eye movement sequence patterns in searching with Google. In addition to developing the definitions for *compressed* scanpath and *minimal* scanpath, they characterized users' search strategies into three categories: (1) *complete* scanpath, in which the path preceding an actual click contains all abstracts of rank *n*, for all *n* less than or equal to the rank of the selected web document; (2) *linear* when the minimal sequence of the user's scanpath is monotonically increasing in increments of 1; and (3) *strictly linear* when the corresponding compressed sequence is monotonically increasing in increments of 1.

Figure 2.15 shows an example of scanpath on a Google search results page. When it comes to the ordered sequence of fixation upon the abstracts, the example indicates a scanpath of $2 \Rightarrow 2 \Rightarrow 3 \Rightarrow 2 \Rightarrow 1 \Rightarrow 1 \Rightarrow 1$. The *compressed* scanpath is obtained by aggregating subsequent fixations that remain on the same abstract into one element; in this example, $2 \Rightarrow 3 \Rightarrow 2 \Rightarrow 1$. The *minimal* scanpath is obtained by removing repeat visits, or regressions, from the compressed sequence. The example here would show the minimal path of $2 \Rightarrow 3 \Rightarrow 1$, providing the overall ordering of the abstracts viewed.

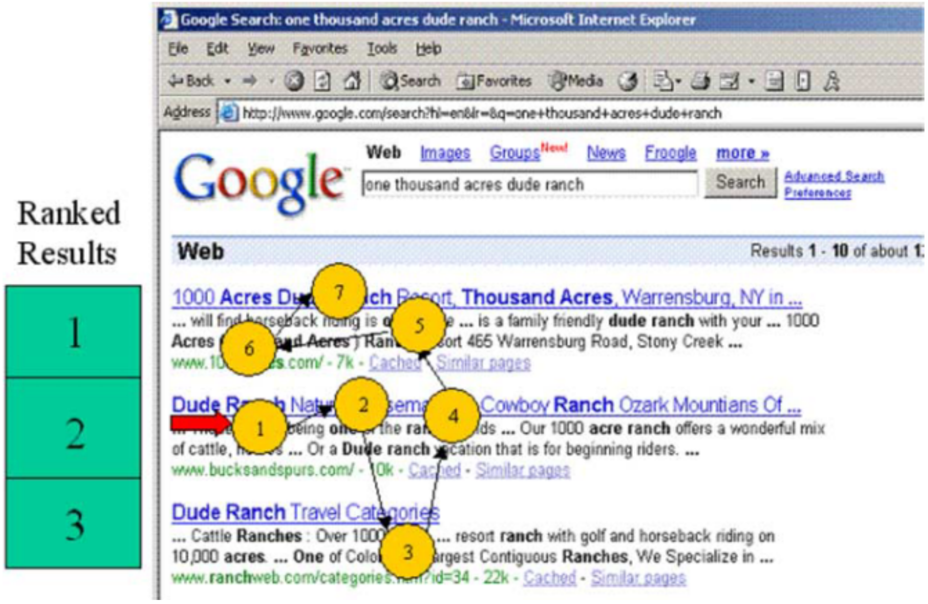


Figure 2.15: An example of a scanpath on a Google results page. Copied from Lorigo et al. (2006).

The results showed the different search behavior for different task types (informational vs. navigational) while there is no significant difference between gender. The conclusion stated that information tasks need more time for completion than navigational tasks, while the time spent reading abstract(s) before making the first click tends to be longer in navigational tasks.

White and Drucker (2007) studied the extent of users' search behavior variability over a five month period. They concluded that information seekers can be classified into two broad categories: *Navigator* sand *Explorers* . Navigators, like filers as presented in Teevan et al. (2004), employ a search strategy to organize information, with directed searches and topical coherence in the search trails. Explorers, similar to pilers in Teevan et al. (2004), have information overlap (re-visits to multiple links) when searching for information.

When it comes to the search behavior on different devices and/or environments, Kim et al. (2012) investigated search examination strategies on different screen sizes with thirty-two participants using Klöckner et al. (2004)'s taxonomy. They observed that users implemented more breadth-first and fewer depth-first strategies on a large screen than on a small screen, contrary to Klöckner et al. (2004)'s findings. These previous works looked at search strategies on desktop and suggested that user factors and individual differences resulted in two distinct search strategies of interaction with search engines.

Li et al. (2009) discussed the concept of good abandonment . It was considered as good abandonment when a user's information need was already satisfied by information displayed on the SERP itself resulting in no result clicks. The good abandonment rate was found to be significantly higher on mobile than on desktop. In general, the ease of query inputs and the difficulty in finding relevant information would both encourage additional reformulations beyond the first queries.

2.3.3 Exploratory Behavior

Exploratory behavior, from a zoological perspective, is defined as "a form of appetitive behavior that may be goal-oriented (e.g. the search for food or nesting material) or concerned with the examination of areas or articles with which an animal is unfamiliar" (Allaby, 1999). The behavior also refers to "the movements made by an animal and humans to learn about a new environment,"[1] or "the tendency to explore or investigate a novel environment,"[2] which is not a clearly distinguishable motivation from curiosity.

Regarding animal foraging behavior, previous studies have shown that different animals exhibit individualistic patterns of foraging (Hawkes and O'Connell, 1985), and that the long-term stable patterns have been demonstrated to have significant associations with an animal's social stature, reproductive success, well being, and other life outcomes (Smith and Sweatman, 1974a; Sih et al., 2004; Groothuis and Carere, 2005; Wilson et al., 1994).

Exploration is most often measured as a change in motor activity (distance traveled, line crosses, rearing, etc.) and sometimes as time spent in, or the frequency of entering, the center of an open field (Platel and Porsolt, 1982; Thiel et al., 1999).

When it comes to measuring and evaluating animals' exploratory behavior, Genaro and Schmidek (1999, 2000) compared the exploratory activity of rats in three different environments: (1) plain open field; (2) open field with a refuge; and (3) complex environment with a refuge. They observed the rats for 15 minutes, measuring the following variables:

- latency to leave the den

[1] http://psychologydictionary.org/exploratory-behavior/

[2] http://www.reference.md/files/D005/mD005106.html

- time spent in the environment
- distance covered
- number of rearings (i.e. standing on hind legs)
- number of fecal pellets

Expecting to see a difference in rats' exploratory behavior after chemical treatment, Dubovicky et al. (1997) measured (1) spontaneous motor activity (number of crossed squares), and (2) vertical exploratory activity (number of rears: both forepaws lifted off the floor). Dubovický et al. (1999) also measured rats' behavior in open field tests.

According to the 'cognitive map' theory (O'keefe and Nadel, 1978), animals and human beings, when placed in a novel environment, started to form an internal representation of the surrounding spatial information.

However, exploratory behavior can hold somewhat different meanings depending on the situations in which an animal or a person is placed. Welker (1957) compared rats' explorations in two circumstances: (1) one in which the animal was forced to occupy an enclosure; and (2) the other in which it was allowed the freedom to choose entry into the same situation. The experiment was conducted over 5 minutes for 21 consecutive days. A rat's activity was counted every time its head moved from one floor sector (marked as a box on the floor) to another. The results indicate that greater activity occurs during forced sessions, and suggest that (a) exploratory behavior may serve to avoid a novel situation as well as to approach one; and (b) unless the animal is allowed to make this choice, researchers cannot be ascertained which variety of exploration is being exhibited.

2.3.4 Exploration in Learning

In a learning context, exploratory behavior is defined as an active interaction on the part of the learner (or trainee) with the learning environment via multiple attempts to solve the problem at hand (Dormann and Frese, 1994). This has been an important tenet of the constructivist theory of learning (Bruner, 1961). Bruner (1961) argued that "Practice in discovering for oneself teaches one to acquire information in a way that makes that information more readily viable in problem solving" (p.26). In a learning process, a person explores to transform rules, principles, and strategies into knowledge and skill.

Curiosity is defined as a desire to know, to see, or to experience; it motivates individuals' exploratory behavior aimed at acquiring new information (Berlyne, 1966; Loewenstein, 1994; Litman, 2005). The exploration begins with a gap between one's current knowledge and the information they need to address a problem. In this sense, Hardy et al. (2014) articulated that learners who explore more will gain a much deeper and complete understanding of the relative effectiveness of a variety of different approaches in response to dynamic stimuli. Given that the exploration represents a systematic process in which people identify, discover, and address knowledge relevant to immediate task performance (Loewenstein, 1994), the effects of exploratory behavior on learning may vary in different types of tasks, for instance, active learning training that demands complex and dynamic decision-making vs. simple instructional repetition.

2.3.5 Exploratory Information Seeking

In the context of information seeking, exploratory behavior can frequently be observed in *exploratory search*. White and Roth (2009) depicted exploratory search as a type of information seeking that is associated with other information behavior models/disciplines such as IR, information foraging, information visualization, and sense-making (See Figure 2.16). In this regard, they defined exploratory search as a sense making activity focused on the gathering and use of information to foster intellectual development. Users who conduct exploratory searches are generally unfamiliar with the domain of their goals, and unsure about how to achieve them.

As the factors relating to exploratory search behavior or task, several aspects have been investigated.

Considering the dynamic and evolving nature of exploratory search, previous studies have investigated the factors relating to this task, such as uncertainty, creativity, innovation, knowledge discovery, serendipity, convergence of ideas, learning, and investigation. Foster and Ford (2003) studied the nature of serendipity, which has been considered in the literature to form an integral part of the creative process in the arts and humanities, social sciences, and natural sciences, as ways by which people keep continuing exploring information space, gathering new,

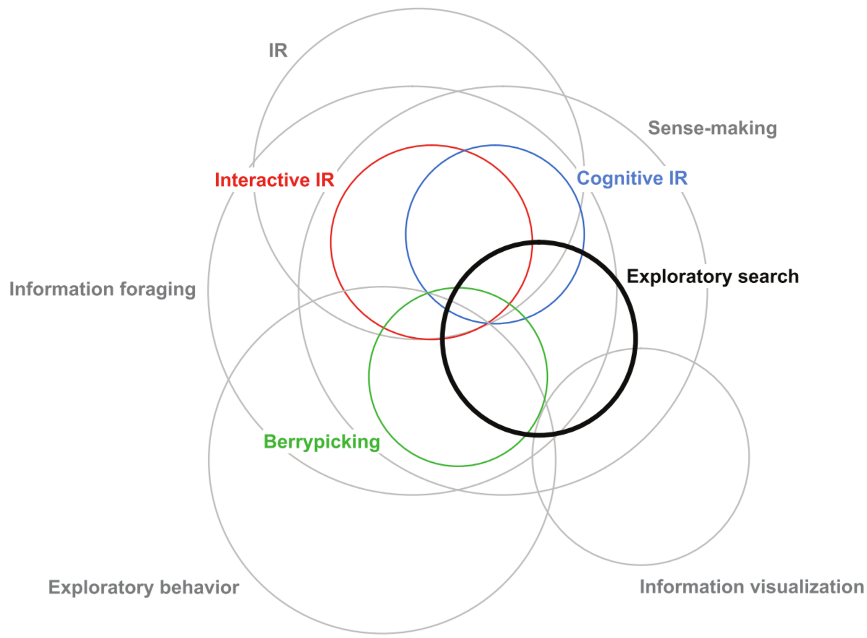


Figure 2.16: Exploratory search relative to related research disciplines. Copied from White and Roth (2009).

novel knowledge.

White and Roth (2009) suggested several features that support exploratory search. First, search systems can help users explore the Web space by providing efficient ways to locate and make sense of information that they encounter during searching. One method for locating relevant information is to support querying and rapid query refinement based on the topics users are interested in. For the documents retrieved via generated queries, clustering and faceted categorization are methods that organize search results into meaningful groups, helping make sense of the results and decide on actions.

While the aforementioned methods are focused on information retrieval mechanism of the exploratory search systems, another approach is to understand users' searching behavior and patterns. Implicit contextual information of users can be extracted from their interaction behavior such as current computing activities (e.g. reading or composing email) (Dumais et al., 2004), display time (Kelly and Belkin, 2004), query history and click activities (Shen et al., 2005). Moreover, to better help users learn more about the subject area in which they are searching, computer-based enhancements can be employed showing historical data of users' engagement to documents.

While previous studies assumed that users have similar behavioral patterns with regards to information searching, Medlar et al. (2017) attempted to provide an interactive information retrieval system that adapts users' changing exploration/exploitation behavior during exploratory search tasks. Implicit feedback data such as clicks and reading time in the system interface and self-reported knowledge level to the given topic explains users' preferable exploration ratio, the higher value of which means the system will provide the more diverse, or exploratory, results to users.

2.4 Preliminary Work

In our previous study (Choi et al., 2016), we identified multiple geographic exploration features that have significant associations with an individual's information exploration behavior, based on a two-week field study with 35 participants. The workflow of this work is presented in Table 2.3.

Table 2.3: Session Workflow

Session	**Procedure**	**Description**	**Time**
Field Session	Introduction	We introduced the study, and install the required app.	30 mins
	Field task	Participants continued to use their phones throughout their everyday lives as the app collects their personal and contextual signals. In the middle of this session, they were asked to answer to the personality questionnaire.	2 weeks
Lab Session	Introduction	We introduced the lab session and information-seeking tasks the participants would conduct.	10 mins
	Lab Task	Participants individually conducted an exploratory search task, including pre-survey and post-survey.	30 mins
	Wrap-up	Wrap-up and (optional) interview.	30 mins

We installed app(s) on their smartphones to collect participants' mobility data and social interactions in their everyday lives. Participants' information behavior was also captured during an exploratory search task via a logging tool (*Coagmento*[3]). The tool recorded users' actions within the browser, including visited Webpages and timestamped queries run on Web search engines. Data allowed us to understand and measure users' search behaviors (Kelly, 2007).

[3]http://coagmento.org/

To investigate exploratory search behavior, we focused on two aspects of the search task: *input to search as expressed by queries*, and *output of search as represented by the nature of the information (Webpages, in this case) discovered*. The former can be measured using inter-query and within-query diversity and the latter can be measured using novelty of discovery suggested in Shah and González-Ibáñez (2011). These three measures are explained below in detail.

Inter-Query Diversity (ID): One indicator of exploratory behavior in the searches conducted by a user is the difference in attempted queries. To find the difference between two queries, we used *Generalized Levenshtein (edit) distance*, a commonly used distance metric for measuring the distance between two character sequences (Levenshtein, 1966).

Within-Query Diversity (WD): In information theory, *entropy* Shannon (2001) refers to the amount of uncertainty of an unknown or random quantity. In information retrieval literature, entropy is used to measure the effectiveness of combination of terms, for example, via the Maximum Entropy Principle (MEP) (Cooper, 1983). Hence, we gauged the relative unique and informative value of a specific query with an entropy-based measure. We first calculated the information entropy as follows:

$$Entropy_{Q_a} = -\sum_{i=1}^{|unigrams_{Q_a}|} p_u log_2 p_u \tag{2.1}$$

Where p_u is the frequency of counts of each unigram, u appearing in each query string, Q_a, found in the entire dataset. The within-query diversity for each user can be defined as the mean of entropy values of each distinct issued query as follows.

$$WD = \frac{\sum_{a=1}^{NQ} Entropy_{Q_a}}{|Q|} \tag{2.2}$$

Higher value of within-query diversity means that the participant has entered diverse keywords in a query during the search task.

Novelty of Discovery (ND): In an exploratory search task where there is plenty of information available for a topic, one does not need to be skilled at exploration to find a large amount of information. Therefore, what really exhibits one's exploratory behavior is the ability to find information that is novel - not found by many. To measure this, we used Likelihood of Discovery (LD), defined by Shah and González-Ibáñez (2011). LD for webpage wp_i is defined as follows:

$$LD_{wp_i} = \frac{-1 \cdot n\{wp_i\}}{|U|} \tag{2.3}$$

Here, $n\{wp_i\}$ is the number of users who found wp_i and $|U|$ is the total number of users. Therefore, LD for a page goes from $-1/|U|$ (highest) to -1 (lowest). The Novelty of Discovery measure for each user can be found as follows:

$$ND = \frac{\sum_{i=1}^{|Coverage|} LD_{wp_i}}{|Coverage|} \tag{2.4}$$

Where $|Coverage|$ is the set of distinct content pages that a user visited. Thus, ND goes from $-1/|U|$ (found most novel pages) to -1 (found most common pages). For a large N this metric ranges between -1 and 0 with a higher value indicating a higher propensity to find novel information.

In terms of geographic exploration, we measured (1) total number of unique locations visited by an individual during the field session; (2) the extent of how evenly a user moves between different locations (Location Diversity); and (3) the repetitions in user movements (Location Loyalty), as explained below.

Unique Locations: This is a measure of location-based activities: the total number of unique locations visited by a user during the field session.

Location Diversity:

$$D = -\sum_i p_i \cdot log_b(p_i) \tag{2.5}$$

Where p_i = percentage of overall visits that were devoted to location i, and b is the total number of unique locations visited.

The diversity score measures how evenly a user's geographic movements are distributed between different locations, using Shannon Entropy Song et al. (2010); Pappalardo et al. (2015a). A user with low diversity distributes her time unevenly across locations, whereas a user with high diversity spends time evenly across many locations.

Location Loyalty: Loyalty characterizes the repetitions in user movements. Similar to an animal going back to the same patch of grass, this characterizes the tendency of a user to go back to his favorite locations.

$$L = \sum_{i}^{k} p_i \tag{2.6}$$

Where p_i = percentage of overall visits that were devoted to location i, and k is the chosen threshold on a user's favorite locations. We considered k to be top-third of a given user's most frequent locations. Note that we employed the meaning of loyalty used in Singh et al. (2015) and adjusted it to our context given the limited number of locations visited by the participants. A similar top-third threshold has been adopted by multiple studies to demarcate the groups or the relationships with highest tie strength or social prestige in the past Lippitt and Gold (1959). In essence, the loyalty feature captures the degree of repetition in a participant's movement patterns.

The resulting values are between 0 and 1, with the larger numbers meaning higher spatial loyalty. For example, a user with very high spatial loyalty will spend almost all of her time (e.g. 80%) in her favorite locations, while a user with low spatial loyalty might spend only 40% of her time in the top-third of her visited locations.

Table 2.4: Correlation between variables (*: $p < 0.05$, **: $p < 0.01$).

Variables	Inter-Query Diversity (ID)	Within-Query Diversity (WD)	Novelty of Discovery (ND)
Unique Locations	.285	-.318	.263
Location Diversity	-.261	.433*	-.460**
Location Loyalty	.401*	-.440*	.548**

We first looked at if and how different aspects of geo-exploration relate to aspects of search behaviors that exhibit exploration. The results are presented in Table 2.4. The results show that Location Diversity was positively correlated with Within-Query Diversity (WD), while negatively related to Novelty of Discovery (ND). This indicated that those who visited more diverse locations were also likely to have more within-query diversity and find less unique content. Though we considered the work to be potentially transformative, it lacks an understanding of participants' intentions and contexts regarding "exploration," and requires a bridge that connects information behavior in a lab setting and geographic exploration in a natural environment.

While this preliminary work provided interesting results and possible relationship between onine and physical exploratory behavior, it lacks (1) the extent to which these behavior are related to each other, (2) what determines the similarity/dissimilarity between the behavior. The limitations inspired me to examine physical search behavior in the smaller scale that is comparable to the PC monitor screen (online space).

Chapter 3

Conceptual Framework

In this section, several theoretical frameworks that guide the dissertation, including the research questions, are presented. These are: Wilson's nested information behavior model, everyday life information seeking (ELIS), information foraging theory (IFT), human information interaction (HII), hierarchical behavioral model, and general search process model. First, Wilson's nested information behavior model outlines how information behavior can be viewed as a particular perspective of peoples' general behavior. Everyday life information seeking (ELIS) outlines how people engage in information interactions in context. While information foraging theory (IFT) draws an analogy between humans' foraging for information and animals' pursuit of food, human information interaction (HII) investigates the way in which people interact with their external environments, sometimes even in relation to internal factors. Last, the hierarchical behavioral model and the general search process model in cognitive literature ground my research problem, comparing search behavior in different information spaces.

3.1 Information Behavior Model

Peoples' behaviors related to information consist of different constructs regarding context and levels of focus and understanding. To understand individuals' exploratory behavior in both physical and online spaces, it would be useful to investigate the diverse territory and categories that are associated with information behavior. In this sense, Wilson has developed and proposed several models of information behavior. Wilson (1981) proposed a model representing the user, the systems employed during the seeking process, and the information resources as a final goal, as described in Figure (3.1). In the context of a "universe of knowledge," the *user's life world* refers to the totality of experiences centered on the person as an information user. The user interacts with various types of *information systems*, in which two sub-systems exist:

the ”mediator,” which refers to a living system such as a human being; and the ”technology,” which here represents whatever combination of techniques and tools constitute the information system. Through the information system, the user can reach various ”embodiments of knowledge” that indicate final goals, such as locating documents or finding people who own the knowledge.

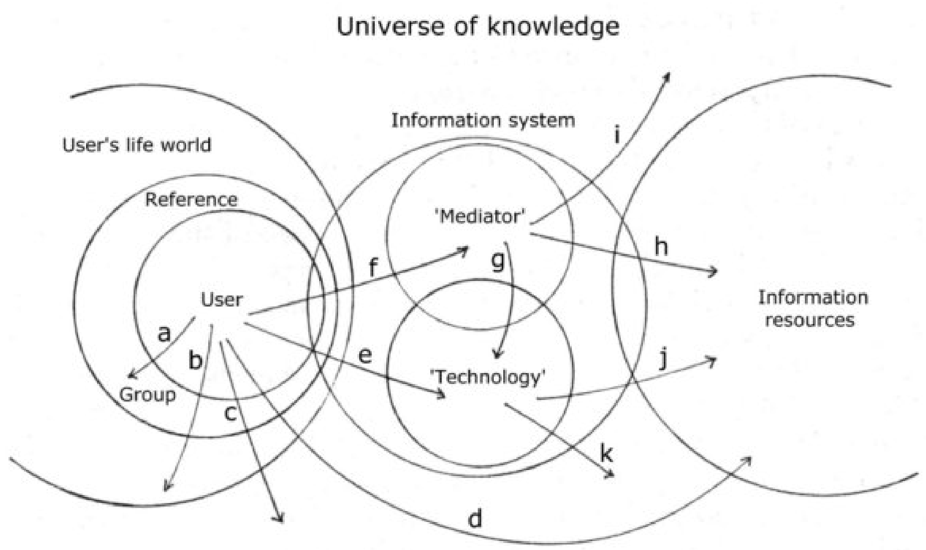


Figure 3.1: The information user and the universe of knowledge. Copied from Wilson (1981).

Wilson (1997) suggested a revised version of his information behavior model to incorporate theories from a variety of disciplines such as decision-making, psychology, innovation, health communication, and consumer research. This model attempts to include several factors - or mechanisms - that explain whether a particular need invokes information seeking behavior, as well as why an individual prefers specific information sources and intervening variables. Showing the relationships between information behavior models, Wilson (1999) proposed to integrate said models into a more general framework, or nested model (see Figure 2.3).

Significant attributes of Wilson’s models included the idea that an information seeker, or user, is operating in their own “universe of knowledge,” while (general) information behavior has several sub-categories (information-seeking behavior, and information search behavior) that can apply to broader general behavior. This demands thorough understanding across various disciplines regarding behavior and decision-making.

3.2 Information Seeking in Everyday Life

Regarding both the general and specific behaviors people have in their daily lives, everyday life information seeking (ELIS) is a holistic framework for understanding how people seek and utilize information within their typical routines. Savolainen (1995) provided the concept of human information seeking behavior and describes the way in which people get a sense of information around them. Two substantial elements in the model are the ”way of life” and the ”mastery of life,” which are inspired by the concept of habitus (Bourdieu, 1984). *Way of life* refers to the internalized ”order of things,” and *mastery of life* describes actions taken to maintain order during tumultuous times in which people have to (re)form their short-term or long-term information behaviors. The study of ELIS pointed out that everyday life and work/job related tasks are inseparably tied. People may seek information to solve their personal problems as well as look for relevant information for their professional and/or academic tasks. An important implication from ELIS to this dissertation is that the importance of specific problem-solving contexts can be applied to geographical exploration in everyday life. For instance, sometimes a person may need to explore, or visit, several places in a day due to their job, regardless of personal preference.

3.3 Information Foraging

To investigate the relationship between an individual’s geographical movement and their information exploration behavior, the current proposal employs Information Foraging Theory (IFT). The theory (Pirolli, 2007; Pirolli and Card, 1997) attempts to explain information seeking behavior in humans. The food foraging mechanisms in living organisms, such as animals, inspires the idea to compare humans’ information foraging to animals’ food foraging. Researchers propose that optimal foraging theory (Stephens and Krebs, 1986) can help them understand foraging behavior in human actors who consume information for their needs.

In Information Foraging Theory, people face the recurrent problem of finding task-relevant information. Information flows into the environment to be represented in different types of external media - such as books, manuscripts, and online documents - that each have different costs of interpretation and access. Faced with recurrent tasks, a human ”informavore” chooses information types, repositories, and interfaces that optimize benefits over associated costs and values (Pirolli and Card, 1997).

Athukorala et al. (2014) utilized the framework to examine exploration and exploitation analysis, and Ruotsalo et al. (2013) employed the foraging model to support exploratory search tasks considering interactive user modeling.

3.4 Human-Information Interaction in Seeking Information

In fact, we can say that we are surrounded by all types of information in daily life. What we see, what we hear, and what we feel by sensors in our bodies can be inputted into our cognitive systems for information processing. In this regard, in addition to human-computer interaction (HCI), which is a discipline that studies how humans and computers interact and how technologies can help that interaction, human-information interaction considers a much broader range of interactions between humans and their environments. This proposed work also considers the environment, specifically in regard to physical spaces that people visit in their daily lives to accomplish their given personal and professional tasks.

Fidel (2012) explained two primary, established research areas in human information interaction that relate to information seeking behavior (ISB) and information retrieval (IR): "acquiring information" and "evaluating information." Saying that ISB "represents only one form of *acquiring information*" (p. 21), Fidel is expanding the concept of *seeking information*, which is typically perceived as *looking for information*, or in a broader sense *getting information.* In this regard, *acquiring information* can include three types of behavior: (1) seeking information, in which people *purposely* look for information to support actual decision-making or to resolve an information problem; (2) surfing, which means that people browse through an information source without a specific goal just to see what it contains; and (3) encountering, in which people find information they were not intentionally seeking. When it comes to the IR side, *evaluating information* is most important to judge whether or not something is relevant to the searcher's current problem (Fidel, 2012).

Regarding these two activities - "acquiring information" and "evaluating information" - as well as geographical exploration, this proposal suggests a research framework: visit and see. *Visit* in this sense refers to visiting a place (e.g., a particular office or Website), with the presumption that the place will hold relevant information or benefits. *See* describes an action that evaluates whether the expected benefit occurred after consuming the information.

3.5 Hierarchy of Behaviors

While Wilson's nested model considers the hierarchical framework in which different layers of information behavior manifest (Wilson, 1999), scholars in Cognitive Psychology have suggested a similar hierarchy of human behavior in general. Newell (1994) and Card et al. (1983) viewed human behavior as a hierarchically organized system in which different types of behavior operate based on different time scales (see Figure 3.2).

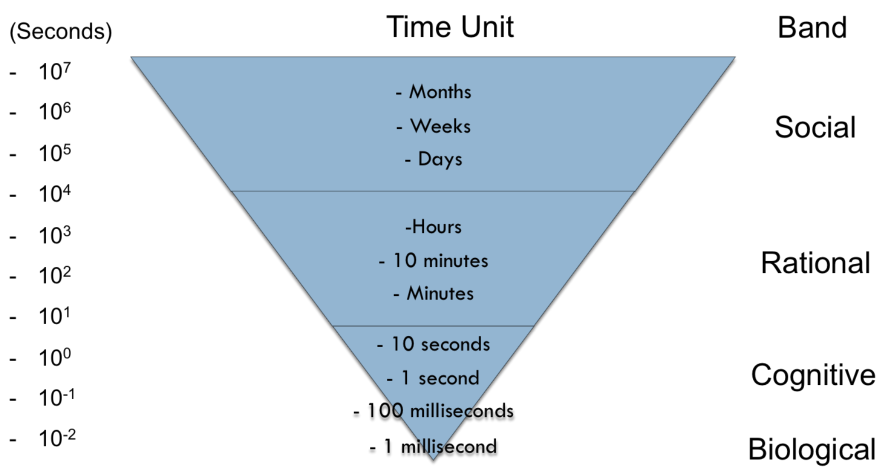


Figure 3.2: Time scales of different bands of behavior. (Adapted from (Newell, 1994))

For instance, behavioral analysis at the *biological* band level (approximately milliseconds to tens of milliseconds) is governed by biochemical, biophysical, and especially neural processes. At the level of *cognitive*, or *psychological* band, the typical unit of analysis is a single response function, which involves a perceptual input stage, a cognitive stage, and a stage of output action. As the time scale of activity increases, at the *rational* band, the behavior is analyzed based on *task*, which is defined by a *goal*. It is assumed that a person has *preferences* for *actions* that they *perceive* to be applicable to their *environment* and that they *know* will move the current situation toward the goal, goals, knowledge, perceptions, actions, and preferences that shape their behavior. On the other hand, the structure, constraints, and resources given in the environment where the task occurs (*task environment*) will also shape behavior. Behavioral analysis at the rational band is dominated by rational principles that are shaped by the structure and constraints of the task environment.

3.6 General Search Process in Different Domains

Previous studies in cognitive literature have supported the existence of the general executive control over different domains in our cognitive system. When it comes to search process, which is of interest in this dissertation, Hills et al. (2008) discovered behavioral tendencies over different search spaces - a spatial search and a lexical search task - to suggest the priming effect on the domain-general search process. Through the comparable experiments of spatial search, which was simulated on PC screen, and lexical search with letter sets, they found that those who conducted the spatial search in a clustered space tended to continue searching longer in each letter set, which indicates they transferred their behavior for one task to a superficially dissimilar task.

3.7 Summary of Theoretical Frameworks

The dissertation aims to gain a better understanding of an information user's searching behavior in physical and online spaces, seeing if they present similar or dissimilar behavioral patterns in different information environments. To examine information behavior that is expressed in different contexts, this study views users' behavior regarding the theoretical framework presented in Figure 3.3, which consists of (1) information behavior perspective and (2) cognitive psychology perspective.

The left part of the figure represents theories related to information behavior. People can acquire information through various means, which includes three ways of human information interaction suggested in Fidel (2012): *seeking information*, *surfing*, and *encountering*. While Wilson (1997) provides a hierarchical information behavioral model that expands research analysis into a user's more general behavior, the social interactions and other personal contexts and constraints in our everyday life also need to be considered (Savolainen, 1995). Presuming individuals' rational decision making with regard to maximizing information gain, information

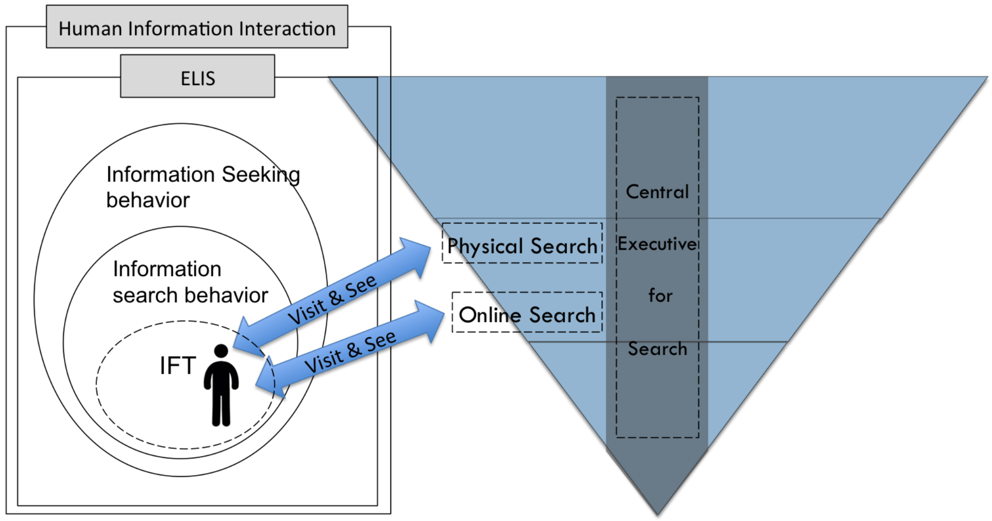


Figure 3.3: The relationship of theoretical frameworks in the dissertation

foraging theory guides how people explore in information space (Pirolli and Card, 1995, 1997).

The part of the figure to the right depicts the central executive for search in the behavioral model, which dominates operating related to the search tasks - searching in physical space as well as in online Web space. In the time-scale based hierarchical behavioral model, suggested in Newell (1994); Card et al. (1983), this dissertation assumes the existence of the generic, central executive that is significantly involved with search tasks. While central executive for search does not explain the whole process, the framework in the figure supposes common behavioral traits between physical search and online search.

To understand individuals' information search behavior, more specifically visiting and seeing behavior (two arrows in Figure 3.3) in each space, several experiments were designed and behaviors of interest were defined. The detailed methodology will be presented in the following chapter.

Chapter 4

Methodology

This chapter describes the methodology I used in the study of information seeking behavior regarding exploration in physical and online spaces.

4.1 Research Questions

The purpose of this dissertation is to investigate peoples' searching and exploratory behavior in online and physical spaces utilizing the behavioral models that demonstrate commonalities between both spaces. In their daily lives, people seek information either to solve specific problems or to make sense of various topics they face, interacting with various contexts of information needs, task environments and information spaces. To examine this, the following research questions are proposed:

- RQ1: To what extent, if any, does an individual's information seeking behavior online relate to his/her behavior in physical space?
- RQ1a: To what extent, if any, does an individual's patterns of visiting and seeing physical spaces relate to his/her visiting and seeing in online spaces?
- RQ2: What aspects, if any, and how much, of an individual's physical exploration is related to his/her online information seeking behavior?

4.2 Research Design

Addressing the research questions requires defining and classification of information seeking contexts in physical space and online space. First, physical search and online search are defined corresponding to the environment in which the search activities occur. For instance, physical search takes place when looking for information presented in the physical space in our ordinary lives, such as in documents, books, posters, etc., in various scales of geographical areas, from a single room to a building to a society and a country. On the other hand, online search refers to searching for information online, such as in Web documents and social media that we can access through a variety of information devices (e.g., PCs, smartphones, tablets).

One of the important aspects of information exploration relevant to this study is *target orientation* (browsing vs. querying) (Waterworth and Chignell, 1991). Browsing is distinguished from querying in that browsing does not have a specific target in the mind of the person. Also from a behavioral perspective, while querying starts with target identification, browsing begins with a starting context which is relatively less specific, such as the table of contents of a book or a portal site that the user usually opens with a Web browser.

In this regard, situations of information seeking in physical space and online space can be represented visually, as in Figure 4.1. The dimension of target orientation is referred as *everyday life* vs. *goal-driven*, the vertical axis. Everyday life context, more specifically, is usually depicted with behaviors that include *home*, to which people regularly return, and habitual, long-term activities. On the other hand, goal-driven behavior is described with specific target(s) in a short-term period without home places.

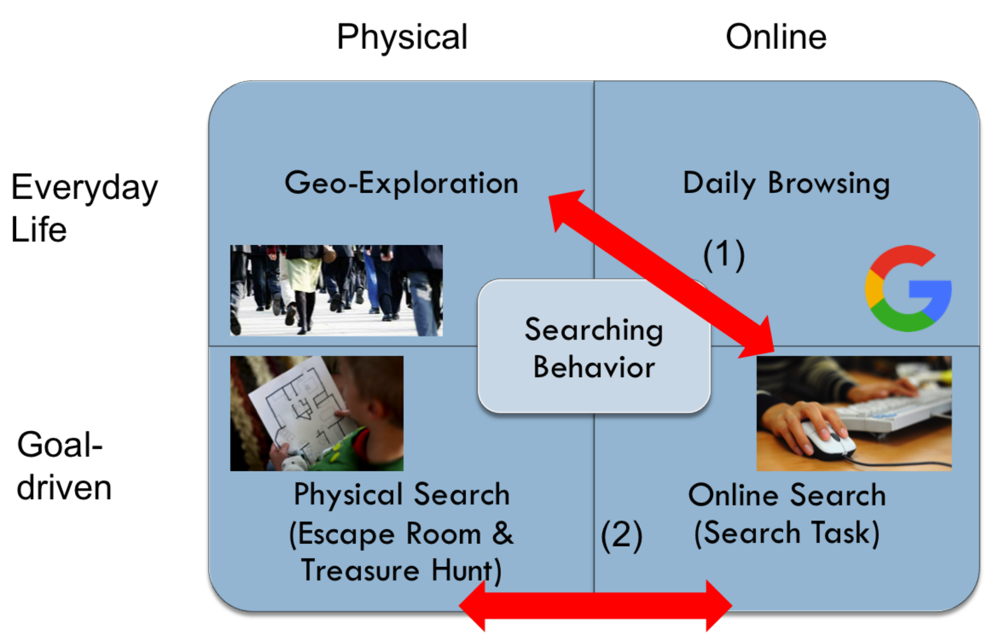


Figure 4.1: Experimental design

The left-upper box (physical & everyday life) represents the exploratory behavior of people in their daily life, while the left-bottom box (physical & goal-driven) means the information seeking in physical space to solve given problems. In online space, the right-upper box (online & everyday life) is associated with our search logs and the right-bottom box (online & goal-driven) indicates Web search tasks with specific goals.

Our previous study (Choi et al., 2016) examined geographical exploration and online exploration to find the interconnection between them (see (1) in Figure 4.1), but the different task environments (everyday life vs. goal-driven task) that might have affected peoples' behavior in different ways were not considered in that study.

This limitation inspired me to design middle-ground sessions between the field session (physical & everyday life case) and lab session (online & goal-drive case): escape room and treasure hunt game, which refer to the activities involved in finding clues and information placed in a certain location - a room or a building.

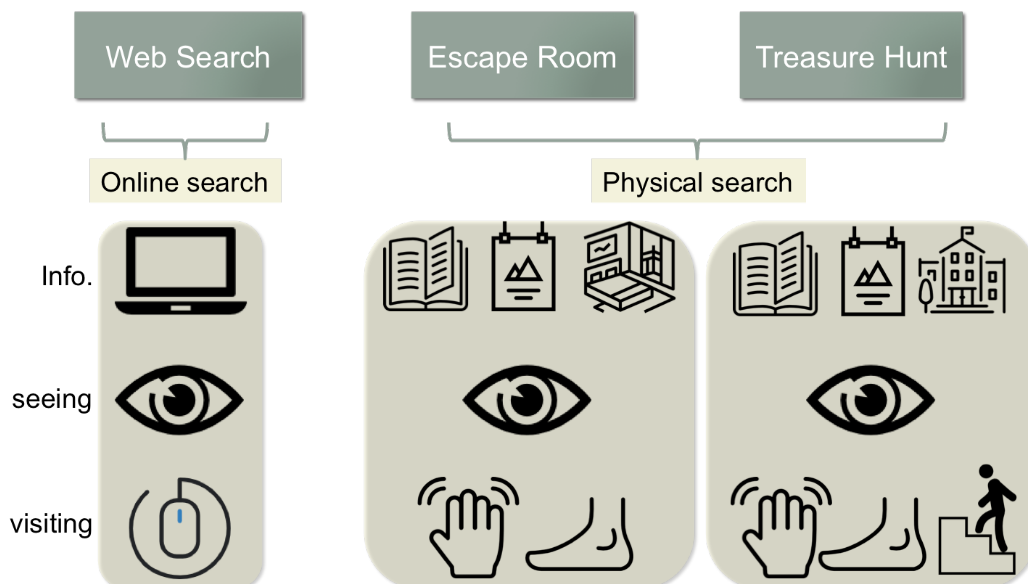


Figure 4.2: Study design

The dissertation study consists of three experimental sessions: escape room (ER), treasure hunt (TH), and Web search (WS). These sessions are designed to investigate individuals' information searching behavior in different contexts (Figure 4.2). This study design attempts to connect behavioral patterns in information searching in physical and online space to address research questions. While Web search supposes information is located in online space, physical search in escape room and treasure hunt expects people to look for information from books, posters, bulletin board, etc. in a room or a building, visiting by hands and feet.

4.3 Workflow

Table 4.1 presents a brief description of the workflow. This study was conducted over several weekends in December, 2016 with 31 undergraduates at Rutgers University. The study consists of *Escape Room*, *Treasure Hunt*, and *Web Search* tasks.

Table 4.1: Session Workflow

Session	**Procedure**	**Description**	**Time**
Escape Room	Introduction	Introduce the escape game and put wearable devices on.	2 mins
	Game Play	Participants play an escape room game, solving problems and finding clues in a room.	20 mins
Treasure Hunt	Introduction	Introduce the treasure hunt game and put wearable devices on.	2 mins
	Game Play	Participants play a treasure-hunt task, finding clues in multiple places in the School building.	20 mins
Web Search	Introduction	Introduce the lab session and set up the task PC.	5 mins
	Problem Solving	Problem solving task up to 10 A-Google-A-Day type questions	20 mins
	Exploratory Search	Exploratory search for a given topic	20 mins
	Wrap-up	Additional surveys and wrap-up.	10 mins

4.4 Target Population and Sample

Thirty-one undergraduates from Rutgers University participated in the experiment phase of the research. The participants were recruited via various email-lists, social network sites (e.g., Facebook and Twitter), and flyers. Since the participants will conduct several tasks (Escape Room, Treasure Hunt and Web Search), they are required to be fluent in English, have normal or corrected-to-normal vision and hearing, as well as normal motor control.

Each participant was compensated $100 in cash upon completion of the study.

4.5 Data Collection

The study utilized several ways of collecting participants' behaviors in different contexts. To observe their visiting and seeing behaviors, this study used wearable video recorders, a browser plugin, and an eye-tracker.

4.5.1 Wearable Video Recorder

During escape room and treasure hunt sessions, each participant was given a wearable video recorder (See Figure 4.3). The device recorded participants' behavior, visiting, and seeing information provided in the game environments.

Figure 4.3: Example of Wearable Video Recorder

4.5.2 Browser Plugin

To collect data related to their search histories, I installed the Coagmento[1] browser plugin on the PC on which the search task was conducted. The plugin collected data about searching activities as follows:

- userID

[1] http://coagmento.org/index.php

- timestamp
- questionID
- query
- visited URL (Uniform Resource Locator)
- title of Web page
- host of Web page
- date and time

An example of recorded search logs is presented in Figure 4.4.

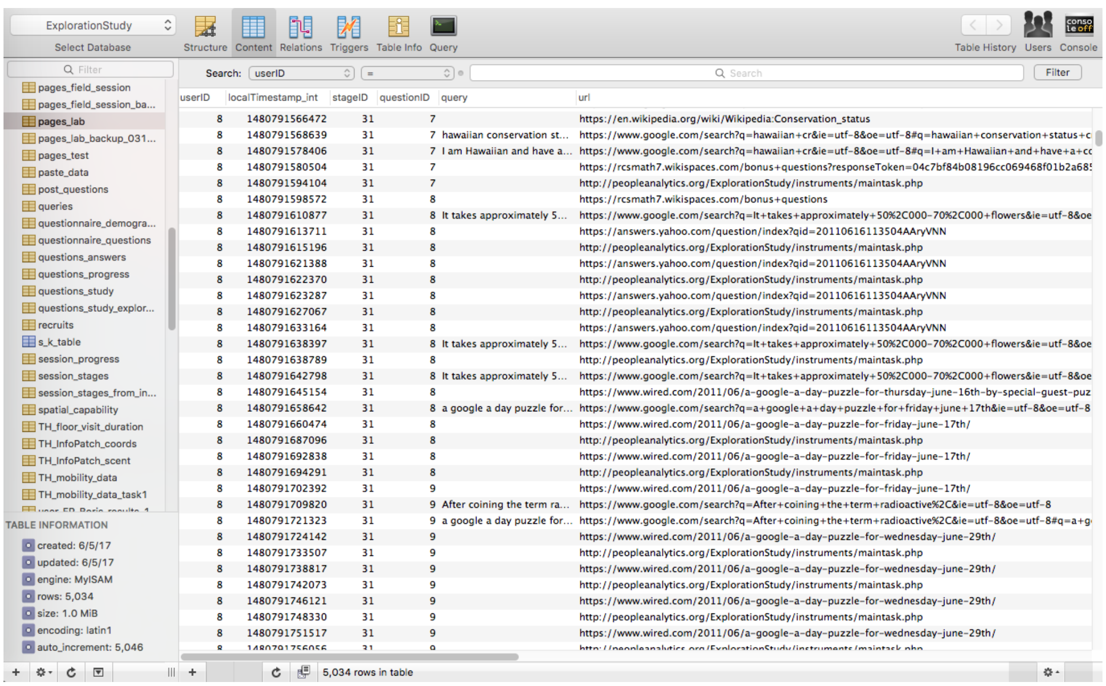


Figure 4.4: Example of recorded search logs

4.6 Escape Room Game

4.6.1 Purpose and Data

The purpose of escape room game is to capture *exploration in physical space* in a smaller territory than the subsequent treasure hunt session. While the focus of the treasure hunt session is on the *geographical exploration,* escape room is focused on observing the participants' cognitive behavior represented by viewpoint and eye gaze. Even though the video recording on glasses does not capture the eye gaze as accurately as a mobile eye-tracker does, with the time-stamped data, it is able to simulate where a participant was looking for a certain period of time for reading and reasoning. In reality, the escape room game is usually played as a team, at least of two people, but since the unit of analysis of the dissertation is individual, the game was played individually.

4.6.2 Task

In the game room, a participant needs to explore and search first to locate possible clues that provide following clues toward finding the key to escape that room. Given that there are several different things that can be suspected to contain a clue, a person needs to judge the relevance of each thing as to whether to invest his/ her time and effort. All his/her activities were recorded by the wearable video recorder.

Figure 4.5 shows the escape room set up in a classroom.

Figure 4.5: Escape Room Game. Participants are supposed to search books (left bottom), posters (left top), and movie posters (right bottom) to unlock boxes presented in the room (right top).

The introduction to the game and tasks used in the preliminary study are as follows.

The Escape Room Story:

A Professor named Tim Murphy is missing. You have entered his office to track possible clues he left, but you are also locked in his room. You need to keep accomplishing tasks until you get the final key.

- Task 1: "Multimedia search" is a sub-topic in information retrieval. Find the page of the chapter of "multimedia search" in a book. Use this page number to open the 3-digit lock.

There are four books related to information search and retrieval in the room. The participant is expected to pick some books and look at the table of contents of each book to get the page number, which is 207. Participant will unlock the 3-digit lock with this number and see the next task.

- Task 2: Find the poster of a movie that was presented by Paramount Pictures and Warner Bros. What is the first name of the hero of that movie? Then, find a research poster in which the first author's name is the same as the actor's first name. (1) Find out the last name of the first author. (2) Find how many undergraduate students participated in the experiment outlined in that research poster.

  The first two letters in the answer are the initials of the author's first and last name. Next, three digits are the square of the number of undergraduate participants. Use the answer to unlock the 5-letter lock (_ _ _ _ _). For instance, if the author is Tim Murphy and 20 undergraduates were involved in the experiment, the answer is TM400.

Among the movie posters there is one of *Interstella*, one of whose stars was *Matthew McConaughey*. And among the research posters, there is one poster written by a researcher named *Matthew Mitsui*. 20 undergraduates participated in the study presented in his poster, so the answer for 5-letter lock is MM400. The participant will open the lock to access the next task.

- Task 3: Hint - Computer [****]s, Olympic [****]s. Look the word in the bracket up in the dictionary. You should see a word that allows you to open the 4-letter lock.

The word in the bracket is **game.** The participant is expected to open the dictionary to look up the word to see a highlighted word, **play**, in the explanation of game. The participant will open the 4-letter lock to get the next question.

- Task 4: Five Effects of Prediction are: (1) the prediction effect, (2) the data effect, (3) the induction effect, (4) the ensemble effect, and (5) the ( ) effect (hint: see p. 221 of a book). Use this word to unlock the tablet PC.

There is a book about prediction analytics, in which one chapter talks about the five effects of prediction. When opening the book, the participant will figure out that the fifth effect of prediction is *persuasion*. This word is the passcode for a table PC in the room. The next task comes up on the screen when opening the tablet.

- Task 5: [Picture of silver medal] This is a ( ) medal. Find the publication year of a book that ( ) wrote. Use this publication year to open the 4-digit lock.

The word in the bracket is silver and there is a book written by *Nate Silver*, in 2012, which is the 4-digit for the participant to get the key - The end!

4.7 Treasure Hunt Game

4.7.1 Purpose and Data

The purpose of the treasure hunt is to observe participants' *geographical exploration* as well as *physical searching* captured by video recording through a wearable video recorder. Recorded video with timestamp was used to examine where the participant *visits* and what she *sees* during the game.

4.7.2 Task

Instructions regarding the game was provided:

1. Solve the given questions in the order.

2. All information needed is only in the hallways including doors, posters, papers, flyers, and bulletin boards. So you are not supposed to open any doors or get inside of offices and classrooms.

3. Set the timer to 20 minutes and come back to this room when time is up, even though you did not complete all tasks.

The tasks and clues given to participants are as follows.

- Task 1: Find a flyer about an event that will be held at **State Theatre, New Jersey on October 21, 2016.**

I put a flyer with the information about a singer's (Brian McKnight) concert on a bulletin board at a corner on the third floor. The participant is expected to find the flyer by walking around the hallways in the building, starting from a room on the second floor.

- Task 2: There is a professor **whose first name is the same** as one in the flyer. Find this professor's office. What is the office number? Keep this number as A.

There is a professor named *Brian Householder*, whose office is on the second floor. Participant is expected to find his room and keep the room number (215) for later.

- Task 3: Can you find an office that has a picture of **Beyoncè** nearby. What is the office number? Keep this as B.

There was a picture of *Beyoncè* next to the door of office (room 112) on the first floor. The participant is expected to wander through the halls to look at the doors to locate the picture.

- Task 4: A - B = ? (What is the difference between A and B?) Then, go to the room with this number in reverse (For example, if A-B=407, then go to the room 704.)

The difference between A and B is 103 and the reverse number is 301. So participant is expected to go to room 301.

- Task 5: On this floor, can you find information about a **Rutgers event that President Obama attended,** and get how many students attended it?

I put a magazine on a filing cabinet, which has a picture of President Obama in a graduation gown when attending the commencement of Rutgers University. The participant is expected to find the magazine and read an article in it to get the number of students who attended the event.

Figure 4.6 shows pictures of the treasure hunt game.

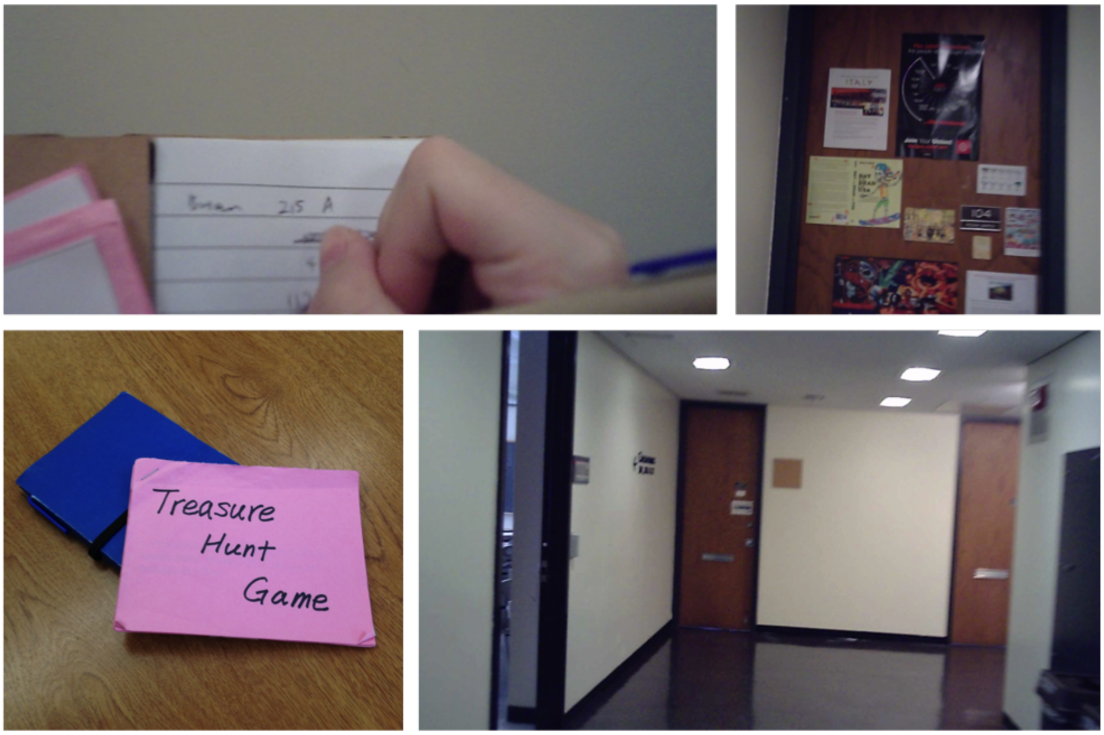


Figure 4.6: Treasure Hunt game: Participants explore hallways of the School of Communication & Information building to find out clues and information to solve problems given to them.

4.8 Web Search

4.8.1 Purpose and Data

The main focus of the Web Search session was to observe participants' information seeking behavior during the online search: what they see on the screen and where (what pages) they visit on Web. To observe the behavior, the logging software installed on the lab PC recorded participants' search histories with timestamp, and the eye-tracker recorded their eye movement during the session.

4.8.2 Problem-solving task

The problem-solving task here refers to a task in which a person searches to find the exact answer to the given question/problem. For problem-solving type questions, the participants were presented with A-Google-A-Day (http://agoogleaday.com) questions. I provided them with 10 questions and asked them to solve as many as they could in 20 minutes. The questions are as follows:

- Question 1: Who choreographed the musical based on the first novel by the 2003 winner of the Medal for Distinguished Contribution to American Letters?
- Question 2: In the poem that concludes the second section with "Not that final meeting In the twilight kingdom," to what historical figure does the second epigraph allude?
- Question 3: Steven Spielberg gained notoriety for a series released in 1957. Who was the star of this series?
- Question 4: Who, along with his wife, gave Harper Lee the gift of a year's wages so that she could quit her job "to write whatever you please"?
- Question 5: This planet's slow retrograde rotation results in the solar system's longest day. How many Earth days equal one day here?
- Question 6: In the century following Columbus's trip to the New World, people began playing an organized sport on a frozen surface. Where did that sport begin?
- Question 7: I am Hawaiian and have a conservation status of CR. My cousin, also a CR, is Mediterranean. Our crab-eating cousin, however, has an LC status. Where does he live?
- Question 8: It takes approximately 50,000 - 70,000 flowers to make one dry pound of the world's most expensive spice by weight. What part of this particular flower is used to make the spice?
- Question 9: After coining the term radioactive, a scientist discovered two radioactive elements, one of which is easily found in cigarette smoke. What is the element?

- Question 10: I am the 19th-century founder of the country that now has the world's largest Ferris wheel. In what year was I born?

4.8.3 Exploratory search task

Following the problem-solving task, I asked participants to conduct an exploratory search task for twenty minutes. The topic of the search is as follows:

One of your close friends talks to you about his current health and wellness issues, and since he is not tech-savvy you are trying to assist him in finding useful information so that he can read the report you write within this task to get more information about his health and wellness requirements.

He is a 30-year-old male with type 2 diabetes who wants to lose weight. He has internet access and an iPhone but is not tech-savvy. However, he is usually very busy with work and family and can only spare three hours each week to exercise. He has asked for your help.

Assemble a diet and exercise program for him, including its benefits and risks. This report should also cover aspects of possible applications he could easily use to monitor and control his wellness.

When conducting this task, you should collect as much information as you can by searching online. Nevertheless, the article should be written with proper context to cater to your friend's needs and should elaborate on the various options he has to be healthy. Your article should be around 700-800 words.

Chapter 5

Analysis

This chapter reviews important concepts and the ways of data analysis used in this dissertation.

5.1 Important Concepts

5.1.1 Information Patch

When Bates (1989) depicts an information seeker moving through an information space in general, Bates assumes *information chunks,* between which the seeker wanders and moves looking for information. Information foraging theory (Pirolli and Card, 1995; Pirolli, 2007) uses the term *"information patch"* to depict the documents, or Web pages, that the user visits to consume the information from that patch. More specifically, the task environment of an information forager has a *patchy* structure (Card et al., 2001): information that a person looks for to meet her needs may reside in piles of paper documents, file cabinets, bookshelves, libraries, or in various online documents.

In this study's Web searching task, the information patch refers to (1) search engine results page (SERP) and (2) each Web page that the user visits. In the escape room and treasure hunt session, an information patch can be a book, a poster, a flyer, or a door that has name tags, stickers, or papers on and near it. Definition of information patches are presented in Table 5.1.

Table 5.1: Definition of information patch in Web Search, Escape room, and Treasure Hunt session.

Session	**Information Patch**
Web Search	(1) search engine results page (SERP) and (2) Web page that user visits
Escape Room	books and posters presented in the room
Treasure Hunt	information document and corresponding area that the participant pauses to see information

Web Search

Information patch in Web search refers to (1) search engine results page (SERP) and (2) each Web page that the user visits, either chosen from the SERP or the pages through user's directly typing it in.

Treasure Hunt

To identify and annotate corresponding behavior regarding information patches in the treasure hunt session, I first listed and described all the doors, bulletin boards, directories, posters, flyers, and signs as shown in Table 5.2.

Table 5.2: Types of information patch in the building where treasure hunt played

Types	**Description**
Door	door of the room and the name tag next to it
Bulletin board	bulletin boards located far enough from other information patches so the person should move to see the other one.
Directory	Directory information of the building
Poster/flyer	posters and flyers on walls in the hallways, far enough from the doors, bulletin boards, etc.
Sign	Signs with recognizable size, such as fire extinguisher, advertisements, logos, etc.

I clustered the defined information patches in the previous procedure into one patch when (1) they are closer than 5 inches and (2) people can see them together without serious problem from 3-feet distance. Figure 5.1 shows the information patches in the building.

Escape Room

Information patch in *Escape Room* refers to books, movie posters, and research posters, which were presented to participants.

5.2 Video Data Coding

Searching patterns were identified by analysis of video data that were recorded during all the tasks. This section reviews how the behavioral data was annotated.

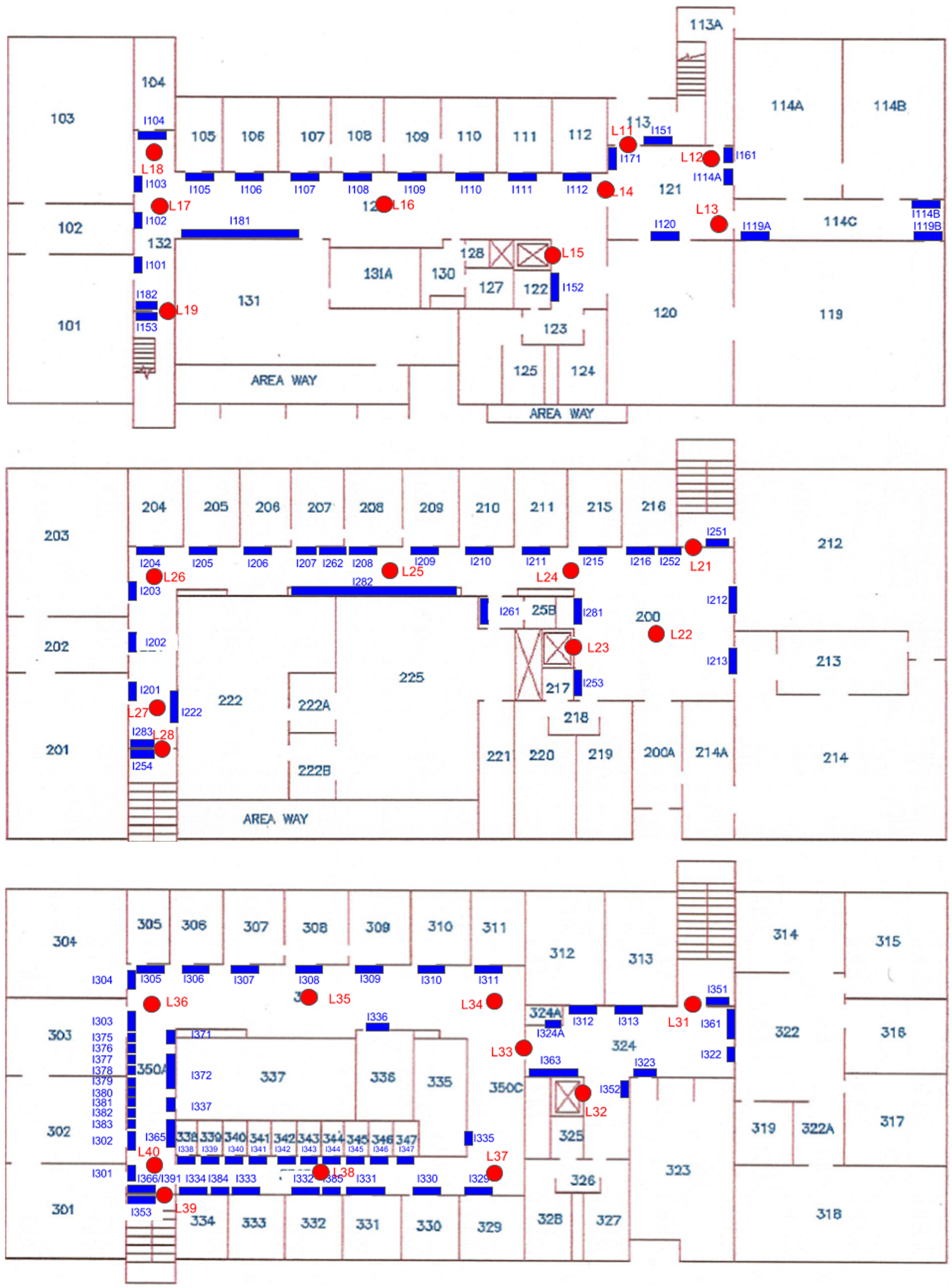


Figure 5.1: Information patches in treasure hunt: Information patches on the first, second and third floor. Blue rectangles refer to the defined information patches, while circles are location marks for coding their trajectories.

5.2.1 Web Search

To understand and identify participants' Web searching behavior, the web search log and recorded screen video during the search tasks were transcribed and coded. Web search logs were captured through the browser plug-in. Video data includes normal screen capture as well as eye gaze data. While normal screen capture represents users' interaction such as mouse cursor movement and keystrokes on the web browser and other computer systems, the eye gaze data is annotated with circles, increasing along with dwell time for a particular area of interest, and timestamps. The application for the eye tracker provides a video file that combines both of screen capture and eye gaze data per one user's session (see Figure 5.2), and the capture Web searching behavior were played and replayed several times to examine their behavioral pattern regarding the online exploration.

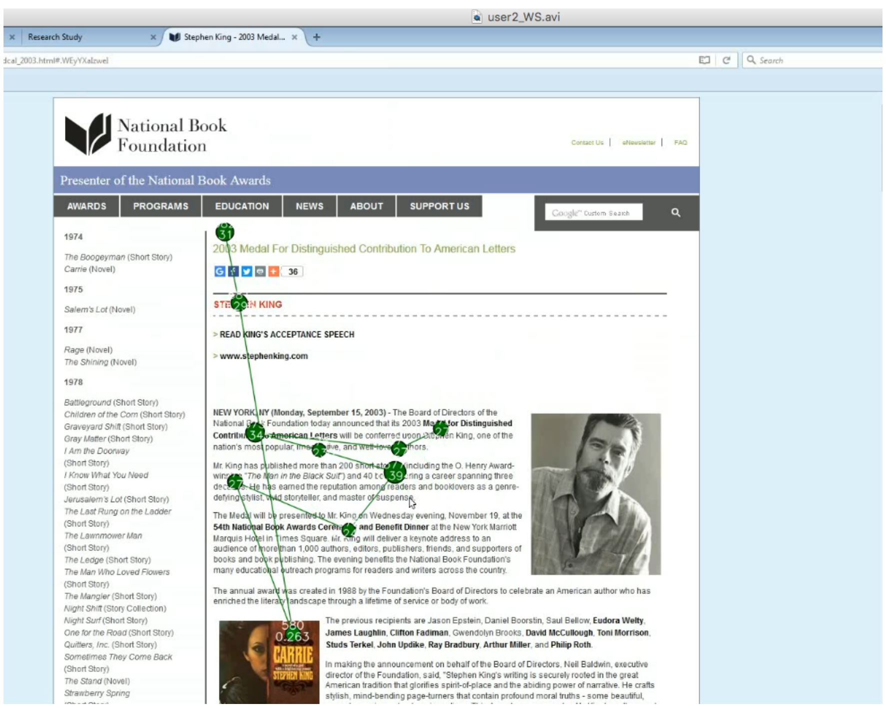


Figure 5.2: Video captured during Web search tasks. Green circles represent the user's area of interest, or eye gaze, along with timestamps and the order.

I examined participants' Web searching behavior based on three key aspects:

- *Exhaustive vs. economic examination*: based on how they scan the Web pages, both of results pages and content pages.

- *Web navigation styles*: based on how users navigate during Web searching;
- *Information processing approaches*: based on how they view and process search results or retrieved result pages;

Exhaustive vs. Economic Examination

Aula et al. (2005) defined two kinds of search strategy - "economic" and "exhaustive" - based on whether a user scanned less than or more than half of the visible results before making a decision to click.

Inspired by this measure, I categorized the participants' behavior into *exhaustive examination* and *economic examination*. *Economic examination* refers to the case in which only the top *one* or *two* results were inspected before the first click. Otherwise, I defined it as an *exhaustive examination*.

Web Navigation Styles

Kinley et al. (2014) defined *Web navigation styles* as two main approaches to locating information on the Web. While *navigation* refers to a browsing behavior in which the user assesses the online information and content by following a series of links or pages, I coded the video data qualitatively considering issued queries, mouse click, scrolling, etc.

Inspired by their approach, participants' web navigational styles were defined into *unstructured* and *structured*. *Unstructured* users show the navigating behavior in which she performed an unstructured navigation during Web searching. Participants, who have unstructured navigation, tend to formulate their query, scan the first few search result snippets, click the "next" button of the search engine, then navigate back and reformulate their query.

Alternatively, *Structured* users represent behaviors where systematic processes were taking place during the Web searching tasks. They tend to formulate their query carefully, open fewer pages, and read the pages in detail. They may open another search result page to formulate a new query, keeping the previous results.

Information Processing Approaches

Kinley et al. (2014) referred to *information processing approaches* as strategies chosen by users to read, select, and process information during Web searching. I adopted their three categorizations of *scanning*, *reading*, and *mixed*.

Scanning refers to browsing behavior in which the user scans a result page or a content for general information quickly, and makes quick switches between topics and tabs. This type of person is likely to open relatively more result pages because she is not sure if the confronted information is relevant and/or appropriate.

In the opposite way, *reading* refers to the behavior of comprehensively searching, reading a page in detail, spending more time on relatively smaller number of pages. *Mixed* approach adopts both scanning and reading during the Web searching tasks.

Tasks for Coding

From the task 1 (problem-solving task), I examined participants' data up to the third question since most participants solved up to the that question. Regarding the exploratory search task, since there is no success and failure in this task, I observed their behavior on the whole task and defined their behavioral patterns.

5.2.2 Treasure Hunt

Kotseruba et al. (2016) shows an example of behavioral data coding: observing pedestrians crossing a road, the authors defined behaviors such as (1) state events: crossing, stopping, moving fast, moving slow, speeding up, slowing down, clearing a path, and looking; and (2) point events: look, signal, and handwave. While state event may have an arbitrary duration, point events last a short fixed amount of time (0.1 sec) and signify a quick glance or gestures made by pedestrians.

I came up with video data coding scheme for the following purposes: (1) to define information patches in particular information exploration environments; (2) to come up with code that annotates behavior - (a) moving (b) stopping at information patch, and (c) task performance; and (3) to simulate a person's exploratory trajectory in the corresponding information space.

Table 5.3: Definition of entering and leaving information patches

Code	**Description**
Entering	A participant enters into an information patch when starting to engage that patch. It includes (1) stop walking to approach, (2) looking at the same spot while walking slowly, (3) looking back after passing by the patch, (4) getting the answer from the information patch (e.g., writing down the room number), and (5) standing at least 3 feet from the information patch.
Leaving	When a participant leaves the information patch that she has been looking at.

Visiting patch is an event that has a starting and an ending moment. I annotated entering an information patch and leaving as defined in Table 5.3 and a 'visiting patch' is valid only when the person stays in the patch more than two seconds.

Regarding task completion, I annotated five task completions as defined in Table 5.4. I observed participants' behavior for the whole session.

Table 5.4: Definition of task completions

Code	**Description**
T1_done	Participant answers the first question, or task, and is ready for the next task. (locating the flyer with the first answer: the musician of the concert is Brian McKnight.)
T2_done	Participant answers the second question, or task, and is ready for the next task. (locating the faculty's room number, whose first name is also Brian - 215)
T3_done	Participant answers the third question, or task, and is ready for the next task. (locating the room number with a zebra picture next to it - 112)
T4_done	Participant answers the fourth question, or task, and is ready for the next task. (getting the answer of the previous question, which is 301, and going there to see another clue)
T5_done	Participant answers the fifth question, or task, and is ready for the next task. (TH: locating the magazine that covers Obama's Rutgers visit and getting the number of attendees)

I used software named Boris (Friard and Gamba, 2016) to annotate behavioral video data. Figure 5.3 presents the interface of the program with the data from *user2*. Two trained coders examined and annotated participants' visits to particular information patches to get time of visits and the dwell time, or duration. First, a research assistant and I documented a participant's behavioral data individually and met to discuss to make the coding scheme coherent.

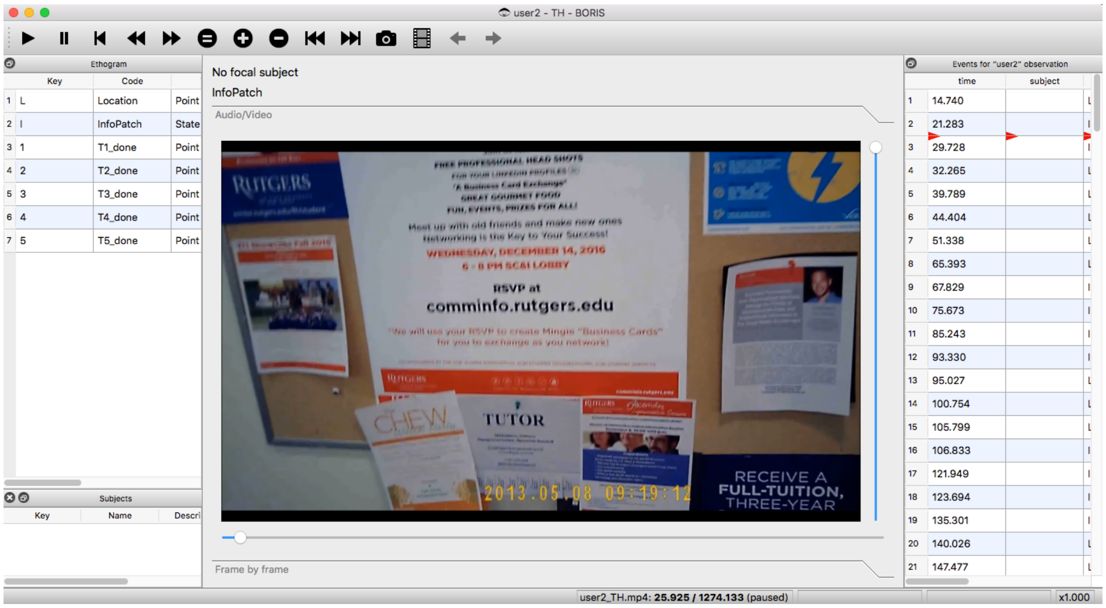


Figure 5.3: Screenshot of Boris with video data from user 2. Ignore the timestamp in the video screen since the time was not properly set in the recorder.

After three rounds of data coding and discussion for three participants, the intercoder reliability of coding was evaluated by Generalized Sequential Querier (GSEQ)(Bakeman and Quera, 2008).

The event-based kappa for the agreement of 'visit' information patches was K =.64 (78% agreement) and time-unit kappa was K =.87-.87 (94%-94% agreement), showing both kappa values were in either good (0.60–0.75) or excellent (over 0.75) spectrums according to the benchmarks suggested in Bakeman (2000).

After coding for the first three participants, the two coders continued with the rest of the data, each analyzing half of the participants and aggregating the behavioral data.

Visiting Behavior

Through annotating information patches in the treasure hunt and the corresponding activities of participants, I categorized the types of visiting behavior on floors in the building where the user study was conducted. The concept of exploitation and exploration to explain their visiting behavior on the floors was adopted from Hills et al. (2015). As shown in Figure 5.4, spatial foraging can be categorized into (1) exploration (exploring more places to find resources) or (2) exploitation (exploiting fewer places sufficiently to harvest resources). In this regard, I identified the visiting behavior into two categories. *Exploitation* refers to visiting more than two information patches[1] on a floor, while *Exploration* means visiting zero or one patch.

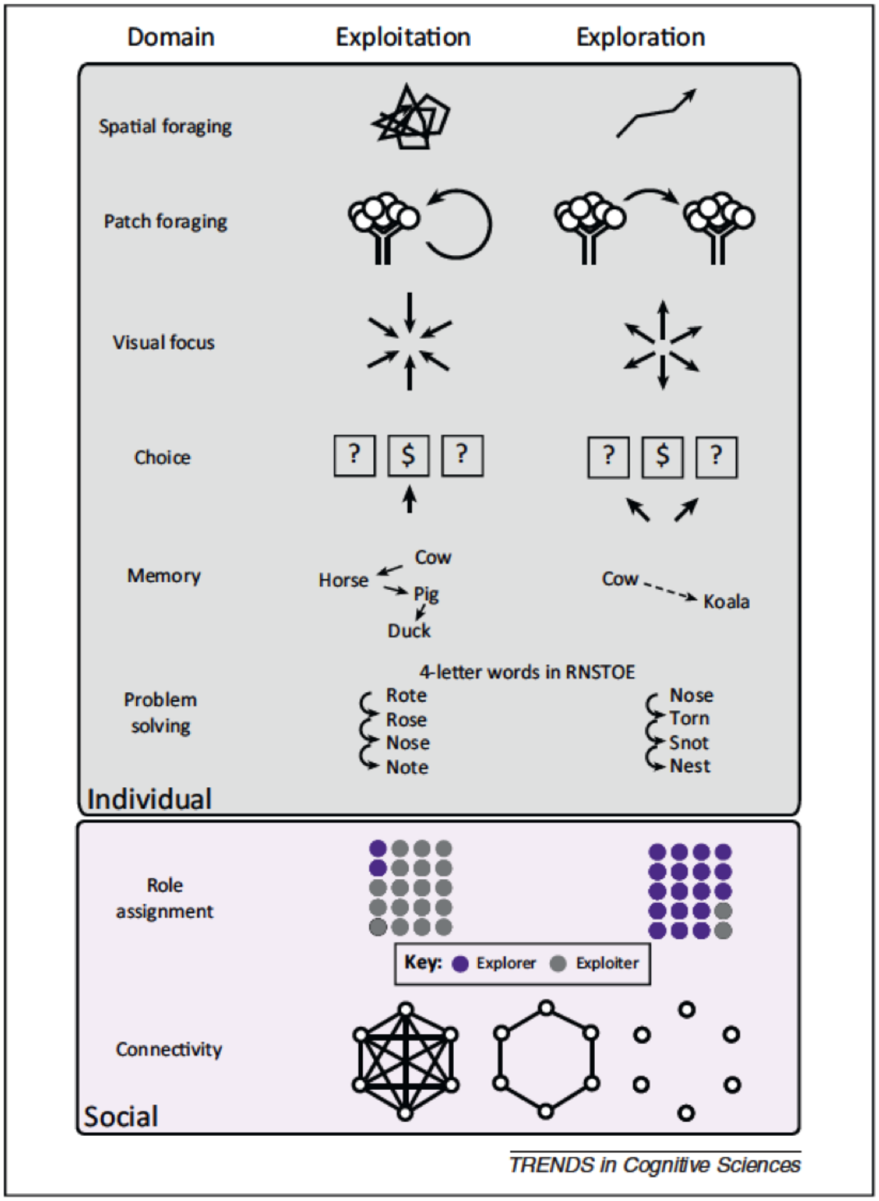
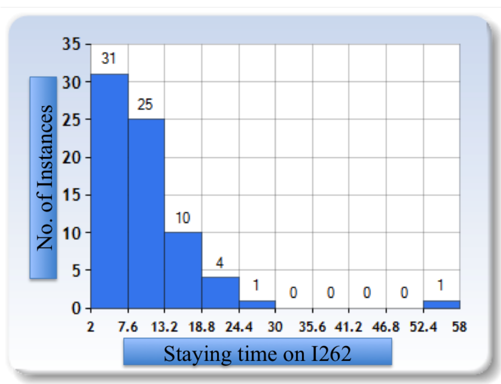


Figure 5.4: Examples of cognitive approaches to the exploration-exploitation trade off. Copied from Hills et al. (2015).

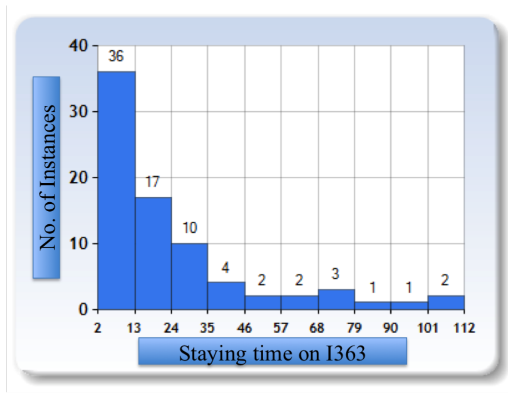
[1]the criteria of two is derived from the data analysis of all participants whose behavior was appropriately recorded by the camera.

Seeing Behavior

In addition to the visiting behavior, *exploration* and *exploitation*, I examined the time the participants spent on information patches to view and assess, as an aspect of *seeing behavior*. Based on the staying time, their seeing behavior was categorized into three types: *long stay*, *medium stay*, and *short stay*. In order to differentiate their staying pattern, I referred several information patches that most participants visited and viewed, such as *I262* on the second floor or *I363* on the third floor. Figure 5.5 shows the distribution of staying time on I262 and I363. First, I measured staying time of each information patch visiting of participants to categorize them into *long stay*, *medium stay*, and *short stay*, according to the distribution. Then, I combined a participants' all staying time labels into one label of *long stay*, *medium stay*, or *short stay*. Note that not all participants visited the same patches and even for a same patch, a participant's staying time varied over time, which required the coder's interpretation.



(A) I262



(B) I363

Figure 5.5: Distribution of staying time on (A) I262 and (B) I363.

5.2.3 Escape Room

The participants' searching activities via their sight movements were captured by a video recorder within provided glasses. Two trained coders created code schemes derived from significant behaviors observed during this session (see Table 5.5). Based on these code schemes the coders manually recorded participants' time-stamped behavioral events by using the information patch map (see Figure 5.6) and Boris video coding software (Friard and Gamba, 2016). Each information patch was arranged with an unique identifier: books (B01 to B20), movie posters (M01 to M08), research posters (R01 to R05), and boxes (L01 to L05). In the code scheme, *type* means the attribute of time for the code: *state* indicates existing time duration and *point* means the moment of action.

Table 5.5: Code scheme of Escape room study

Code	**Description**	**Type**
Looking around	Looking and moving around the room	Point
Scanning books	Scanning books without movement	Point
Scanning movie posters	Scanning several movie posters without movement or with slow movement	Point
Scanning research posters	Scanning several research posters without movement or with slow movement	Point
Passing by a book	Passing by each book	Point
Book	Visiting a book with starting and ending points	State
Movie poster	Visiting a movie poster with starting and ending points	State
Research poster	Visiting a research poster with starting and ending points	State
Reading questions	Reading the task questions at first time	State
Re-visiting questions	Re-visiting the questions during solving tasks	Point
Dealing with a lock	Trying to unlock the lock	State
Calculation	Calculation to solve the task 2	State

Book Task

The first task in *Escape Room* is to find out the chapter page about a particular topic. In order to locate the answer, participants would pick one or more books to see if there is relevant information. Twenty books were left on the tables in a row. If the participant goes along all books first before beginning to read a book, then this person is perceived as exhaustive evaluator.

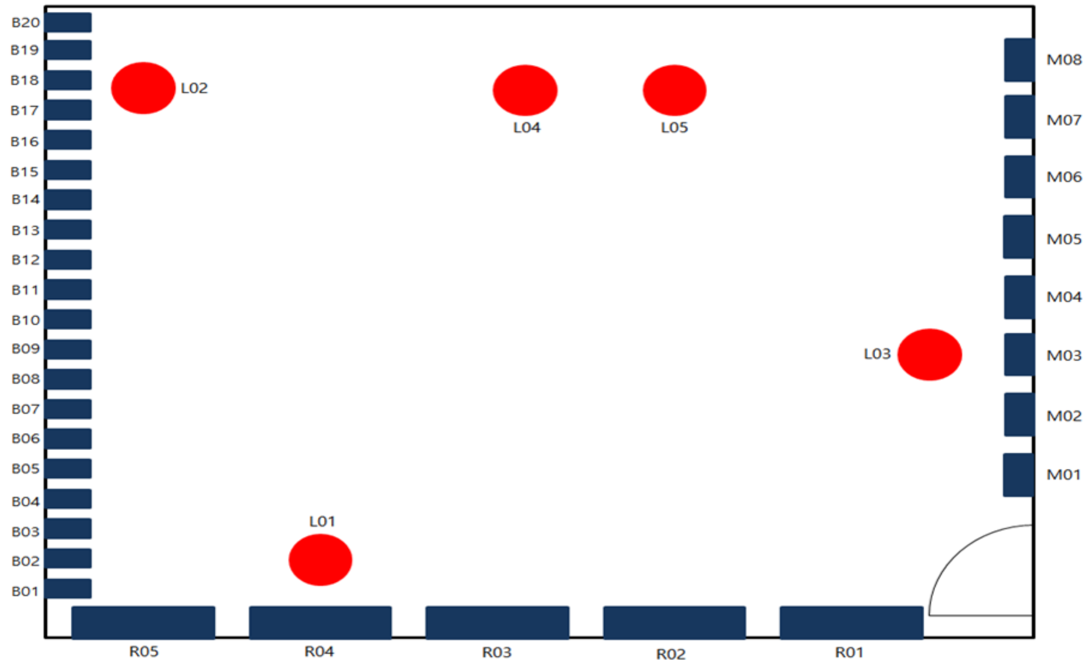


Figure 5.6: Escape room map with information patches: Rectangles indicate the defined information patches, while circles are the question boxes.

Movie Task

The second task is to locate a movie poster about a film produced by particular film production companies. In this case, the letters on the posters are small and blurred, so it is usually difficult to read them from distance. The usual response of participants to begin this task was to take a step to the wall, visit one information patch (movie poster), and start reading the words on it - economic evaluation. However, the video data indicated that some participants, even for a very short time, did scanning movie posters before they actually started to reading a poster. Through the scanning behavior, their pattern was annotated as exhaustive evaluation.

5.3 Summary

Table 5.6 summarizes the aspects of information searching behavior of interest in the study, how to measure the aspects, corresponding data, and the analysis method.

Table 5.6: Summary of aspects and measurements

Session	**Aspects**	**Measure**	**Data**	**Analysis**
Web Search	Information Evaluation Type	Whether the participant looks at (1) top one or two results before the first click (*economic evaluation*), or (2) more results (*exhaustive evaluation*)	Eye-tracking data	video analysis
	Web Navigation Style	Whether the participant (1) formulates more queries, clicks more results & pages, and navigates more pages (*unstructured*), or (2) formulates fewer queries with caution, opens fewer pages, and reads pages in detail (*structured*)	logs and recorded video	video analysis
	Information Processing Approaches	Whether the participant (1) scans a result page or content quickly, makes quick switches between topics and tabs (*scanning*), or (2) reads a page in detail, spends more time on fewer pages (*reading*), or (3) *mixed*	logs and recorded video	video analysis
Escape Room	Information Evaluation Type	Whether the participant looks at (1) top one or two books/posters before the first reading (*economic evaluation*), or (2) more books/posters (*exhaustive evaluation*)	recorded video	video analysis
Treasure Hunt	Visiting Behavior	The number of information patches the participant visits on floors	recorded video	video analysis
	Seeing Behavior	The staying time on information patches the participant visits	recorded video	video analysis

Chapter 6

Results

This chapter overviews findings that address the following research questions:

- RQ1: To what extent, if any, does an individual's information seeking behavior online relate to his/her behavior in physical space?
- RQ1a: To what extent, if any, does an individual's patterns of visiting and seeing physical spaces relate to his/her visiting and seeing in online spaces?
- RQ2: What aspects, if any, and how much of an individual's physical exploration is related to his/her online information seeking behavior?

6.1 Participant Demographics

Participants were recruited via targeted email and social network channels such as the Facebook group for Rutgers University members. Thirty one (15 male and 16 female) undergraduate students participated in the study. Participants' majors vary such as Information Technology, Business, Computer Science, Psychology, etc. The participants were invited the lab to conduct *Escape Room*, *Treasure Hunt* and *Web Search* session on a weekend day during November and December of 2016. After completing the whole study sessions, each of them received $100 in cash.

6.2 Descriptive Analysis

This section presents descriptive analysis results regarding participants' characteristics and performance during the experimental sessions.

6.2.1 Escape Room

Out of thirty one participants' experimental data, twenty nine students' recorded video was valid for the analysis. While there are five tasks that the players need to accomplish in the game, Table 6.1 shows the number of tasks they were able to finish within twenty minutes. Less than half (42%) of the participants (thirteen) completed the total five tasks, and four participants could finish only the first task.

Table 6.1: Completed tasks by participants

Task completed	Number of Participants
1	4
2	7
3	2
4	3
5	13
Total	29

When it comes to the time taken to complete each task, Table 6.2 shows the corresponding data. For twenty nine participants who completed the first task, it took in average 261.6 seconds from reading the question until unlocking the first lock.

Table 6.2: Completion time per task

Task	Completed participant	Avg. time (sec)	standard deviation (sec)
1	29	261.6	140.5
2	25	339.3	87.0
3	18	235.9	140.4
4	16	100.5	64.5
5	13	51.0	27.1

6.2.2 Treasure Hunt

Due to the technical problem of the wearable video recorder[1], four participants' were lost. Thus, 27 participants' video during Treasure Hunt session was used for analysis. While 19 participants completed all five tasks, 8 of them even could not finish the first one.

[1] It either stopped recording during the experiment or even did not start recording.

Table 6.3: Completion time per task in Treasure Hunt

Task	Avg. time (sec)	standard deviation (sec)
1	366.4	276.1
2[2]	215.7	149.4
3[3]	191.1	179.9
4[4]	242.3	316.5
5[5]	158.7	71.0

6.2.3 Web Search

In task 1 of Web Search session, participants were supposed to solve ten questions. Table 6.4 presents the number of questions they were able to finish within twenty minutes. While five participants solved all ten questions, one participant could find only one answer. Note that there is no success or failure for the second task of Web search, which is an exploratory search.

Table 6.4: Completion questions in Web Search session

Completed questions	# of participants
2	1
3	1
5	9
6	5
7	3
8	2
9	5
10	5
Total	31

6.2.4 Spatial Capability and Treasure Hunt

Since participants will scan and locate clues and information in physical space during playing escape room and treasure hunt, I asked participants to take the spatial ability test (Ekstrom et al.,

[2]calculated with 18 participants' video data: user22's data is missing.

[3]calculated with 18 participants' video data: user22's data is missing.

[4]calculated with 16 participants' video data: data of user8, user22, and user35 is missing.

[5]calculated with 15 participants' video data: data of user8, user22, user35, and user46 is missing.

1976). I used two test scores of *spatial orientation* and *spatial scanning*. The spatial orientation defines our natural ability to maintain our body orientation and/or posture in relation to the surrounding environment (physical space) at rest and during motion. The spatial scanning is to visualize a path out of a maze or a field with many obstacles. The actual tests are presented in Appendix.

Table 6.5: Independent and dependent variables

	Variable	**Definition**	**Measurement**
Independent Variables	Total test scores (TS)	Total spatial ability scores	Spatial orientation + spatial scanning
	Spatial orientation (SO)	Spatial orientation test score	Test score of spatial orientation
	Spatial scanning (SC)	Spatial scanning test score	Test score of spatial scanning
Dependent Variables	Task completion (TC)	Task success or fail	Whether completed task 5 or not
	Completion time (CT)	Time to complete tasks	Time up to task 5 completion

I tested the relationship of independent variables and dependent variables presented in Table 6.5. The results of t-test between the variables indicate that spatial capability measured by spatial orientation and scanning is not related to participants' performance in treasure hunt. When comparing TS, SO, and SC based on whether they success or fail (TC), resulting statistics are as follows: (1) TS and TC: $t(30) = 1$, $p = 0.2$; (2) SO and TC: $t(30) = 1$, $p = 0.2$; and (3) SC and TC: $t(30) = 1$, $p = 0.2$.

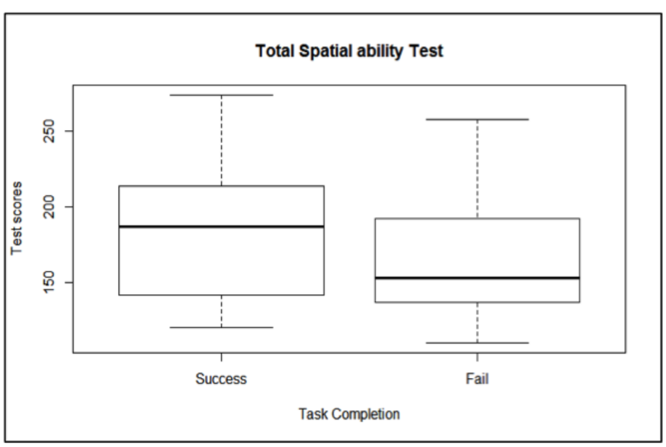


Figure 6.1: Total spatial test score (TS) and task completion (TC)

The Figure 6.2 shows the correlation between total test score (TS) and completion time (CT), and there is no correlation between two variables: correlation coefficient = 0.2.

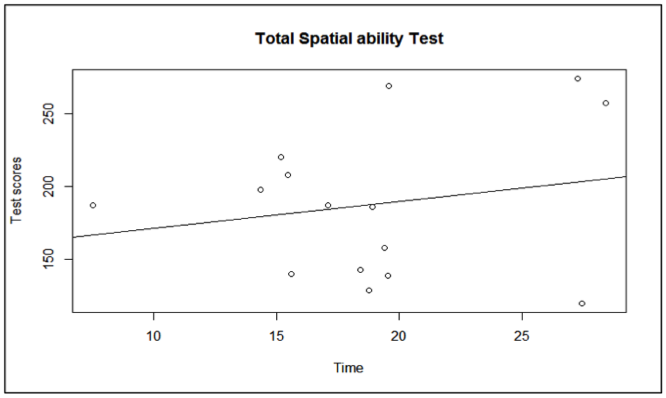


Figure 6.2: Total spatial test score (TS) and completion time (TC)

6.2.5 Gender and Treasure Hunt

I tested the gender difference regarding whether they success to complete the treasure hunt session. Out of 14 female participants, 9 participants were able to complete all tasks in treasure hunt, while 4 participants failed. On the other hand, out of 13 male participants, ten finished the treasure hunt session and three failed to complete the final task.

A chi-square test of independence was performed to examine the relation between gender and the performance in treasure hunt. The relationship between these variables was not significant, $\chi^2(1, N = 27) = 0.5163, p > .05, (p - value = 0.472423)$, indicating gender does not affect success/fail in treasure hunt.

Table 6.6: Gender and success/fail of treasure hunt session

Gender & TH		Treasure hunt		Total
		Success	Fail	
Gender	Female	9	5	14
	Male	10	3	13
Total		19	8	27

6.3 RQ1. Relationship Between Online Exploration and Physical Exploration

This section answers RQ1, which asks: To what extent, if any, does an individual's information seeking behavior online relate to his/her behavior in physical space? Findings from data analysis suggest that there is individual preference, or behavioral tendency, in information seeking regardless the information space: online vs. physical environment. More specifically, this section compares participants' searching behavior presented in the online space (*Web search tasks*) and the physical space (*Escape Room*).

6.3.1 Evaluation in Web Search

Observing and annotating users' behavior through recorded video and eye gaze data, 31 participants were categorized into *exhaustive* evaluation and *economic* evaluation type. Participants might have different evaluation strategies for different search tasks, identifying the patterns between task 1 and task 2 as shown in Table 6.7.

Table 6.7: Number of participant for evaluation type during task 1 and task 2 in Web Search

Behavioral Patterns		Web Search: Task 2		Total
		Exhaustive	Economic	
Web Search: Task 1	Exhaustive	13	0	13
	Economic	6	12	18
Total		19	12	31

For task 1 of Web Search, problem-solving task, 13 participants adopted exhaustive evaluation, while 18 used the economic evaluation. For task 2 of Web Search, exploratory search, on the other hand, 19 users used exhaustive evaluation approach while 12 used economic evaluation (Figure 6.3).

A chi-square test of independence was performed to examine the relation between these behavioral patterns. The relationship between these groups was significant, $\chi^2(1, N = 31) = 11.47, p < .05, (p - value = 0.0007073)$, indicating their evaluation behavior in task 1 and task 2 are independent.

Data indicates that economic evaluation was preferred in task 1 and exhaustive evaluation was preferred in task 2, suggesting the effect of task type on the evaluation strategy, there a group of participants who kept their behavioral tendency even in a task in which the opposite behavior is preferred. For instance, 12 participants who adopted economic evaluation to quickly solve the questions in task 1 adhered to the economic evaluation in task 2, opening the top first or second result page in the retrieved list without reading abstracts below them. This finding indicates the existence of highly and strongly preferred and habitual behavioral strategy in evaluation regarding visiting information patch behavior during online search.

A group of people, who used economic evaluation for task 1 but changed their behavior in task 2, using exhaustive evaluation, can be perceived as adjusting their behavior corresponding to the given task. They think the exhaustive evaluation is more helpful to accomplish the exploratory search. This finding enhances the effect of task type on users' behavior.

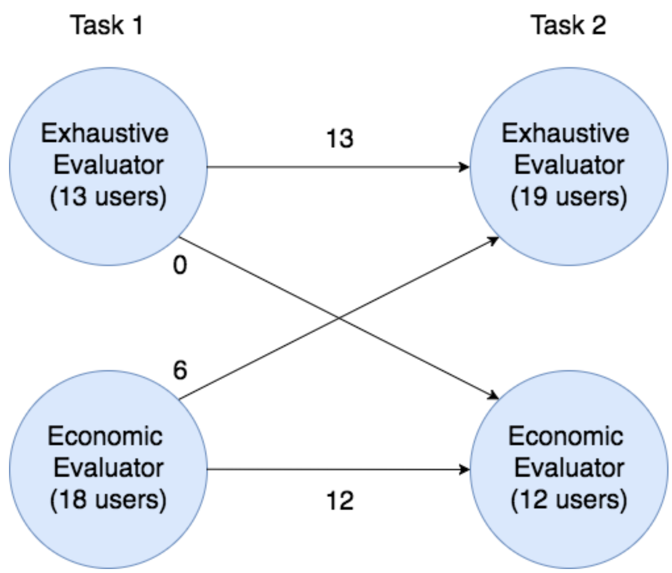
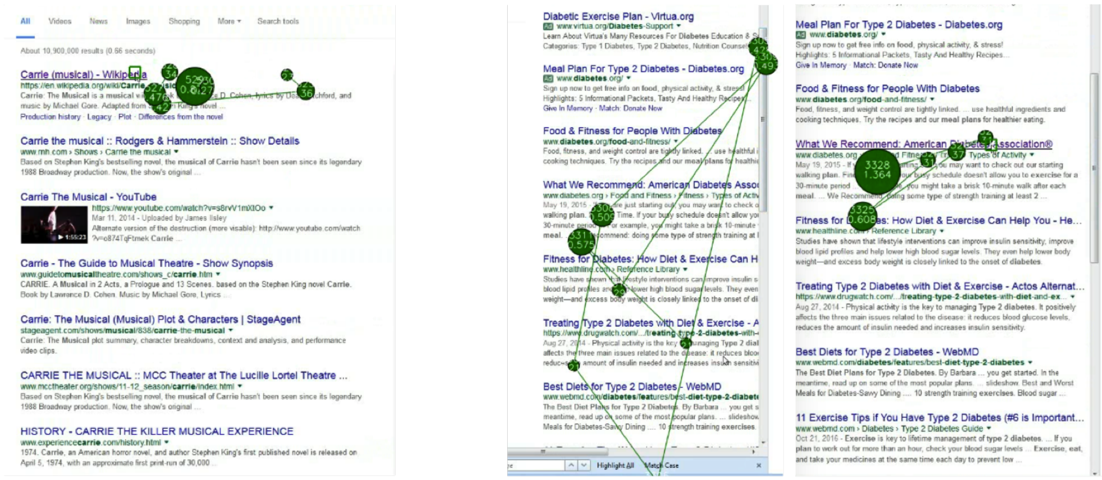


Figure 6.3: Behavior change between task 1 and 2 of WS

Annotated behavioral pattern of examining the online information shows individuals have general preference to either exhaustive or economic investigation over two tasks.

Tasks that were analyzed here have different characteristics. For instance, the problem-solving task in Web search session was a fact-finding search task, which is assumed to have the least complexity, requiring participants to use basic searching skills. For exploratory search task, however, a user needs to spend enough time to understand the topic and requirements, construct necessary knowledge through Web exploring, and build a narrative that convinces the potential readers.



Task 1 Task 2 (a) Task 2 (b)

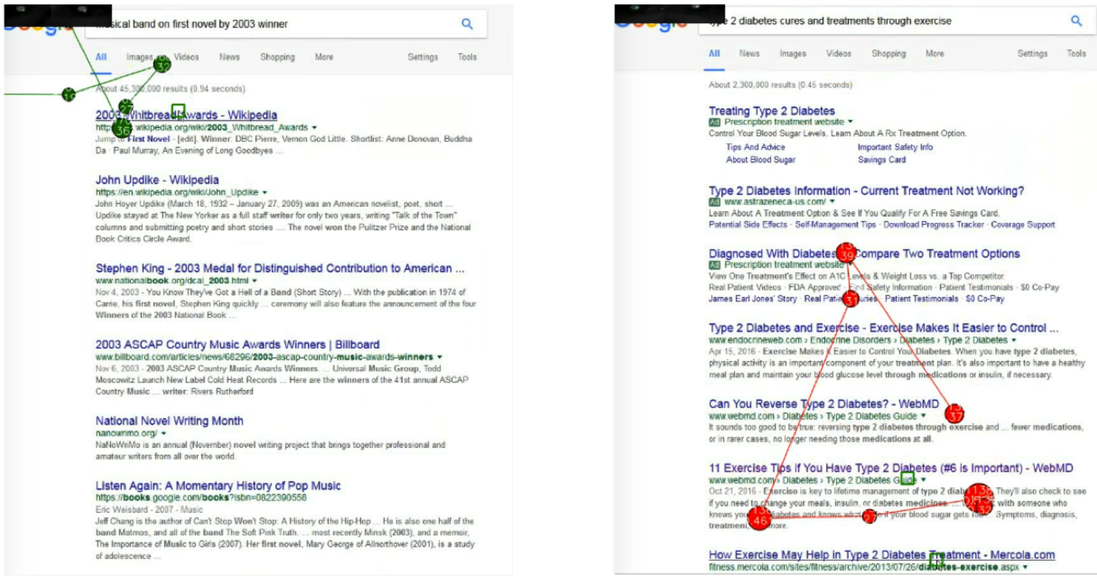
Figure 6.4: Examination type of user20 in Web Search. Left picture shows the economic examination during Task 1, while the right two pictures show the exhaustive investigation of a query session within Task 2.

The observed behavior change indicates that participants tend to prefer a particular strategy to a certain task type. Compared to a fact-finding type task, exploration-first strategy in an exploratory search task helps user make sense of a given topic and navigate to a looking-better path, encountering and collecting more information and knowledge.

For instance, six participants shifted their approach from economic examination in fact-finding task to exhaustive examination in exploratory search task: *user20*, *user21*, *user22*, *user27*, *user28*, and *user35*. Figure 6.4 shows *user20*'s examination strategies in Task 1 and Task 2. In the left picture of Task 1, the participant clicked the top one result without exploration on that SERP. On the other hand, the right two pictures are from one query session in Task 2: the person scrolled down the SERP up to the middle part, reading the results list, to open a page in the middle.

Another example is from user21's Web Search behavior data. Figure 6.5 shows user21's examination strategies. While the person selected the top result in task 1 without exploring further below in the results list, when being asked to understand and accumulate relevant knowledge, the participant spent more time reading and viewing the presented information.

This findings are along the same line with previous studies. Lorigo et al. (2006) found the effects of question types - informational (e.g. *Who discovered the first modern antibiotic?*



Task 1 Task 2

Figure 6.5: Examination type of user21 in Web Search. Left picture shows the economic examination during Task 1, while the right picture shows the exhaustive investigation of a query session within Task 2.

and navigational search questions (e.g. *Find the page displaying the route map for Greyhound buses*) - on search and evaluation behavior. They found that the general time spent to solve the questions and pupil dilation were influenced by whether the search task is informational or navigational.

Based on the discussion above, participants' evaluation behavior can be explained as follows:

1. *Online_Exhaustive_Evaluator*: 13 participants who kept exhaustive evalution both in task 1 and task 2
2. *Online_Economic_Evaluator*: 12 participants who kept economic evaluation both in task 1 and task 2
3. *Online_Evaluation_Adapter*: 6 participants who adapted, or changed, their evaluation behavior based on the task type

However, while Lorigo et al. (2006) claimed that the ways for evaluating the results page are influenced by gender and not by task type, which is not the case in this work.

6.3.2 Evaluation in Escape Room

Observing and annotating users' behavior through recorded video, 29 participants were categorized into *exhaustive* evaluation and *economic* evaluation type in Escape Room. Participants might have different evaluation strategies for different search tasks, identifying the patterns between task 1 and task 2 as shown in Table 6.8.

Table 6.8: Evaluation type during Book task and Movie task in Escape Room

Behavioral Patterns		Escape Room: Movie Task		Total
		Exhaustive	Economic	
Escape Room: Book Task	Exhaustive	6	9	15
	Economic	3	11	14
Total		9	20	29

Conducting the Book task of Escape Room, 15 participants adopted exhaustive evalution, while 14 used the economic evaluation. For Movie task of Escape Room, on the other hands, 9 users used exhaustive evaluation approach while 20 used economic evaluation.

Based on the discussion above, participants' evaluation behavior can be explained as follows (see Figure 6.6 for visualization):

1. *ER_Exhaustive_Evaluator*: 6 participants who kept exhaustive evalution both in Book task and Movie task
2. *ER_Economic_Evaluator*: 11 participants who kept economic evaluation both in Book task and Movie task
3. *ER_Evaluation_Adapter*: 9 participants who adapted, or changed, their evaluation behavior based on the task type or environment
4. *ER_Evaluation_Maverick*: 3 participants who used economic evaluation in Book task and exhaustive evaluation in Movie task.

For some reason, *ER_Evaluation_Maverick* showed interesting behavioral change: exhaustive evaluation intention before reading the information. This will be discussed in discussion.

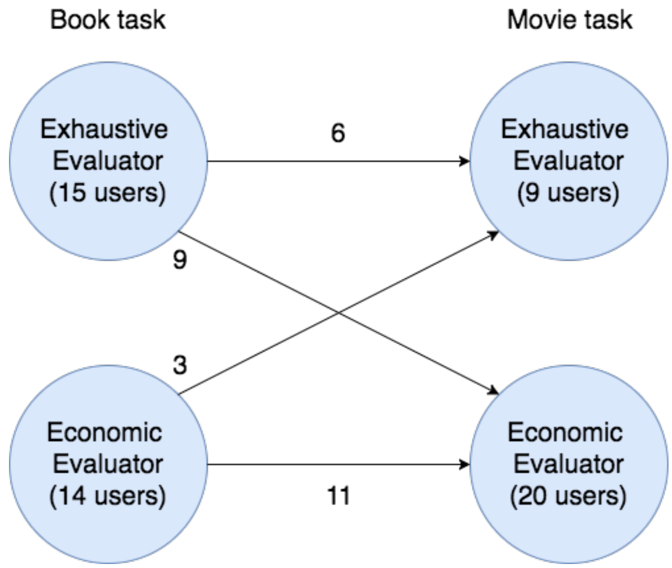


Figure 6.6: Behavior change between book task and movie task of ER

6.3.3 Comparison between Evaluation Web Search and Escape Room

Tables 6.9-6.12 show the categorized behavioral types in two information space. Note the number presented in tables below do not necessarily show the generality as well as causality between behavioral patterns and tasks in the search tasks. Rather, it should be viewed as a way showing tendency from a broad view.

Table 6.9 represents the identified behavioral patterns revealed during *Task1*, problem-solving type task, of Web search session and *Book* task in Escape Room session. In the problem-solving task in Web Search 11 participants showed exhaustive examination and 18 showed economic examination. In the book task in Escape Room 11 participants adopted exhaustive examination and 18 used economic examination.

Table 6.9: Behavioral patterns in online searching (Task1: problem-solving) and physical searching (Book task in Escape Room)

Behavioral Patterns		Escape Room: Book Task		Total
		Exhaustive	Economic	
Web Search: Task 1	Exhaustive	6	6	12
	Economic	9	8	17
Total		15	14	29

Data indicates that a person does not always show the similar behavior patterns in every task. For instance, while four participants showed similar behavior, exhaustive examination, both in task 1 of Web Search and Book task in Escape room, seven participants who utilized exhaustive investigation in online search shifted their approach to economic selection when viewing books in physical space (see Figure 6.7).

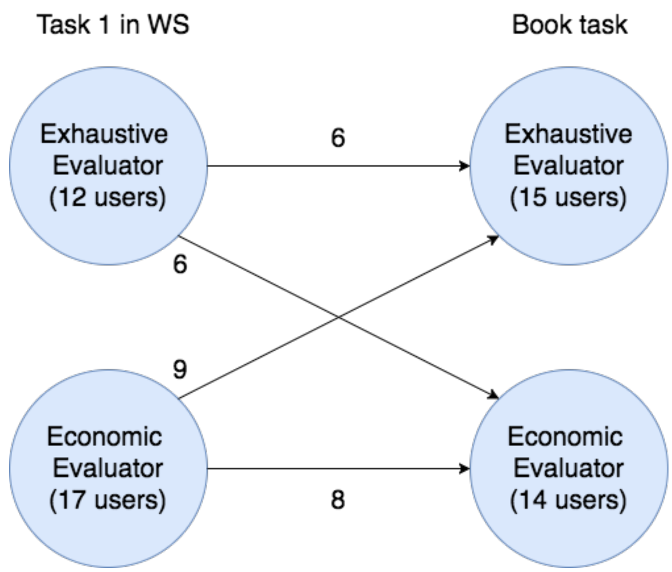


Figure 6.7: Behavior change between task 1 of WS and book task of ER

Table 6.10 represents the identified behavioral patterns revealed during *Task1*, problem-solving type task, of Web search session and *Movie* task in Escape Room session. For the movie task, participants seemed to use more economic examination than in the book task: nine people investigated the relevant information using exhaustive approach, while twenty started to look into each information first before exploration.

Table 6.10: Behavioral patterns in online searching (Task1: problem-solving) and physical searching (Movie task in Escape Room)

Behavioral Patterns		Escape Room: Movie Task		Total
		Exhaustive	Economic	
Web Search: Task 1	Exhaustive	5	7	12
	Economic	4	13	17
Total		9	20	29

When comparing with Book task, data shown in Figure 6.8 indicates the participants' tendency, or preference, to a particular behavioral pattern - exhaustive examination - is enhanced in the Movie task. This phenomenon will be covered in the discussion section below.

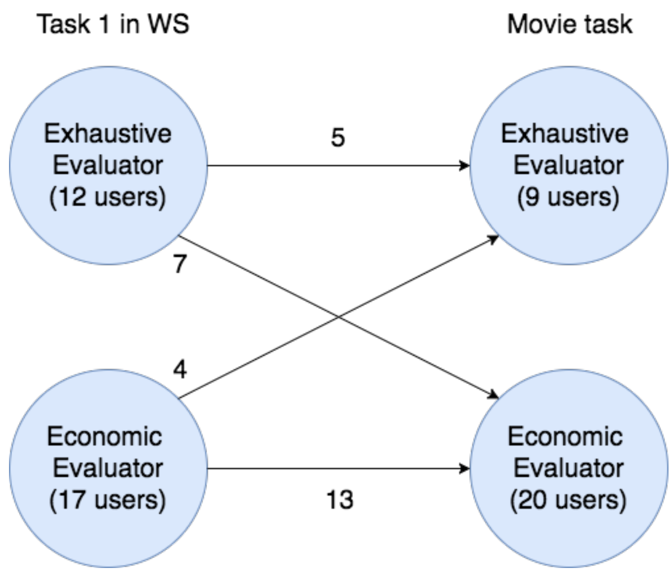


Figure 6.8: Behavior change between task 1 of WS and movie task of ER

Table 6.11 represents the identified behavioral patterns revealed during *Task2*, exploratory search task, of Web search session and *Book* task in Escape Room session. Note that the distribution of two behavior patterns in the exploratory task is different from the one revealed in the problem-solving task (Table 6.9 and 6.10). Regarding the behavioral pattern in online searching, more participants utilized the exhaustive examination (18 students) than the economic approach (11 students).

Table 6.11: Behavioral patterns in online searching (Task2: exploratory search) and physical searching (Book task in Escape Room)

Behavioral Patterns		Escape Room: Book Task		Total
		Exhaustive	Economic	
Web Search: Task 2	Exhaustive	9	9	18
	Economic	6	5	11
Total		11	18	29

Table 6.12 represents the identified behavioral patterns revealed during *Task2*, problem-solving type task, of Web search session and *Movie* task in Escape Room session.

6.3.4 Behavioral Patterns over Online and Physical Space

Addressing RQ1, the research identified participants' behavior during Web search tasks and Escape Room game, as a physical search in a room, this work identified behavioral patterns

Table 6.12: Behavioral patterns in online searching (Task2: exploratory search) and physical searching (Movie task in Escape Room)

Behavioral Patterns		Escape Room: Movie Task		Total
		Exhaustive	Economic	
Web Search: Task 2	Exhaustive	8	10	18
	Economic	1	10	11
Total		9	20	29

how individuals interact with different tasks in different environments. Table 6.13 shows the behavioral patterns in Web Search and Escape Room.

Table 6.13: The behavioral patterns in online (Web Search) and physical search (Escape Room)

Behavioral Patterns		Escape Room: Evaluation Style				Total
		Exhaustive	Economic	Adapter	Maverick	
Web: Search Patterns	Exhaustive	4	5	2	1	12
	Economic	0	4	6	1	11
	Adapter	2	2	1	1	6
Total		6	11	9	3	29

Comparing the behavioral patterns from two tasks in online space and two tasks in physical space, participants out of 29 valid samples were identified into groups as follows. Table 6.14 represents the behavioral groups and the number of participants in each of them.

Group A refers to people who show behavioral tendency to exhaustive approach both in Web Search and Escape Room, while *group E* means, on the other hand, participants who have preference to economic examination both in Web Search and Escape Room. For instance, group A of *user3*, *user7*, *user23*, and *user38* exhaustively evaluated results page before opening a Web page for further reading, they did the same way when being asked to choose and pick relevant books and movie posters. Figure 6.9 presents *user7*'s examination path during the Book task in Escape Room. The participant went through the all placed books in the area first before grabbing the book #17 on the way back. Comparing online searching behavior, this behavior can be viewed as a user goes all through the results page down to very bottom of the page, scrolling down the screen, before clicking one of the results.

There are seven participants in group B, who showed both economic evaluation in online search and physical search: *user9*, *user25*, *user34*, and *user37*. Figure 6.10 shows *user37*'s

Table 6.14: Groups based on the behavioral patterns in online (Web Search) and physical search (Escape Room)

Group	Task		N
	Web Search	Escape Room	
A	Exhaustive	Exhaustive	4
B	Exhaustive	Economic	5
C	Exhaustive	Adapter	2
D	Economic	Exhaustive	0
E	Economic	Economic	4
F	Economic	Adapter	6
G	Adapter	Exhaustive	2
H	Adapter	Economic	2
I	Adapter	Adapter	1
J	Maverick	Exhaustive	1
K	Maverick	Economic	1
L	Maverick	Adaptor	1

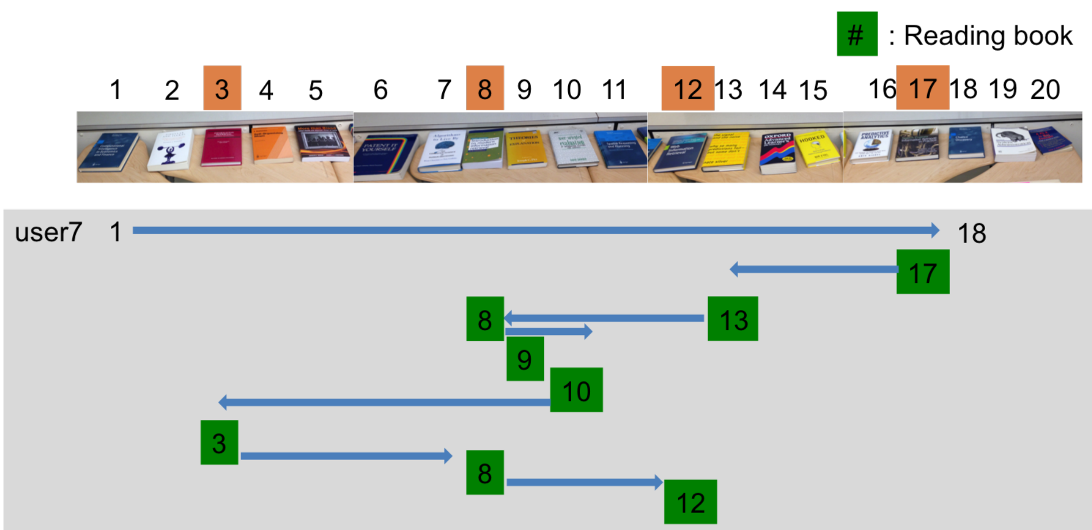


Figure 6.9: Examination type of user7 in Escape Room, Book task. Picture in top presents the displayed books in Escape Room game session and the relevant books with orange square. Following the order of time, from top to bottom, the arrows mean the person's path and green squares mean the books that the user visited to read.

Figure 6.10: Examination type of user37 in Escape Room, Book task. Picture in top presents the displayed books in Escape Room game session and the relevant books with orange square. Following the order of time, from top to bottom, the arrows mean the person's path and green squares mean the books that the user visited to read.

economic evaluation picking up a book for further investigation.

While there are five participants in group B, who changed, or adjusted their searching behavior in different environment, from exhaustive examination in Web Search to economic examination in Escape Room, no users altered their way of searching from economic to exhaustive way - group D.

Group C and F refer to people, who showed consistent behaviors in Web Search regardless of the task type, adjusted their behavior to the contrasting task type in Escape Room. Whereas, group G and H modified their examination strategy during Web Search but showed consistent behavior in Escape Room. Group I can be viewed users who altered their action very easily depending on the given situations both in online and physical space.

6.3.5 Physical Searching Behavior and Task Type

The annotated behavioral pattern of examining information in a small physical space (Escape Room) shows some individuals have consistent preference to either exhaustive or economic investigation over two tasks.

However, as shown in the Web search and discussed regarding the task types, the characteristics of physical search are observed to affect participants' behavior as well. In the Escape Room, the way I designed the book task and movie task seemed to encourage users to prefer particular strategy to the other. For instance, in the book task, having 20 books spread over the tables in front of a user, I gave her a tip saying "multimedia search is a sub-topic in information retrieval," imposing the best way to locate relevant information is select first books that are associated with information retrieval. So, in this *book* task, it is natural to expect for a participant to look around the series of books, from either end of them, to get exposed to relevant information patches, in other words, through an *exhaustive examination.*

On the other hand, the *movie* task has different setting. While the first thing that the participant needs to do is locating a movie poster of the film produced by particular studios (Paramount Pictures and Warner Bros. Pictures), the letters on the posters are too small to read from even a step distance from it. So, it is natural for a person to start read the first poster (either the right-most one or the left-most one), approaching closer to the information to understand in detail: *economic examination* or *exploitation first* approach is preferred in this case.

6.4 RQ1a. Visiting and Seeing Behavior in Online Exploration and Physical Exploration

This section answers to RQ1a, which asks: *To what extent, if any, does an individual's patterns of visiting and seeing physical space relate to his/her visiting and seeing in online space?* Since this question is focused on the way in which people visit and see information patches in physical space, I examined how people visit and see while conducting treasure hunt to understand the relationship of their physical searching behavior with web search behavior.

6.4.1 Exploratory Behavior on Floors

Through annotating information patches in treasure hunt and the corresponding activities of participants, I categorized the types of visiting, as one aspect of examination strategy of information foraging, on floors in the building where the user study was conducted. *Exploitation* refers to visiting more than two information patches[6], while *Exploration* means visiting zero or one patch.

In addition to the *exhaustive examination* and *economic examination*, *visiting behavior*, I examined the time the participants spent on information patches to view and assess, as an aspect of *seeing behavior*. Based on the staying time, their seeing behavior was categorized into three

[6]the criteria of two is derived from the data analysis of all participants whose behavior was appropriately recorded by the camera.

types: *long stay*, *medium stay*, and *short stay*. In order to differentiate their staying pattern, I used several information patches that most participants visited and viewed as reference points, such as *I262* on the second floor or *I363* on the third floor. However, since participants' staying time even to those popular patches varied, note that the categorization does not provide statistically accurate differentiation or conclusion. The analysis presented here gives a brief patterns of the behavior.

Visiting Behavior

The visiting behavior, or examination strategy, was observed and categorized into three types: *exploitation*, *exploration*, and *mixed*. An example of exploitation examination is presented in Figure D.1. In the first floor session (2nd floor)[7], the participant visited four information patches. Fortunately, *user3* was able to locate the answer to the first task on the second *floor session* (3rd floor) in the second information patch that the person visited, which is *I361*, letting the participant accomplish the task even without exploring the first floor.

Another example of *exploitative* visiting is in *user46*'s data (Figure D.2). In the first *floor session* (2nd floor), the participant visited five information patches, and examined eight information chucks in the second *floor session* (1st floor).

On the contrary, *user38* exhibited *exploration* (Figure D.3). The participant visited only one information patch in the first *floor session* (2nd floor)[8]. The participant effectively explored the 2nd floor and found out the answer right way after entering the second *floor session* (3rd floor).

Annotated behavior of *user26* shows the *exploration* as well (Figure D.4). The participant visited one information patch in the first *floor session* (2nd floor) and made two visits in the second *floor session* (1st floor). Even when investigating the 2nd floor again in the third *floor session*, *user26* only visited one place that had not been investigated before.

Aggregating participants' visiting behavior during *Treasure Hunt*, Table 6.15 exhibits the distribution of the behavioral patterns. Out of 27 participants, whose data was valid for the

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[7]Since the treasure hunt started from a lab (room 222), the first *floor session* is always the second floor. To avoid ambiguity, the *floor session* will be written italic through the dissertation.

[8]Note that even though there are two circles in the figure but the circle on *I210* was not considered as visiting, because the coding scheme specifies three seconds to be annotated as an information patch visit

analysis, 10 were identified to show *exploitation*, 16 to show *exploration*, and 1 to show *mixed* approach. An example of *mixed* approach is *user23*'s case. The participant showed very different visiting behavior for particular floors: *exploration* for the 2nd floor and *exploitation* for the 3rd floor.

Table 6.15: Participants' visiting behavior on the floors during *Treasure Hunt*

Visiting Behavior	No. of Participants
Exploitation	10
Exploration	16
Mixed	1
Total	27

Behavioral Change over Time

While Table 6.15 represents the identified visiting behavior, it should be noted that their behavior patterns changed with the advance of search task. For instance, a participant who started *exploration* first in the early stage of search could change the approach to *exploitation* attempting to get the proper information.

Figure D.5 and D.6 present the first half and second half of search paths of *user16*. In the beginning of *Treasure Hunt*, *user16* adopted exploration: one visit in the first *floor session* and three visits in the second *floor session* in Figure D.5. Struggling to locate the right answer, however, the participant started to visit more information patches. In the second half of *Treasure Hunt*, *user16* looked into more information, repetitively, seeing the content more thoroughly (Figure D.6).

There are four participants (*user7*, *user16*, *user22*, and *user33*) who changed their searching strategy from *exploration* to *exploitation* during Treasure Hunt. In addition to the example of *user16* (Figure D.5 and D.6), *user7*'s data presents the similar behavioral change. Figure D.7 shows the participant's exploration behavior for the first and second *floor sessions*, while Figure D.8 indicates that *user7* adopted exploitation in the later part of physical search.

While the behavioral change is significant from the data and one of the important findings regarding searching behavior, note that I considered the **initial** responses in the physical search when comparing the behavioral patterns in later sections.

Seeing Behavior

Table 6.16 presents the extent to which participants relatively spend time seeing information patches during *Treasure Hunt*. Since all participants had not visited the same information patches, this identification is based on time spent on several information chunks most participants visited.

Table 6.16: Participants' dwell time on information patches during Treasure Hunt session

Dwell Time	Long	Medium	Short	Total
No. of Participants	7	8	12	27

6.4.2 Relationship Between Visiting and Seeing Behavior

Table 6.17 represents the patterns of visiting and seeing behavior observed in *Treasure Hunt*. Of 10 participants of *exploitation* type, six people spent long time to read the information patches, while two spent medium, and other two spent short amount of time for assessing the information. Among 16 people of *exploration* type, one spent long time reading information patches, while six spent medium, and nine spent short time. The one participant who showed mixed pattern tended to spend short time for assessing information.

A chi-square test of independence was performed to examine the relation between *exploitation* and *exploration* and the corresponding seeing behavior. The relationship was significant, $\chi^2(2, N = 26) = 9.1274, p < .05, (p - value = 0.01042)$, indicating *exploitation* people tend to investigate information for longer time, while *exploration* people move onto other patches or spaces quickly. In this regard, dichotomic patterns of *exploitation* and *exploration* can represent the visiting and seeing behavior during physical search in general.

Table 6.17: Behavioral patterns in visiting and seeing behavior in Treasure Hunt

Behavioral Patterns		Seeing			Total
		Long	Medium	Short	
Visiting	Exploitation	6	2	2	10
	Exploration	1	6	9	16
	Mixed	0	0	1	1
Total		7	8	12	27

6.4.3 Experience with the Space and Searching Behavior

Table 6.18 shows the relationship between the experience with the physical space and the searching behavior. The result of chi-square test of independence between the experience and the searching behavior is not significant ($\chi^2(2, N = 27) = 2.0925, p > .05, (p - value = 0.3513)$), but Table 6.18 suggests that people who had visited the building before to have some sense of the structure tended to make quick decisions, moving onto exploration of the space.

Table 6.18: Experience of the building in which *Treasure Hunt* was conducted and participants' searching behavior

Behavioral Patterns		Treasure Hunt: Searching Behavior			Total
		Exploitation	Exploration	Mixed	
Experience of Buidling	Yes	4	10	1	15
	No	6	6	0	12
Total		16	10	1	27

6.4.4 The Way Information is Structured and Presented in Physical Space

Treasure Hunt was conducted in an ordinary school building in which faculty, students and staffs work and spend their daily lives. In this very natural setting, the way information is structured and presented on each floor in the building varied. For instance, the second floor of the building, which was usually the first *floor session*, is organized as in Figure D.9. After a participant leaves the starting point (the yellow star in the map), the person would go through the hallway, along with the classrooms and faculty offices. Most information patches on the floor were office number, name tag for professor and employees, except one bulletin board and a few doors with a couple of posters or sticky notes. The green arrow shows one possible path, which is in a linear way.

On the contrary, on the 3rd floor (Figure D.10) there are more diverse types of information patches other than office labels and small pieces of paper on the doors, such as posters regarding research projects, academic publications, and advertisements of a few student groups. Additionally, the circular layout of the offices and classroom made participants move around the hallway, providing higher chance to encounter the same place again.

This difference of information type and the way the information is structured and organized were found to affect participants' interaction in the physical space. For instance, picture (a) in Figure D.11 represents *user2*'s exploration on the 2nd floor, while picture (b) represents the user's exploitation on the 3rd floor.

6.4.5 Online Search and Physical Search

Table 6.19 represents the behavioral patterns observed during *Task1* of *Web search* and *visiting behavior* in *Treasure Hunt*. Out of thirteen participants who showed exhaustive evaluation, five adopted exploitation, seven did exploration, and one did mixed searching strategy. Among fourteen people of economic examination for online search, five showed exploitation and nine showed exploration during the physical search process.

Table 6.19: Behavioral patterns in online searching (Task1: problem-solving) and physical searching (Examination in floors)

Behavioral Patterns		Treasure Hunt: Searching Behavior			Total
		Exploitation	Exploration	Mixed	
Web Search: Task 1	Exhaustive	5	7	1	13
	Economic	5	9	0	14
Total		10	16	1	27

Table 6.20 represents the behavioral patterns revealed during *Task2* of *Web Search* and visiting behavior in *Treasure Hunt*. Out of nineteen participants who showed exhaustive evaluation, eight adopted exploitation, ten did exploration, and one adopted mixed visiting behavior. Within eight people of economic examination for online search, two showed exploitation and six showed exploration during the physical search process.

Table 6.20: Behavioral patterns in online searching (Task2: exploratory search) and physical searching (Examination in floors)

Behavioral Patterns		Treasure Hunt: Searching Behavior			Total
		Exploitation	Exploration	Mixed	
Web Search: Task 2	Exhaustive	8	10	1	19
	Economic	2	6	0	8
Total		10	16	1	27

Comparing the behavioral patterns from two tasks in *Web Search* and *Treasure Hunt*, 27 participants were identified into groups as shown in Table 6.21.

Table 6.21: Groups based on the behavioral patterns in online (Web Search) and physical search (Treasure Hunt)

Behavioral Patterns		Treasure Hunt: Searching Behavior			Total
		Exploitation	Exploration	Mixed	
Web: Search Patterns	Exhaustive	5	7	1	13
	Economic	2	6	0	8
	Adapter	3	3	0	6
Total		10	16	1	27

Without *Mixed* group in *Treasure Hunt*, Table 6.22 represents possible behavioral groups and the number of participants in each of them.

Table 6.22: Groups based on the behavioral patterns in online (Web Search) and physical search (Treasure Hunt)

Group	Task		N
	Web Search	Treasure Hunt	
A	Exhaustive	Exploitation	5
B	Exhaustive	Exploration	7
C	Economic	Exploitation	2
D	Economic	Exploration	6
E	Adapter	Exploitation	3
F	Adapter	Exploration	3

Group A and *group D* can be viewed participants who showed similar behavior in online search and physical search: people in group A showed the exhaustive approach in *Web Search* and exploitation in *Treasure Hunt*, while group D had preference to economic examination in *Web Search* and exploration in *Treasure Hunt*.

On the contrary, *group B* and *group C* refer to people who showed the opposite behavioral patterns in online and physical space. People in group C evaluated information in the exhaustive way but preferred exploration in physical search, while users in group D made economic decisions in online search but spent more effort in local exploitation in physical search.

Group E, and *Group F* refer to people who have the online evaluation type of *adapter* and adopted exploitation and exploration in physical search, respectively.

6.5 RQ2. Relationship Between Aspects of Online Exploration and Physical Exploration

This section answers to RQ2, which asks: *what aspect, if any, and how much of an individuals' physical exploration is related to his/her online information seeking behavior?* In order to understand the relationship between searching behaviors in online and two different physical spaces, the identified behavioral patterns presented in previous sections will be compared.

In addition to the evaluation behavior in *Web Search*, this section presents the results that compare aspects of online searching behavior (*Web navigation style* and *information processing approaches*) and the patterns identified in *Escape Room* and *Treasure Hunt*.

6.5.1 Web Search, Escape Room, and Treasure Hunt

Table 6.23 presents the behavioral groups based on *Web Search*, *Escape Room*, and *Treasure Hunt*. Ignoring *maverick* group in *Escape Room* and *mixed* group in *Treasure Hunt*, there are twelve groups representing twenty two participants.

Table 6.23: Groups based on the behavioral patterns in *Web Search*, *Escape Room*, and *Treasure Hunt*

Environment			N	Group
Web Search	Escape Room	Treasure Hunt		
Exhaustive	Exhaustive	Exploitation	1	A
		Exploration	2	B
	Economic	Exploitation	1	C
		Exploration	4	D
	Adapter	Exploitation	2	E
Economic	Economic	Exploitation	1	F
		Exploration	1	G
	Adapter	Exploitation	1	H
		Exploration	4	I
Adapter	Exhaustive	Exploitation	2	J
	Economic	Exploration	2	K
	Adapter	Exploration	1	L

There are two groups in which people showed consistent behavior in all three environments.

People in group A are likely to investigate and evaluate information in **exhaustive** or **exploitative** way. On the other hand, people in group G prefer to make **economic** or **exploratory** decisions regarding information searching.

6.5.2 Web Navigation Style and Physical Search Behavior

Web navigation sytle refers to the browsing behavior in which the user assesses the online content and information, following a series of opening and reading of links or Web pages. Based on the qualitative coding on recorded video that contains each user's query generations, mouse clicks, and screen scrolls, participants' web navigation behavior was categorized into *structured* and *unstructured* navigation style. Of the 31 participants, eight of them were categorized to have *structured* navigation style, while 23 were perceived to have *unstructured* style.

Table 6.24 and 6.25 compare the Web navigation style and the examination strategy during two tasks of Escape Room game. Note that 29 participants' data was used for these comparisons. In book task (Table 6.24), of 8 people who have structured navigation style, three showed exhaustive examination and five adopted economic evaluation in Book task. Among 21 unstructured participants, eight participants preferred exhaustive examination and thirteen preferred economic examination.

Table 6.24: Web navigation style during Web Search and examination type in Book task of Escape Room

Web Search		Escape Room: Book Task		Total
		Exhaustive	Economic	
Web Navigation Style	Structured	3	5	8
	Unstructured	8	13	21
Total		11	18	29

In movie task (Table 6.25), of 8 people who have structured navigation style, three showed exhaustive examination and five adopted economic evaluation in Book task. Among 21 unstructured participants, six participants preferred exhaustive examination and fifteen preferred economic examination.

Table 6.26 compares the Web navigation style and visiting and seeing behavior during

Table 6.25: Web navigation style during Web Search and examination type in Movie task of Escape Room

Web Search		Escape Room: Movie Task		Total
		Exhaustive	Economic	
Web Navigation Style	Structured	3	5	8
	Unstructured	6	15	21
Total		9	20	29

Treasure Hunt game. Note that 27 participants' data was valid for these comparisons. Regarding visiting behavior (Table 6.26), of seven people who have structured navigation style, two showed exploitation, four showed exploration, and one adopted mixed. Among 20 unstructured participants, eight participants preferred exploitation and twelve preferred economic examination.

Table 6.26: Web navigation style during Web Search and visiting behavior in Treasure Hunt

Web Search		Treasure Hunt: Visiting Behavior			Total
		Exploitation	Exploration	Mixed	
Web Navigation Style	Structured	2	4	1	7
	Unstructured	8	12	0	20
Total		10	16	1	27

While results of the chi-square tests are not significant, data indicates that *unstructured* type of Web navigation tends to be related to *economic evaluation* and *exploration* behavior.

6.5.3 Information Processing Approach and Physical Search Behavior

Table 6.27 and 6.28 compare participants' information processing approaches and the examination strategy in two tasks during Escape Room game. Regarding the examination strategy in book task, Table 6.27 presents the distribution. A chi-square test of independence was performed to examine the relation between these behaviors. The relationship between these groups was not significant, $\chi^2(2, N = 29) = 1.0635, p > .05$, indicating there is no relationship between information processing approach and examination strategy in Book task.

Regarding the examination strategy in Movie task, Table 6.28 presents the distribution.Also

Table 6.27: Web navigation style during Web Search and examination type in Book task of Escape Room

Web Search		Escape Room: Book Task		Total
		Exhaustive	Economic	
Information Processing Approach	Scanning	2	3	5
	Reading	5	12	17
	Mixed	4	3	7
Total		11	18	29

a chi-square test of independence was performed to examine the relation between these behaviors. The relationship between these groups was not significant, $\chi^2(2, N = 29) = 1.0923, p > .05$, indicating there is no relationship between information processing approach and examination strategy in Movie task.

Table 6.28: Web navigation style during Web Search and examination type in Movie task of Escape Room

Web Search		Escape Room: Movie Task		Total
		Exhaustive	Economic	
Information Processing Approach	Scanning	2	3	5
	Reading	4	13	17
	Mixed	3	4	7
Total		9	20	29

Regarding the visiting behavior in Treasure Hunt, Table 6.29 presents the distribution. A chi-square test of independence was performed to examine the relation between these behaviors. The relationship between these groups was not significant, $\chi^2(4, N = 27) = 9.1446, p > .05$, indicating there is no relationship between information processing approach and visiting behavior in Treasure Hunt.

Although the results of the chi-square test are not significant, data indicates that information processing approach of *reading* tends to be related to *economic evaluation* and *exploration* behavior.

Table 6.29: Information Processing Approach in Web Search and visiting behavior in Treasure Hunt

Web Search		Treasure Hunt: Visiting Behavior			Total
		Exploitation	Exploration	Mixed	
Information Processing Approach	Scanning	5	1	0	6
	Reading	2	11	1	14
	Mixed	3	4	0	7
Total		10	16	1	27

6.6 Summary

This chapter presented in detail the results of analysis conducted on the behavioral data from *Web Search*, *Escape Room*, and *Treasure Hunt*. The identified behavioral patterns comparing information evaluation strategy as well as visiting behavior was presented. Other aspects of web searching behavior - web navigation style and information processing approach - were also compared with physical search behavior.

Chapter 7

Discussion

The dissertation focused on gaining a better understanding of behavioral patterns of individuals both in online and physical spaces and the relationship between them. This chapter reviews and discusses the key findings from the results presented in previous chapter, followed by the limitations of the work.

7.1 Human Information Interaction

I see human information interaction as humans and information competing to influence each other (Figure 7.1). A human being has its own characteristics such as personality, cognitive capability, physical capability, personal experience, and social activities. A person approaches information according to these factors. In the meantime, information tries to influence humans with its content, material, structure, etc. As a result of the competition and negotiation between human and information, a person's information behavior has emerged.

In Figure 7.1, the upper arrows labeled A refer to the influences of information on humans who consume the information. The bottom arrows labeled B mean the way humans affect information behavior. Discussion on findings will presented based on this concept.

7.2 Individuals' Behavioral Patterns in Online and Physical Search

As one aspect of searching behavior, I investigated the way in which people read and evaluate before they actually start to look into a particular piece of information (evaluation strategy). First, analysis of video data from *Web Search* and *Escape Room* identified related behavioral patterns in online and physical search. While the number of participants in each behavioral

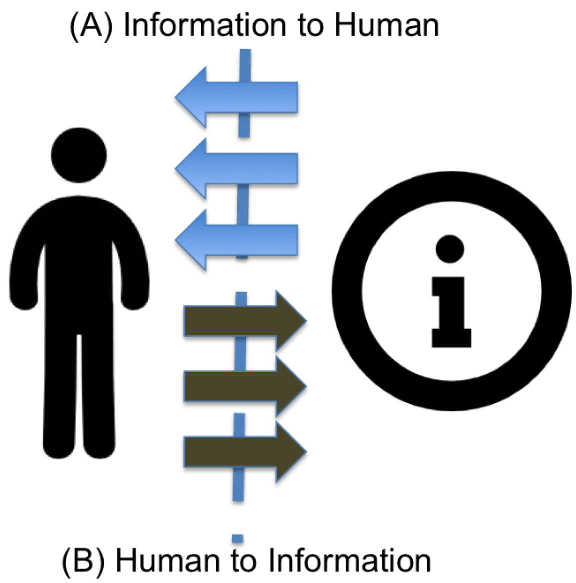


Figure 7.1: Human information interaction. A arrows refer to the ways information influences human, and B arrows mean the ways human influences information.

group does not necessarily mean the popularity of the patterns in general population, the analysis found out that there are significant number of participants who showed the same evaluation strategy even in the different circumstances: *exhaustive evaluators* and *economic evaluators*. Even in a situation where a task by nature demanded a particular approach or strategy to effectively accomplish the task, some participants kept their preferred behavioral pattern. This indicates one way of a human influencing information (*B* arrow in Figure 7.1) and supports the existence of a common algorithm we live by Christian and Griffiths (2016), or a central executive as a search process (CESP, see Hills et al. (2010)). While Hills et al. (2010) compared users' behavior in two experiments of *spatial search* and *lexical search* to find out the prime effect - exposure to one type of search task affects the way to address a similar type of search task, the task environment of spatial search affects their lexical search (prime effect), this work compared people's behavior in two information spaces of *Web Search* and *Escape Room*.

7.3 The Effect of Task Type and Environment on Information Behavior

While some participants showed their consistent strategy of search process in general, some other behavioral groups were found to adjust the strategy, or approach, to the given task and information environment. Even when a person tends to have an innate or habitual strategy to an information problem, it should be considered that the task type affects how to view, access, assess, and accumulate the knowledge during the task. This indicates one way of information influencing a human (*A* arrow in Figure 7.1).

For instance, the tasks that are conducted in user studies in information seeking and retrieval are categorized into several types such as *factual task*, *exploratory task*, and *abstract task* (Kinley et al., 2014). Each of these tasks shows differences in several aspects. While a factual task is easiest in terms of complexity, an exploratory task is relatively complicated, in that it demands a user to interpret the information she encounters and accumulates to create her own understanding, findings, and conclusion on her own.

In this regard, the task type matters in deciding approach(es) to effectively accomplish the task. Exploratory tasks expect the user to explore more information before she makes a quick decision or conclusion, since both the quality and quantity of information collected are important to the final outcome.

This relation between task type and the helpful strategy in a particular context was observed in this work. People adjust to the task type by adopting the appropriate approach for the task. For instance, in the *Movie* task in *Escape Room*, the majority of the participants used an economic evaluation strategy to review the information. Even though a person prefers an exhaustive evaluation in general, the way in which information is presented and provided to the user influences how to respond to the task requirement.

7.4 Information Environment and Exploratory Behavior

This dissertation studied the relationship between the way in which information is structured and the corresponding exploratory behavior. Note that among the users who changed their behavior no one changed from economic evaluators in *Web Search* to exhaustive evaluators in *Escape Room* (6.14). This indicates another way of the information influencing human behavior (*A* arrow in Figure 7.1).

This might be caused by the environment they were forced to be engaged in: online vs. physical space. During online search, more specifically on a desktop in this work, participants had a relatively small area (PC Monitor), to investigate information to accomplish the given tasks. In general, users can look and investigate different areas in the (relatively) small screen, with small effort moving muscles such as the ocular muscle, which controls the eye gaze, and muscles on her fingers and/or hands that control the mouse and keyboard scrolling up and down the screen as well as stroking special keys (i.e., ctrl+F to find a particular word). Also, when it comes to the layout or structure, online information is well designed so *information scent* (Pirolli, 1997; Chi et al., 2001) is properly delivered to the users, providing an efficient way to trace and understand the information, with less effort for information digestion. On the other hand, physical search requires more effort and time of the information user. For instance, in the situation of Escape Room in this work, a participant was supposed to at least move her feet to reach out to the information patches, physically grab the books to open up and look into pages, and sometimes walk between areas in the room to complete several tasks. Moreover, in our everyday life as well as in the Escape Room setting, information scent is not often accurately considered in how things are deployed. These different interactions using physical activities are presented in Figure 7.2. *A* refers to the ocular muscle through which we see and read information. *B* means the activities of fingers and hands interacting with the computer, information devices, information artifacts, etc. C refers to the activities of visiting (walking and running), which relate to physical and physiological conditions of a person. *D* means all personal activities that happen during search tasks.

7.5 Behavior Range on Different Time Scale

Even though the findings in this dissertation suggest a central executive or strategy of individuals, when showing that the online searching behavior is associated with the physical searching activities, we need to consider the different behavioral scales. When it comes to the larger physical space, the relationship between behavioral preference in online search and physical search decreases or diminishes.

This phenomenon can be explained by Newell's hierarchical perspective to human behavior (Newell, 1994). The framework claims that we use different behavioral ranges depending on what time scale is associated with the behavior. For instance, as shown in Figure 2.12, short-term period activities such as those that occur for less than 100 milliseconds are handled by

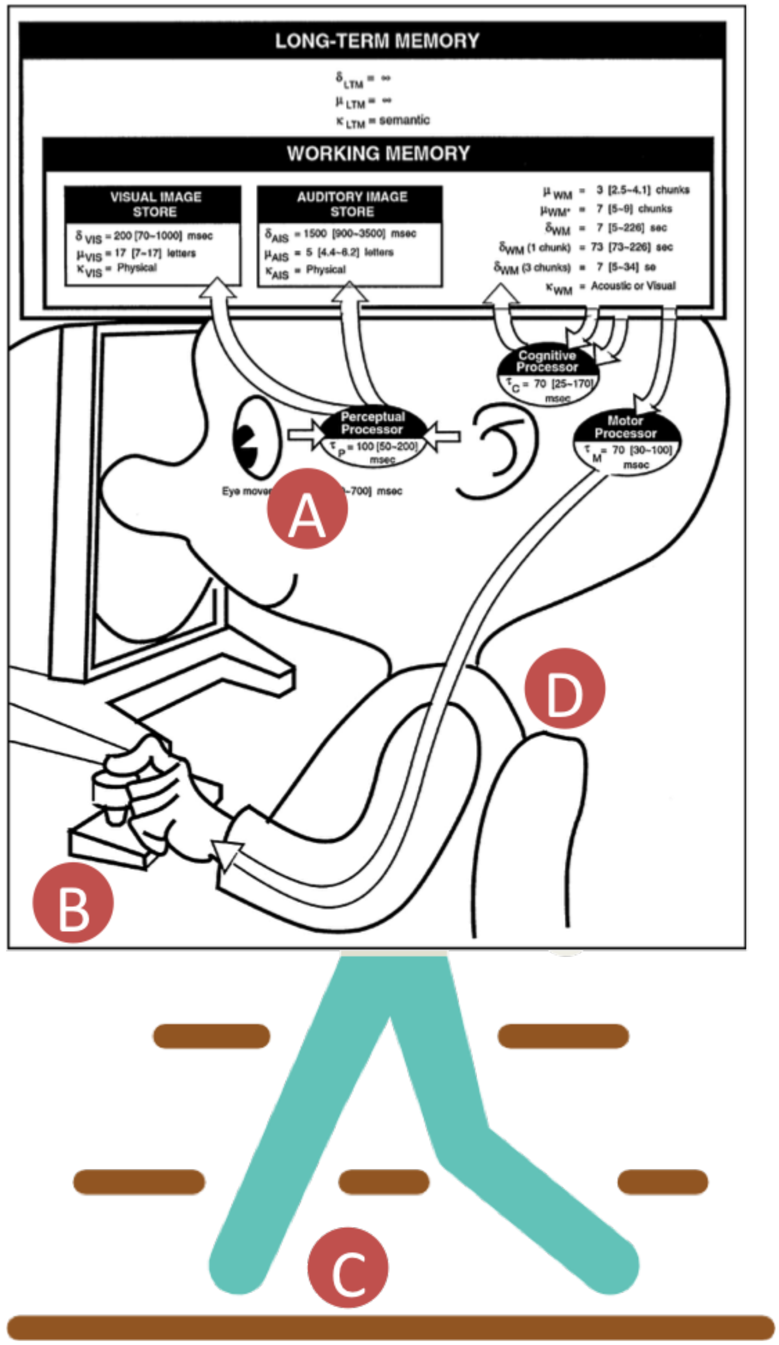


Figure 7.2: The Model Human Processor in physical search. Figure in Card et al. (1983) is modified in the context of the work. *A* refers to the ocular muscle; *B* refers to the activities of fingers and hands; C refers to the activities of walking and running, which relate to physical and physiological conditions of a person; and *D* means all personal activities that happen during search tasks.

biochemical, biophysical, and neural processes. As the time scale increases, the associated behavioral band changes from a purely biological level to psychological, cognitive, rational, and social levels.

Along with the common executive control (Hills et al., 2010), Figure 7.4 suggests that information searching in physical space is associated with more factors than online searching. In addition to the *common executive control*, a substantial part of searching behavior, other individual factors such as physical capability (muscles and motor sensors) and whether she is familiar with the places may affect information seeking behavior.

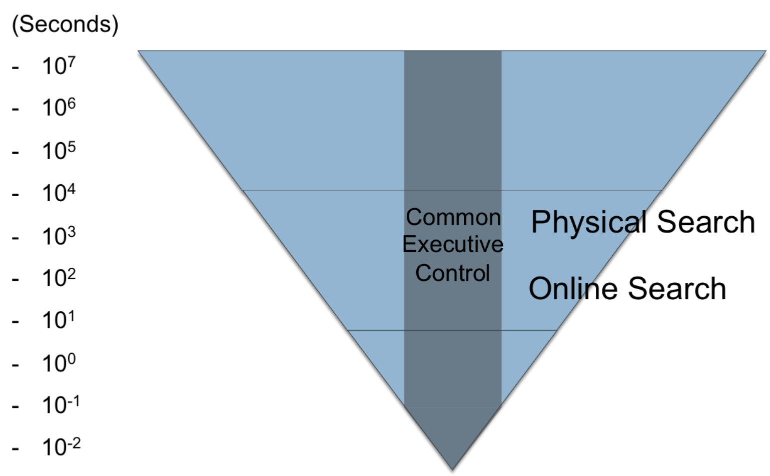


Figure 7.3: Search behavior in different time scale.

7.6 Human Information Interaction in Search Process

Extending model human processor (Figure 7.2) and the extent to which the common executive control governs online and physical search (Figure 7.4) suggest a human information interaction model in the search process. White parts in the dotted rectangle refer to the model human process (Figure 2.4) in a diagram. In addition to the processors and memories of the model, I added the central executive of search process as a component of human information interaction. Black ovals and arrows inside and outside the model human processor indicate human information interaction in the search process, as a result of findings and discussion in this dissertation.

Central executive of search process (CESP) induces the user's innate, and/or preferred searching strategy, through interacting with three processors (*a*). While the motor processor in model human processor only takes the orders from the cognitive processor, in this model, physical and/or physiological conditions of a user give feedback to the cognitive processor, changing the corresponding behavior (*b*). As discussed in the previous sections, the conditions can be response time and walking/running time. *C* refers to ways the user's information visiting traits affect motor processor such as visiting a particular area that has been secured or locked. In general, the search process of a human being is affected by the external task/information factors (*d*).

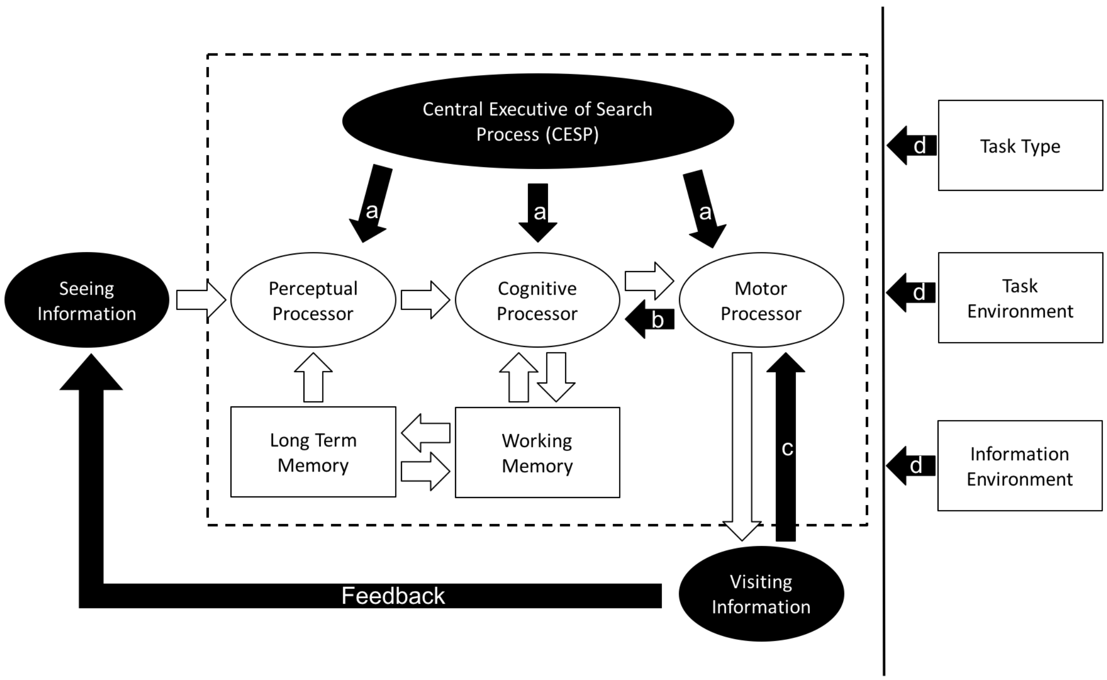


Figure 7.4: Human information interaction in search process

7.7 Limitations of the Research

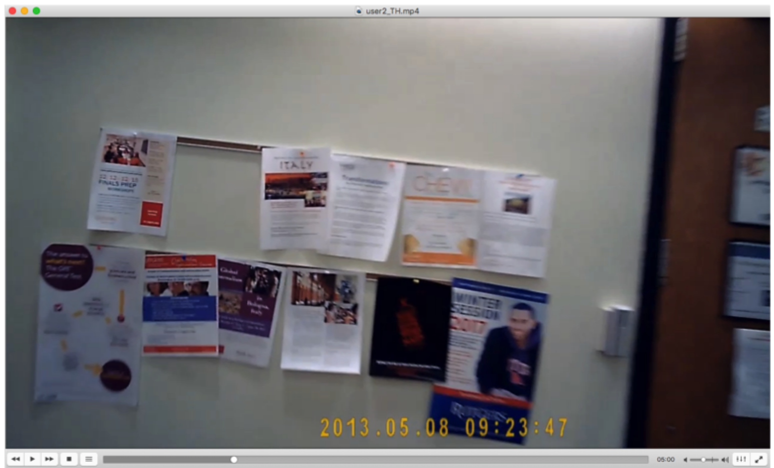
First, limitations of this work include the small, relatively homogeneous sample, which might show similar searching behavior. User studies with a small number of participants can be quick to conduct, with regard to recruiting subjects, operating experiments or performing analyses to address research questions but the interpretation of the results is difficult to transfer to the larger sample in general. Moreover, the fact that all participants of this dissertation are undergraduate students at Rutgers University can add to a selection bias problem.

Regarding *Escape Room*, even though I had tested the experiments several times, there were still points that can improve the quality of study. For instance, in the case of the first *Book* task, participants were supposed to pick relevant-looking books to start searching information for solving the question. An instruction to the first question was provided in the problem sheet, but the extent of individual participants' understanding of the intention of the task is in doubt.

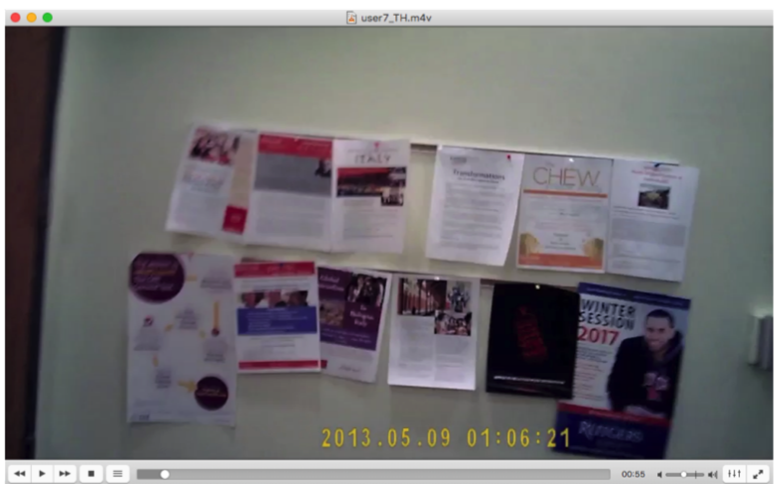
The investigating of online behavior during online search and physical search is based on the assumption that examination on the results page *Web Search* and the corresponding behavior of searching books is comparable. However, while search results from Web search engine provided a list in the order of relevancy, the placed books in *Escape Room* had nothing to do with the relevancy to the question: the books were randomly placed, and only four books that cover the relevant topic to the question were placed and there were other books between them.

The naturalistic experimental environments both in Web search and treasure hunt gave participants less control over information they encountered. For instance, *Treasure Hunt*, which was conducted over three weekends in December 2016, faced different information patches presented in the building each day; flyers for different social events, classrooms occupied for make-up classes, students preparing for the exams, etc. Figure 7.5 shows an example of an information patch that was differently presented in *Treasure Hunt* on different dates and times. These differences might have affected participants' searching behavior in their physical search.

In a similar sense, some SERPs that participants retrieved during the web search included more information than others. For example, a search results page about a famous person contains well-summarized information about that celebrity on its side section, which might influence users' responses to the information and, ultimately, the time they spent on the information patches.



(a) I161 for user2



(b) I161 for user7

Figure 7.5: Example of information patches differently presented to participants: I161. (a) I161 for *user2* and (b) I161 for *user7*.

Chapter 8

Conclusion

As our activities in online space and physical space have been mixed, and the boundary between the spaces is being blurred, peoples' information behavior in each environment needs to be considered from the holistic point of view regarding human information interaction. Yet, while online information behavior has been investigated with respect to various characteristics of the (1) human side and (2) information side, fundamental questions about how online behavior is related to physical behavior still remain.

This dissertation was designed to observe and understand individuals' information searching behavior in online and physical spaces, focusing on their behavioral change corresponding to different information spaces, characteristics of tasks, and information structures. While previous studies have examined individual differences or cognitive styles measured by self-report or survey data, I observed their information search activities through unobtrusive devices such as wearable video recorders, web loggers, and eye-trackers. The research methodology in the study employed both quantitative and qualitative data collection, and analysis provided rich data about human information interaction behavior in online and physical spaces.

The results of the study suggested insightful ideas about how people interact with information environments, adjusting their behavior accordingly. In this chapter, a discussion of implications is presented, followed by future research studies to expand the scope of our understandings of information behavior in different environments.

8.1 Implications of the Dissertation

This work identified individuals' behavioral patterns of exploratory search in online and physical space. The findings from the study provide a useful insight in a number of areas of impact, including three implications discussed here, which would help to improve the understanding of peoples' information behavior and provide efficient ways of interactions: (1) theory and model development; (2) learning environment; (3) collaboration; (4) information interface.

This work expands the theories and models of human information behavior. Information foraging theory (Pirolli and Card, 1997) assumes individuals' rational economic system regarding cost and benefit, moving between information patches. It also focuses on how *external factors* from the environment affect users' information exploration. However, this dissertation suggests individuals' *personal preference* can affect searching strategy. The fact that this phenomenon appeared in physical search suggests that we should consider physical and physiological factors when studying people's information behavior. The findings show the value in interdisciplinary examination connecting theories and models of Information Science to Experimental/Cognitive Psychology and Behavioral Science.

In today's learning environment, often the focus is placed on the technology more so than on an individual student's behavioral and learning traits. The work reported in this dissertation shows that perhaps we could tailor a student's learning path in an online environment if we get to know more about their behavioral patterns in a physical environment. Taking this lesson, a teacher for instance, could organize various games or exercises, similar to the ones used in this dissertation, to gain a better insight into each individual student's abilities and traits, and use that knowledge to customize a learning path for them.

Let us consider a different scenario. It is typically expected that when people work together there can be a synergic effect, accomplishing goals that are difficult for individuals. For collaborative Web search, different roles of people (Shah et al., 2010) and different environments (Shah et al., 2015) have been examined as a mediation method for maximum performance. However, if the working context includes physical interaction between individuals, knowledge about the workers' behavioral traits can improve the configuration of a team. For instance, an explorer and an exploiter, identified through escape rooms or treasure hunt games, can build a team to better accomplish certain tasks. Of course, given a situation, it may make more sense to create a homogeneous rather than heterogeneous group. But the important point here is that we could use the insights developed from observing one's behavior in a physical environment to create an optimized configuration in an online context.

Finally, the findings from this dissertation could have implications on interaction designs.

For instance, currently, the information interface in digital devices attempts to provide a user with a unified interface over different modalities. In other words, they provide similar appearance and interaction on a mobile phone with a small screen and a PC with a large screen. However, when it comes to the way in which people interact in a larger space, such as three-dimensional activities in virtual reality and augmented reality, the design of interfaces in different environments needs to consider the user's behavioral traits in online and physical space together.

8.2 Suggestions for Future Research

This dissertation provided some exploratory results about how individuals search for information in online and physical spaces. Even though the findings from this dissertation may shed light on understanding the behavioral traits in different information spaces, research focusing on users' characteristics that determine their behavior and factors that define information task and environment should be continued. For instance, through the experiments suggested in this dissertation, we can investigate what extent to which the differences different physical and physiological conditions affect their information interaction. Information foraging theory suggested the moving speed of an animal determines how long it will stay in a patch, maximizing the harvest. In a Web searching context, Azzopardi et al. (2013) varied the response time from the query generation in the search engine to see how the cost of interaction affects people's behavior. In the same sense, we could observe how adding a physical burden to 'visiting' influences their exploratory behavior, by adding additional weight.

The tasks conducted in this dissertation have different characteristics: a problem-solving task and an exploratory search task in Web search, and a book task and movie task in escape room. The differences between tasks influenced participants to change their behavior and/or strategy. In order to compare their behavior in online and physical space, it is necessary to conduct as comparable of a task as possible. For instance, in the escape room, relevant books to a particular topic can be used rather than random selection, ordered by the relevancy. In treasure hunt, a task that asks to gather useful information from the environment to produce a certain type of collection can replicate the exploratory Web search task.

In order to test the effect of experience with physical space on their searching behavior, we can conduct the experiments in a room or a building that the participants have never been to. To avoid the seasonal effect and consequential differences in environment, we could invite all participants on the same day. How different information structure influences people's physical search can be investigated via conducting a treasure hunt in a variety of places such as school buildings or museums (Hashemi et al., 2016, 2017).

Further study is necessary in order to gain a more in-depth understanding of users' intention and the purpose of their behavior during the sessions. Thus, future studies may include asking participants their motivations and expectations of each decision during a search. After completing online and physical search with video recording, a researcher and the participant play and watch the video together recalling thoughts and motivations at specific moments.

Also, further enhancements could be achieved by incorporating additional analysis of behaviors regarding information in different hierarchies, such as Web pages, paper pages, books, rooms, hallways, and floors. It would be helpful to employ the mobile eye tracker to monitor and understand what information people see exploring a physical space.

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Appendix A

Recruitment Email

Below is the template for the recruitment email that was used for recruiting participants for the user study.

From: Dongho Choi dongho.j.choi@rutgers.edu

To : [*RECIPIENT*]

Subject : *Recruitment for user study*

—– Message Text —–

Dear [RECIPIENT],

The research project, Predicting Search Behavior Using Physical and Online Explorations, funded by Google, seeks participants in a study of information seeking. We are recruiting participants (18 female and 18 male undergraduate students) who use an Android phone and Chrome Web browser on a daily basis.

All volunteers for this study will receive a $100 cash after a full completion of the study.

This study consists of three elements:

- Introduction (about one hour): Install (1) an app on your Android phone (2) an extension of Chrome browser on your laptop,

- Field Session (four weeks): While keeping the app and extension installed, fill up questions (about 30 minutes) that will be given to you every week (four times in total) regarding your geographical visits and browsing activities,
- Lab session: Play three games (treasure hunt, escape room, web search task - about 2 hours).

For this, the participants will be asked to visit the lab at School of Communication Information (SCI) on CAC, twice:

- Introduction, on 10/31, 11/1, 11/2, 11/3 or 11/4
- Lab session, on 12/03(Sat), 12/04(Sun), 12/10(Sat), 12/11(Sun), 12/17(Sat), or 12/18(Sun)

Taking part in this study will help to advance the understanding of the search process and contribute towards the development of theories and search systems that can adapt to a user's preferred search strategies.

Requirements:

- You must be at least 18 years old to participate.
- Rutgers Undergraduate student.
- Proficiency in English is required.
- Intermediate typing and online search skills are required.
- Normal to corrected vision, hearing, and motor control are required.
- Currently using an Android phone and Chrome Web browser on a daily basis.
- (Optional but preferred) Using a laptop for daily Web search.

NOTE: students who participated in a similar study last August are not eligible for this study.

This study has been approved by the Rutgers Institutional Review Board (IRB Study E16-680), and will be supervised by Dr. Chirag Shah (chirags@rutgers.edu) and Dr. Vivek Singh (*vivek.k.singh@rutgers.edu*) at the School of Communication and Information.

For more information about this study, please send an e-mail to Dongho Choi at *dongho.j.choi@gmail.com*. You can also contact Dongho Choi to ask questions or get more information about the project.

Address of SCI: 4 Huntington Street, New Brunswick, NJ 08901

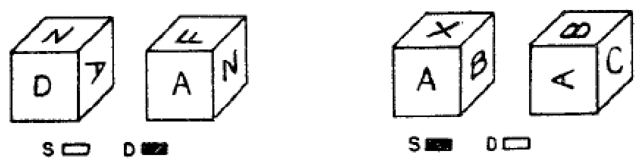
Appendix B

Spatial Capability Test - Spatial Orientation

In this chapter, I present the spatial orientation test, named 'cube comparison test.'

CUBE COMPARISONS TEST -- S-2 (Rev.)

Wooden blocks such as children play with are often cubical with a different letter, number, or symbol on each of the six faces (top, bottom, four sides). Each problem in this test consists of drawings of pairs of cubes or blocks of this kind. Remember, there is a different design, number, or letter on each face of a given cube or block. Compare the two cubes in each pair below.

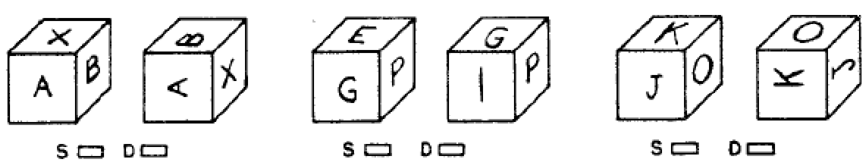


The first pair is marked D because they must be drawings of different cubes. If the left cube is turned so that the A is upright and facing you, the N would be to the left of the A and hidden, not to the right of the A as is shown on the right hand member of the pair. Thus, the drawings must be of different cubes.

The second pair is marked S because they could be drawings of the same cube. That is, if the A is turned on its side the X becomes hidden, the B is now on top, and the C (which was hidden) now appears. Thus the two drawings could be of the same cube.

Note: No letters, numbers, or symbols appear on more than one face of a given cube. Except for that, any letter, number or symbol can be on the hidden faces of a cube.

Work the three examples below.



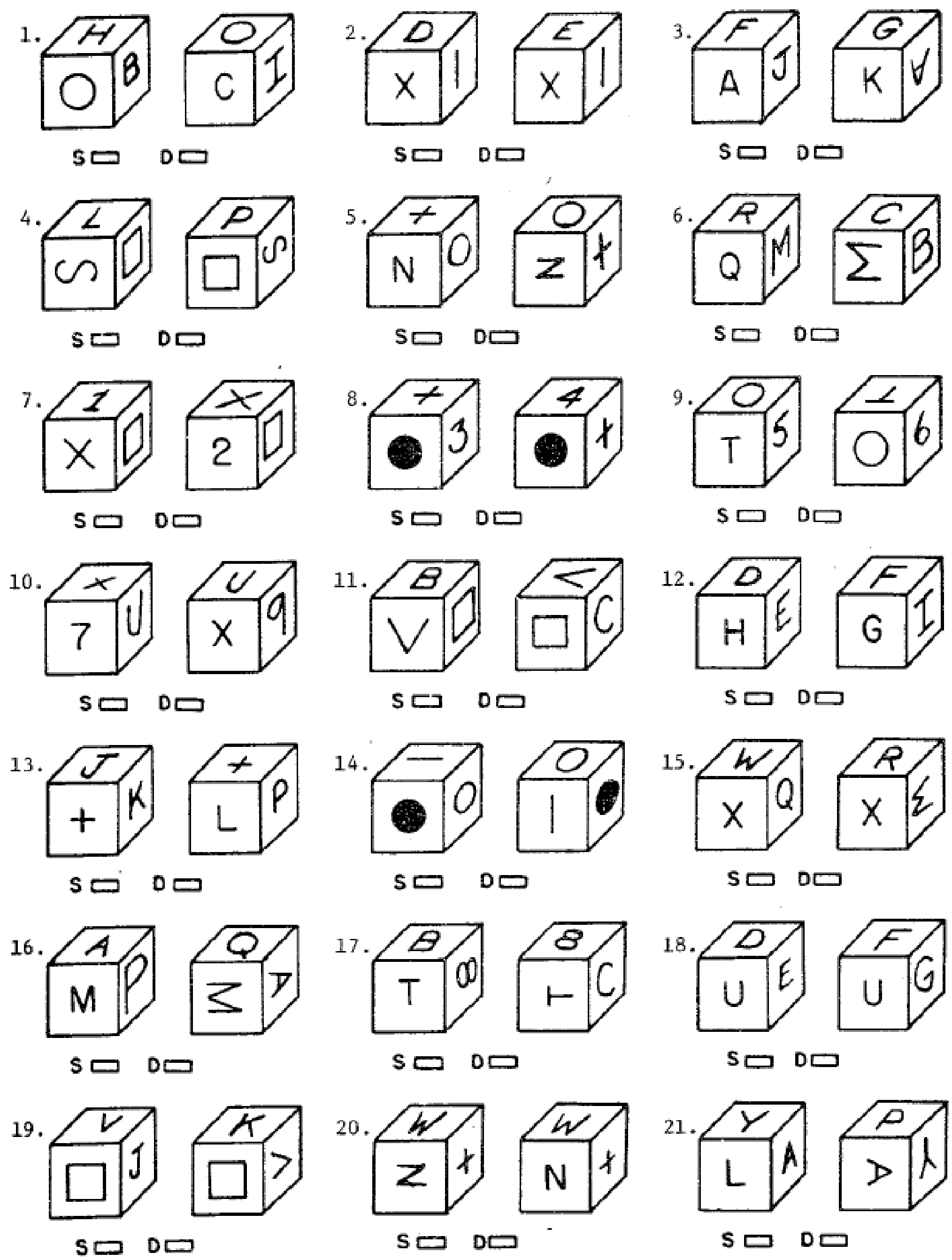
The first pair immediately above should be marked D because the X cannot be at the peak of the A on the left hand drawing and at the base of the A on the right hand drawing. The second pair is "different" because P has its side next to G on the left hand cube but its top next to G on the right hand cube. The blocks in the third pair are the same, the J and K are just turned on their side, moving the O to the top.

Your score on this test will be the number marked correctly minus the number marked incorrectly. Therefore, it will not be to your advantage to guess unless you have some idea which choice is correct. Work as quickly as you can without sacrificing accuracy.

You will have 3 minutes for each of the two parts of this test. Each part has one page. When you have finished Part 1, STOP.

Figure B.1

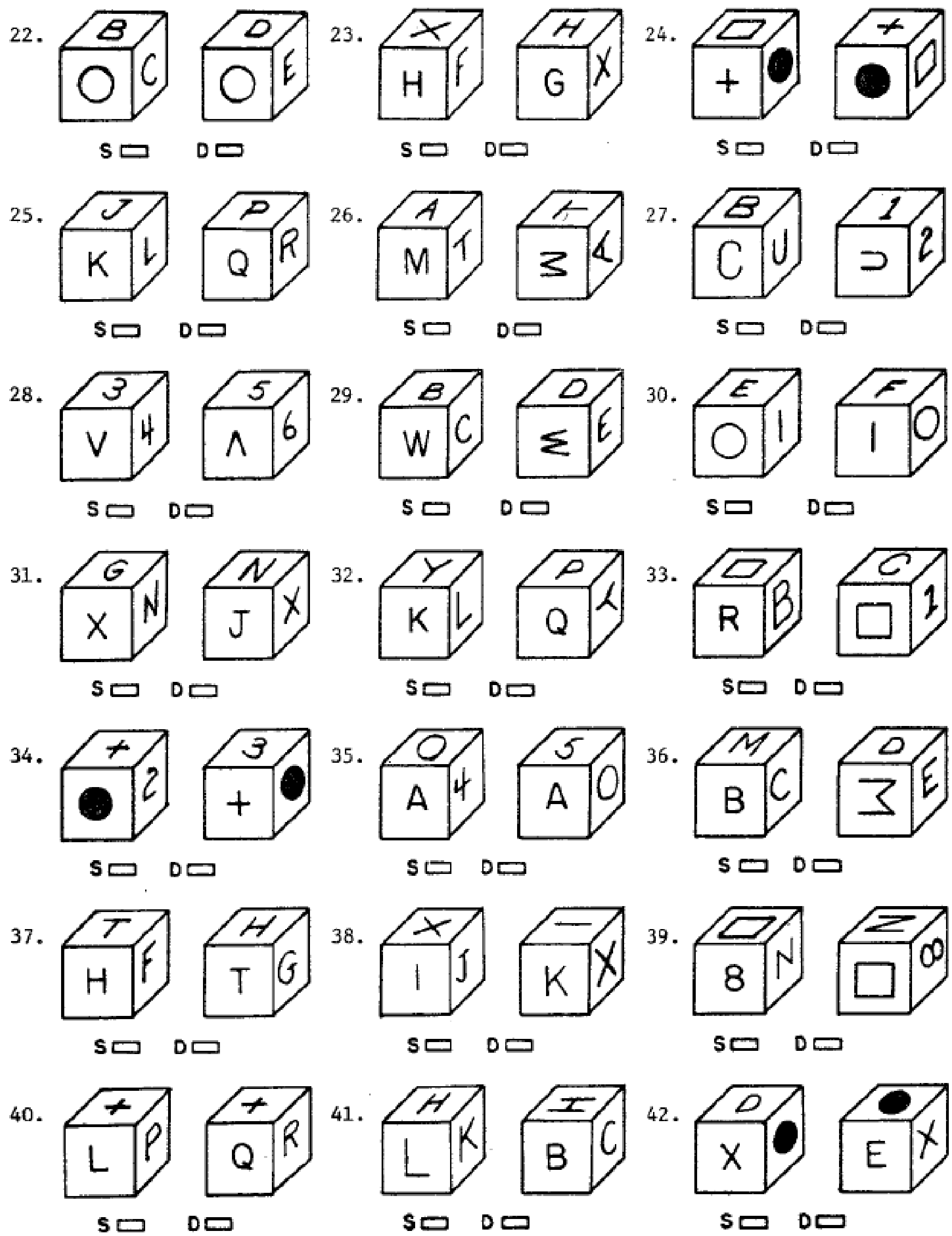
Part 1 (3 minutes)



DO NOT GO ON TO THE NEXT PAGE UNTIL ASKED TO DO SO. STOP.

Figure B.2

Part 2 (3 minutes)



DO NOT GO BACK TO PART 1 AND

DO NOT GO ON TO ANY OTHER TEST UNTIL ASKED TO DO SO. STOP.

Figure B.3

Appendix C

Spatial Capability Test - Spatial Scanning

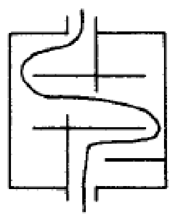
In this chapter, I present the spatial scanning test, named ‘maze tracing test.’

MAZE TRACING SPEED TEST — SS-1

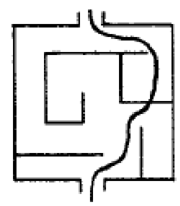
This is a test of your ability to find a path through a maze quickly. You are to draw a pencil line through each maze without having to cross any printed lines.

Look at the two drawings below. In the left square a pencil line has been drawn to show the correct path from top to bottom. The square on the right shows an incorrect path. It is incorrect because the pencil line crosses a printed line.

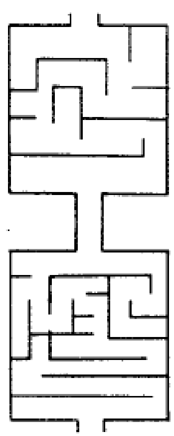
CORRECT



INCORRECT



Practice for speed on the squares below. Remember, you must make a pencil line through each square without having to cross a printed line.



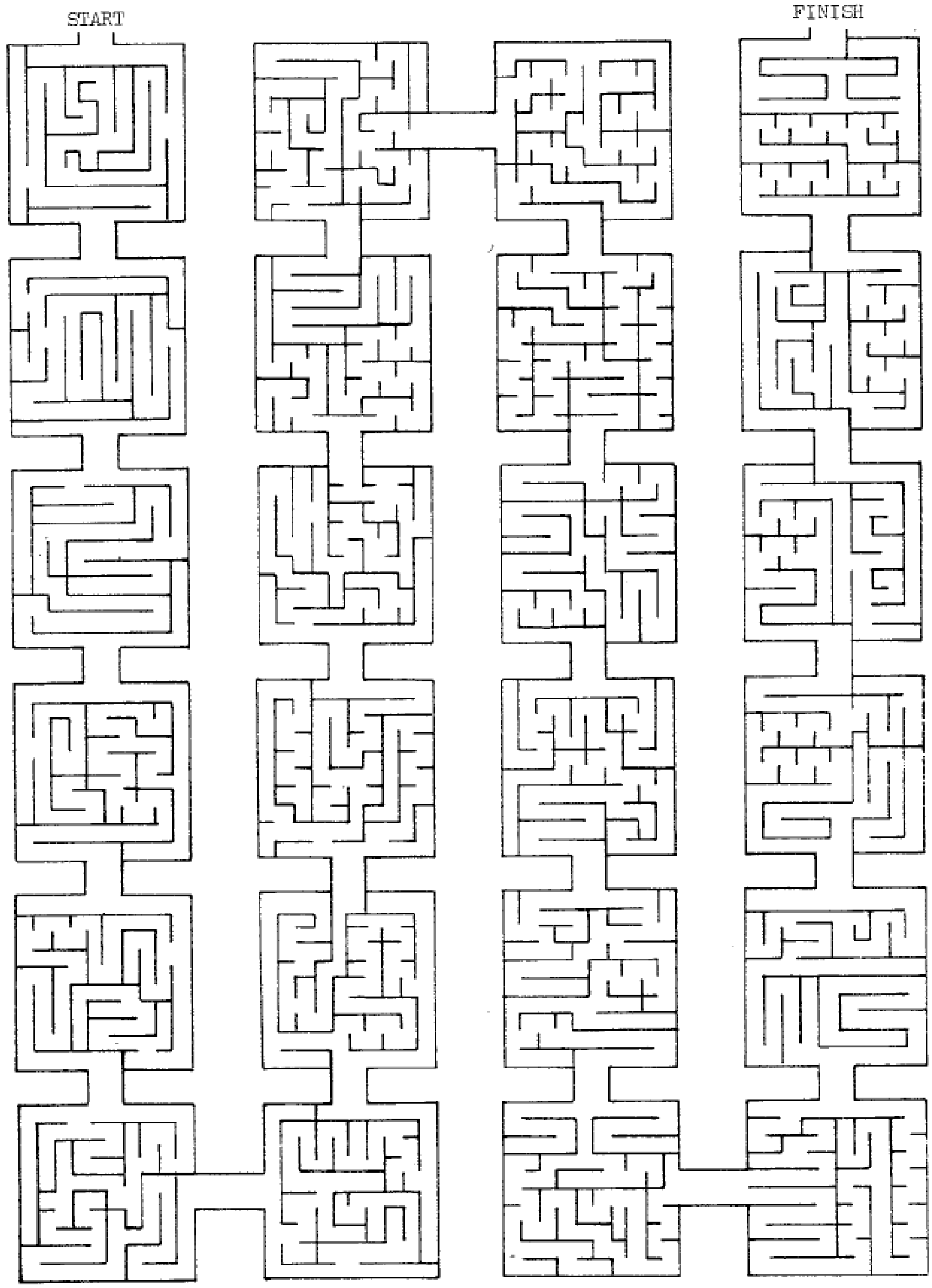
Your score on this test will be the number of squares through which a line has been correctly drawn. If you should become stuck in any square, you may skip to the following one. You should try to avoid making mistakes, but you will not be penalized for lifting your pencil, for retracing a path that leads to a dead end, or for accidentally crossing lines at the sides of the path being taken. Work as quickly as you can without sacrificing accuracy. On the test, follow the squares around the page the way that they are connected, starting at the top of the left-hand column.

You will have 3 minutes for each of the two parts of this test. Each part has 1 page. When you have finished Part 1, STOP. Please do not go on to Part 2 until you are asked to do so.

DO NOT TURN THIS PAGE UNTIL ASKED TO DO SO.

Figure C.1

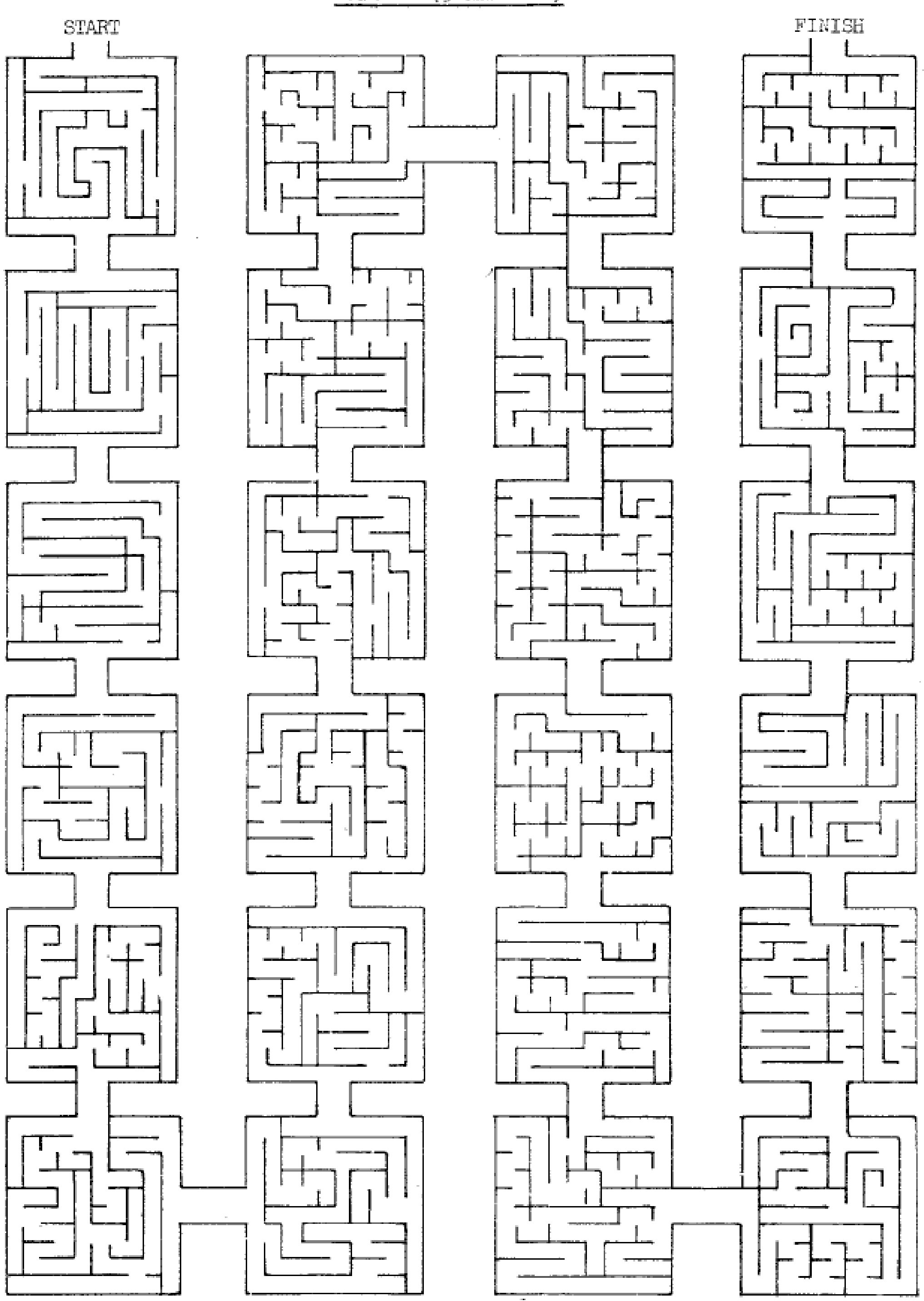
Part 1 (3 minutes)



DO NOT GO ON TO THE NEXT PAGE UNTIL ASKED TO DO SO. STOP.

Figure C.2

Part 2 (3 minutes)



DO NOT GO BACK TO PART 1, AND
DO NOT GO ON TO ANY OTHER TEST UNTIL ASKED TO DO SO. STOP.

Figure C.3

Appendix D

Annotated Maps of Treasure Hunt

In this chapter, I present examples of annotated map of treasure hunt.

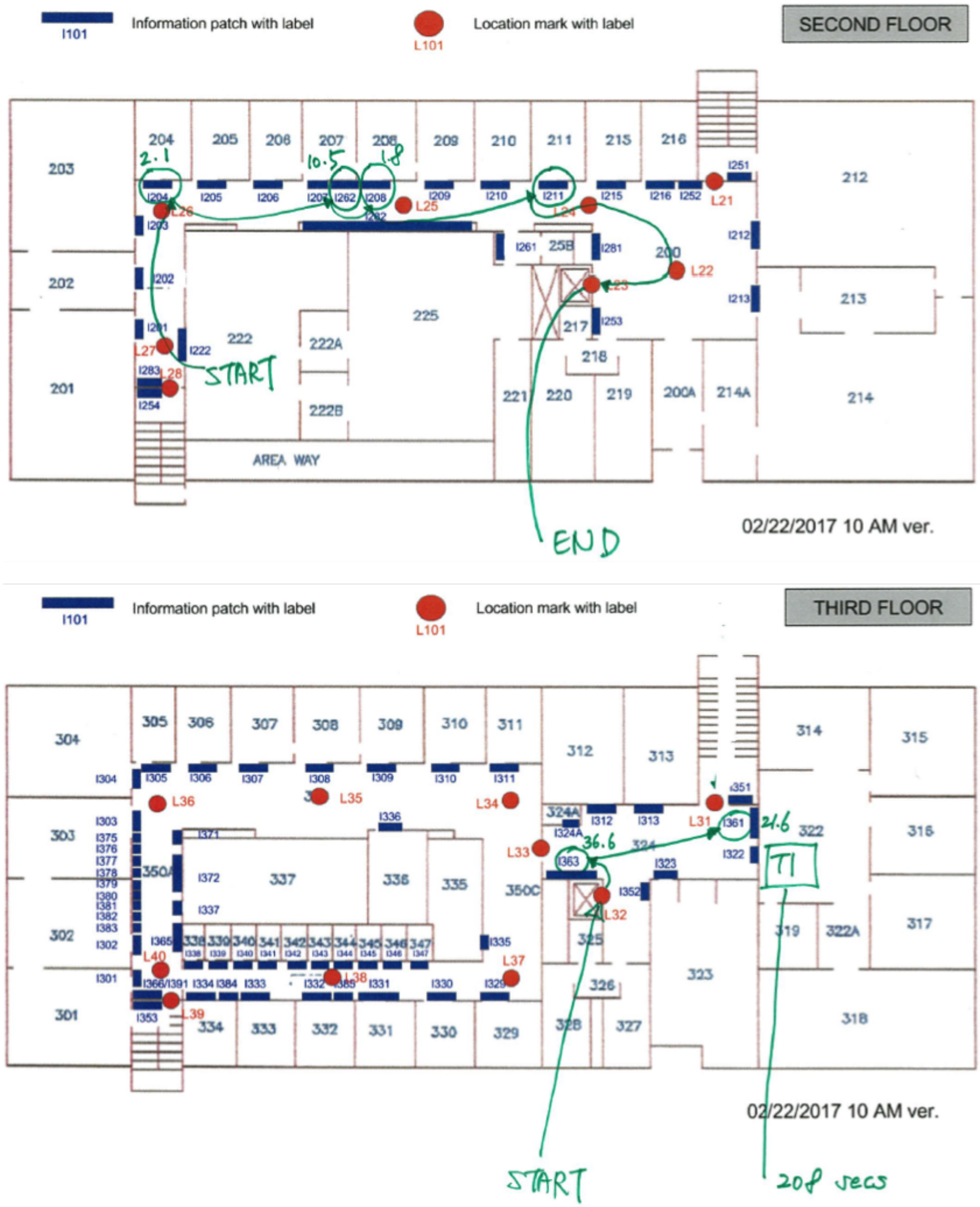


Figure D.1: Annotated behavior of *user3* in *Treasure Hunt*.

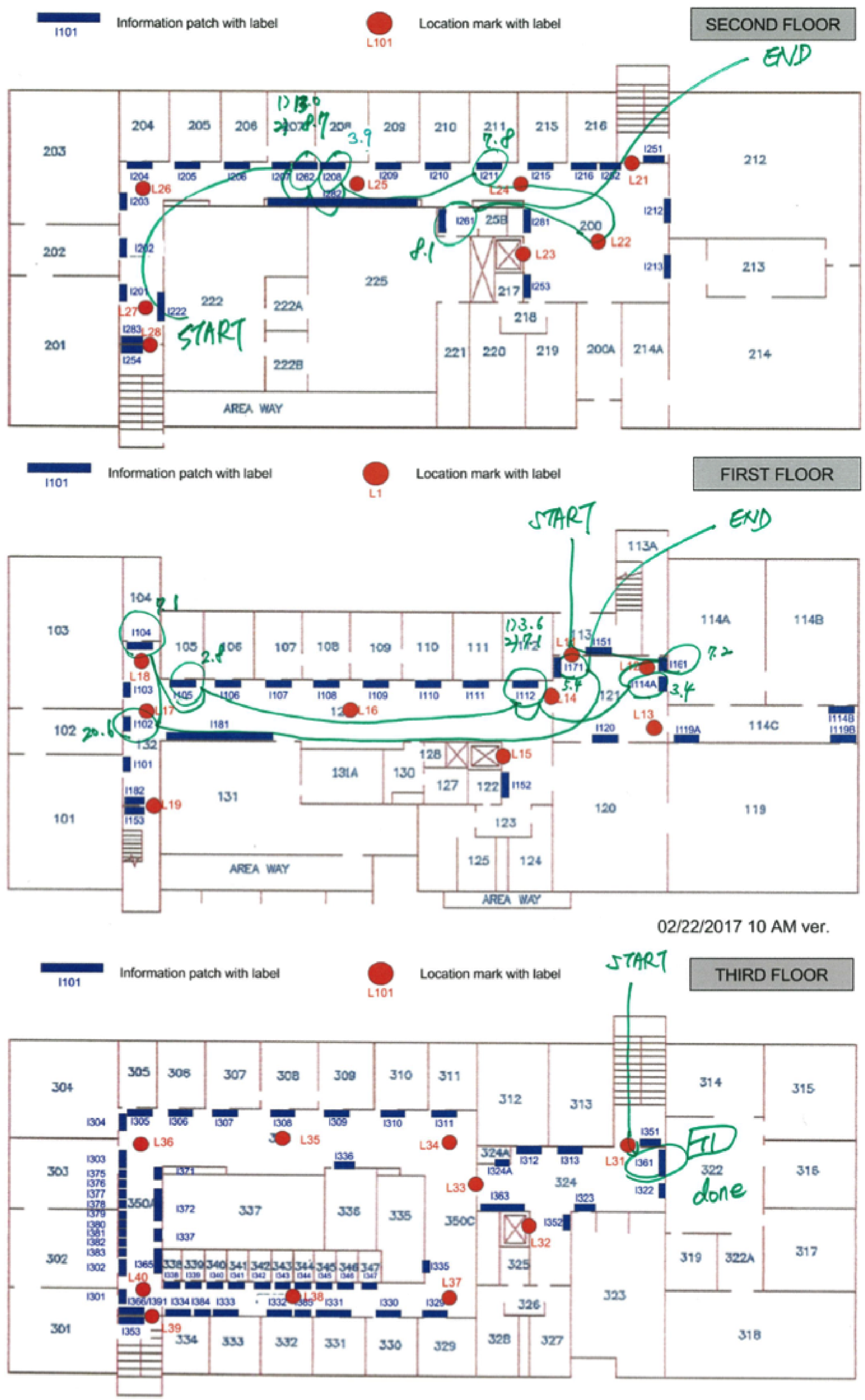


Figure D.2: Annotated behavior of *user46* in *Treasure Hunt*.

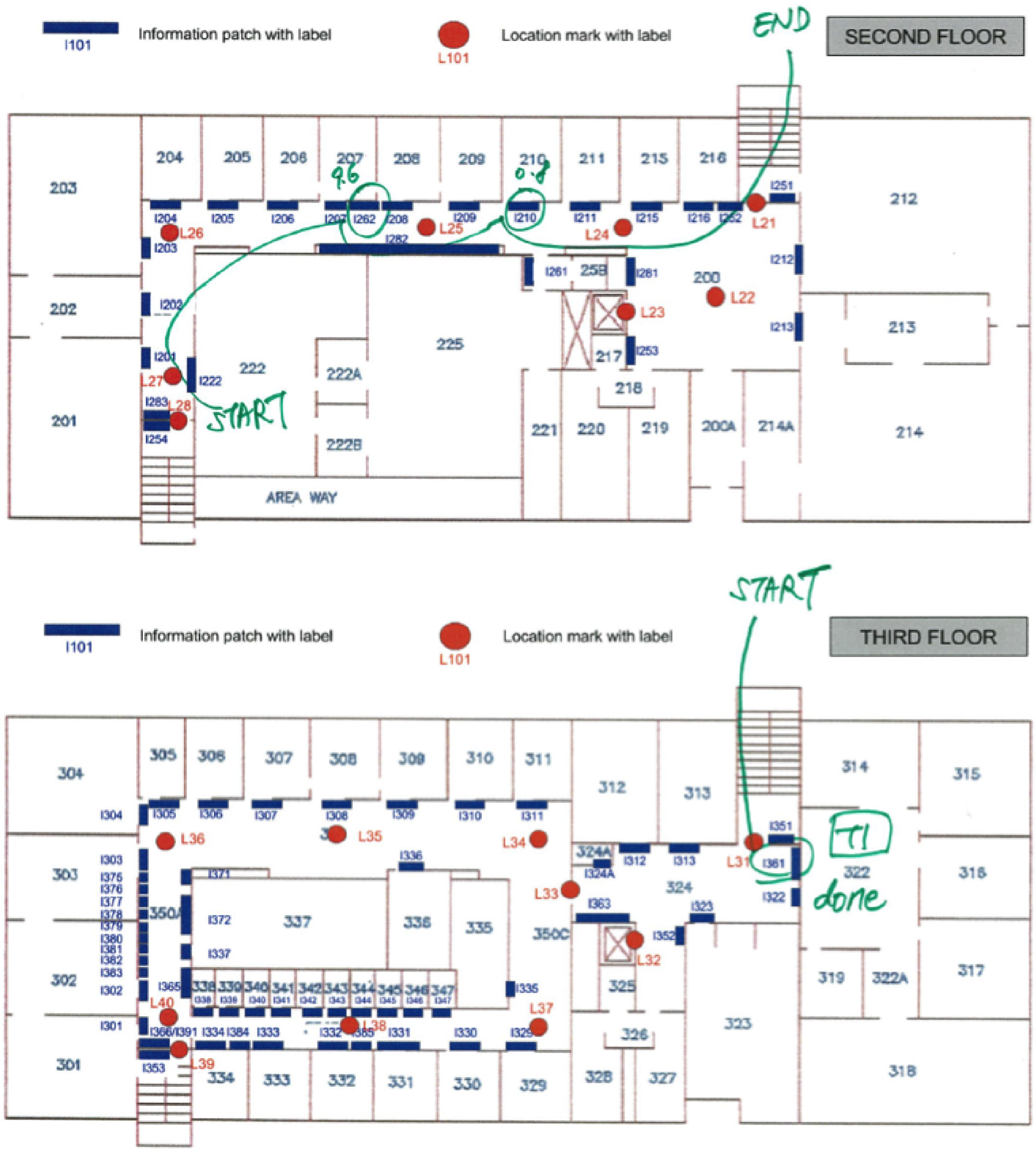


Figure D.3: Annotated behavior of *user38* in *Treasure Hunt*.

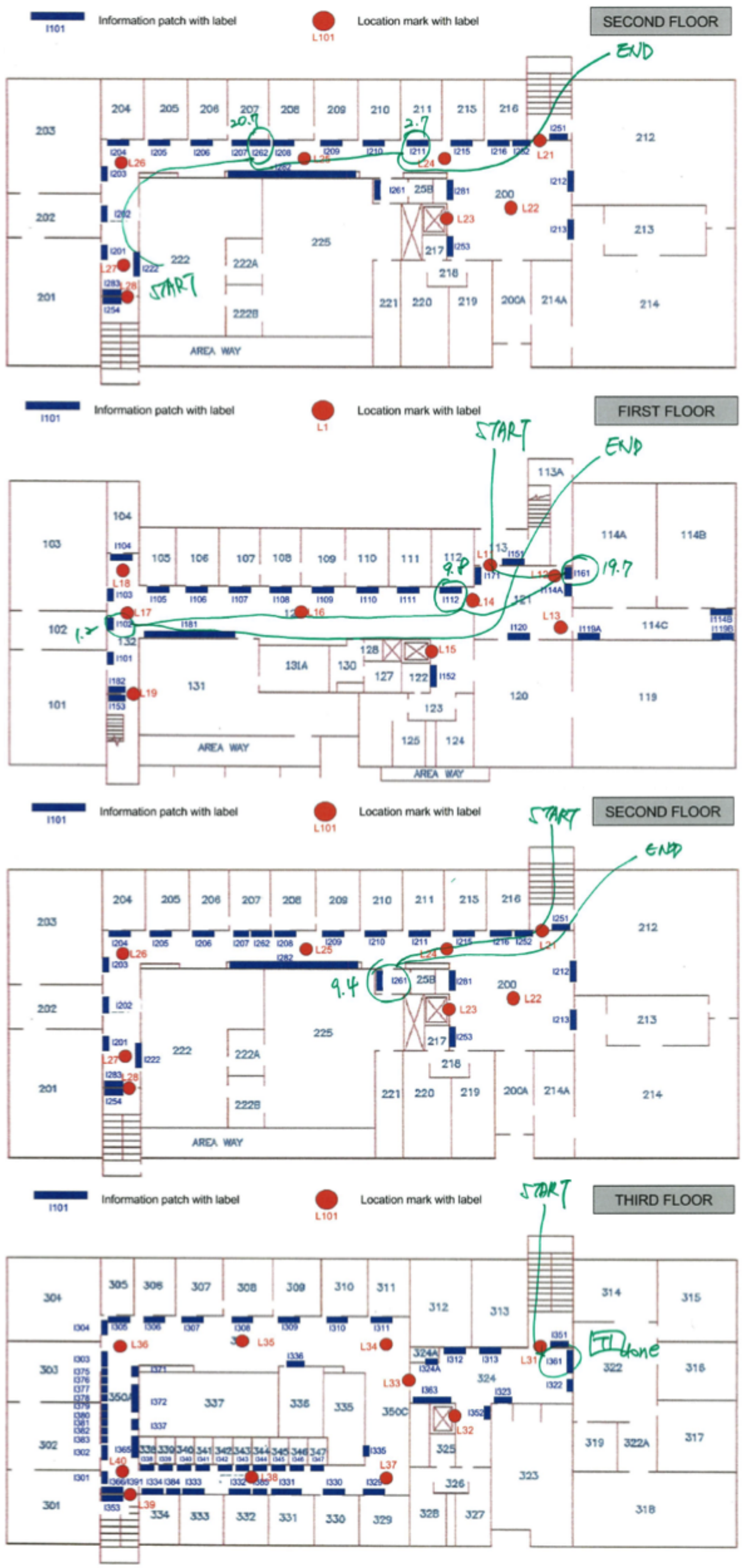


Figure D.4: Annotated behavior of *user26* in *Treasure Hunt*.

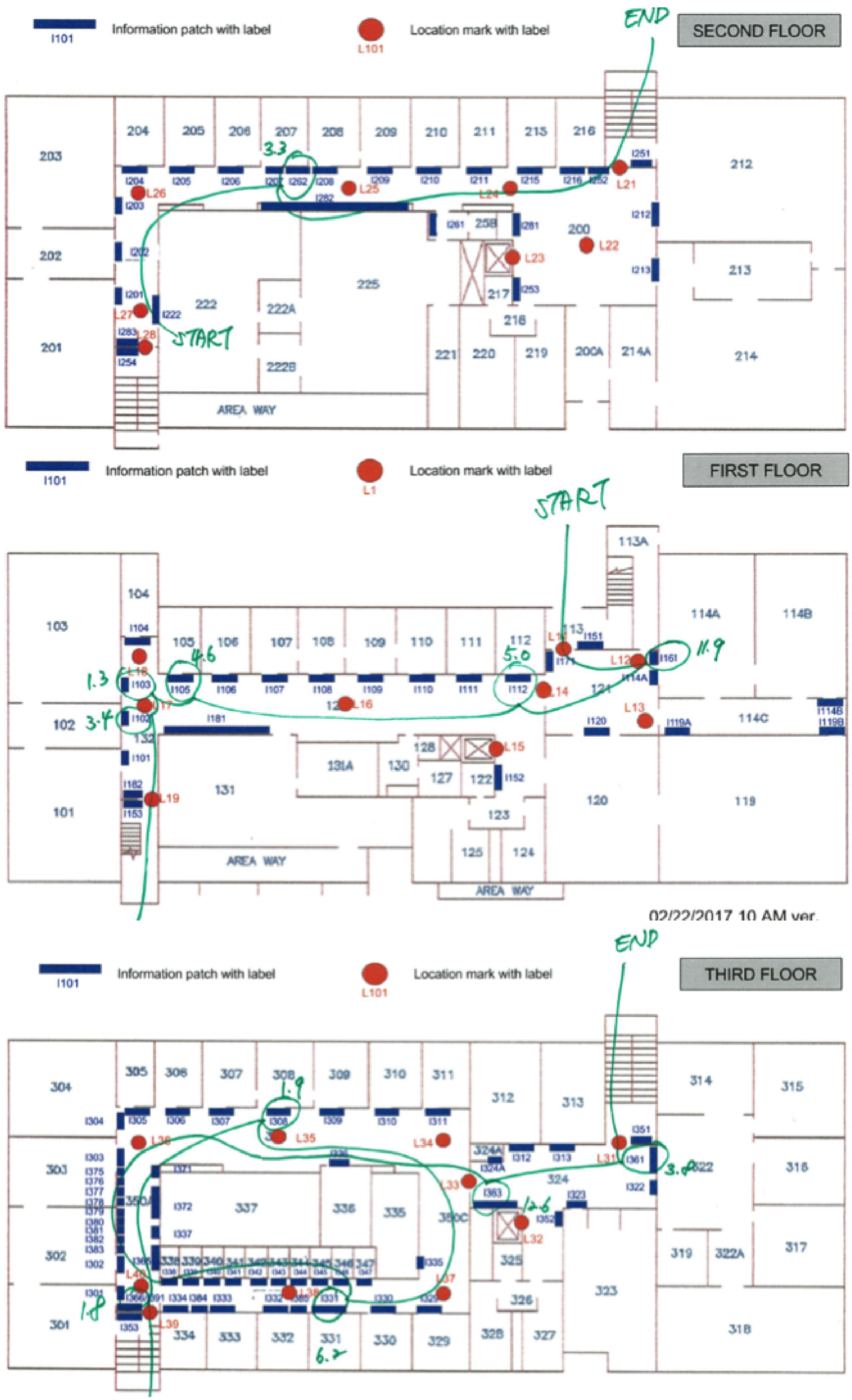


Figure D.5: Annotated behavior of *user16* in *Treasure Hunt*: First half.

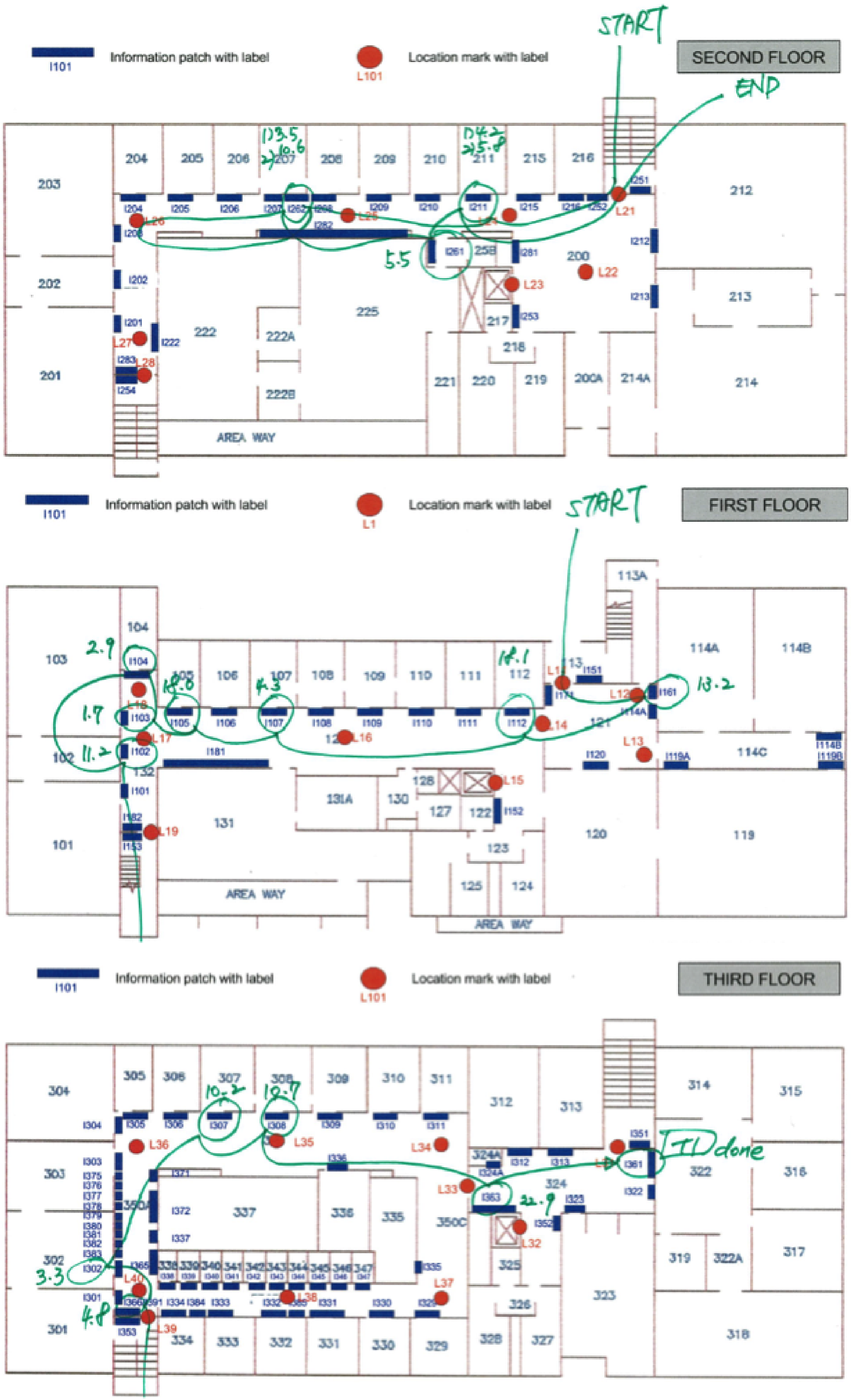
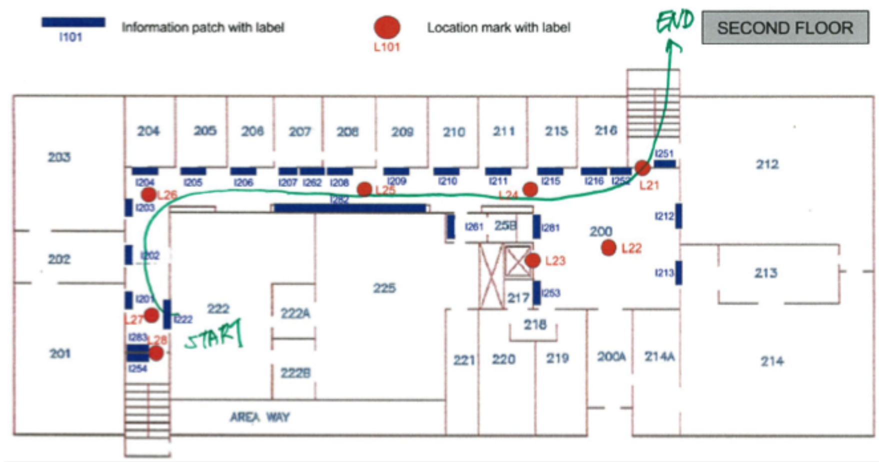


Figure D.6: Annotated behavior of *user16* in *Treasure Hunt*: Second half.

[2nd floor as first floor session]



[1st floor as second floor session]

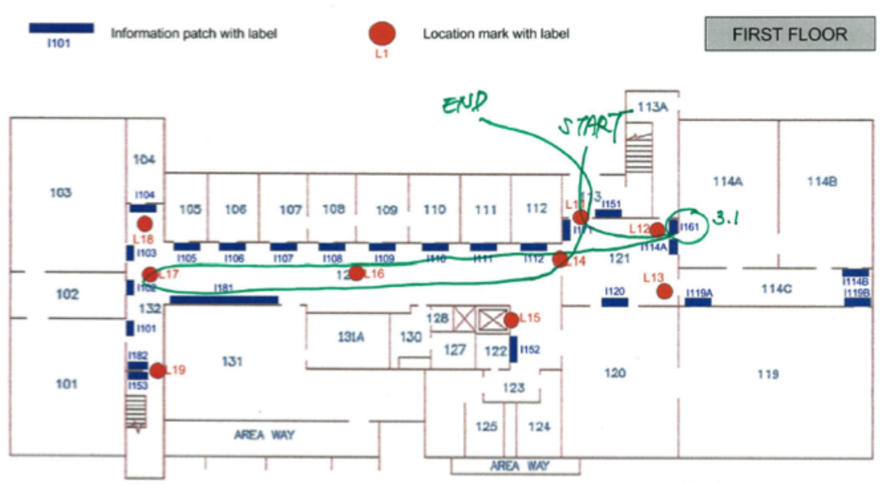
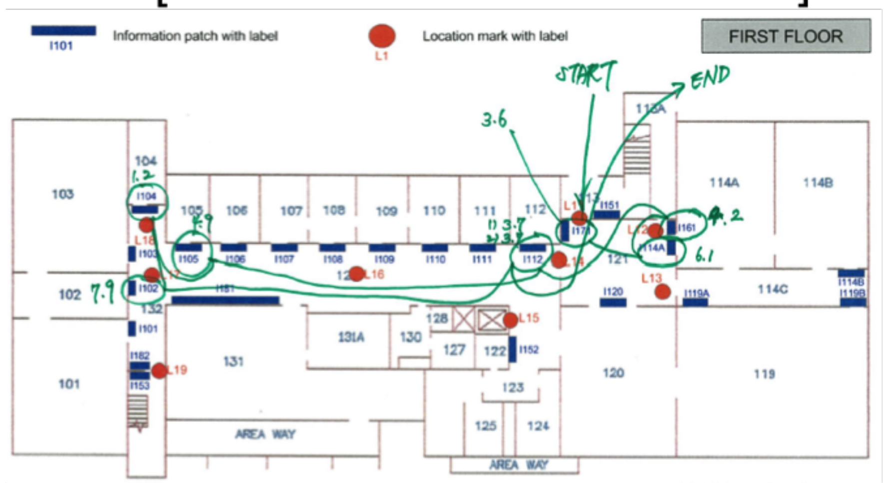


Figure D.7: Search paths of *user7* the first *floor session* (2nd floor) and the second *floor session* (1st floor)

[1st floor as sixth floor session]



[2nd floor as seventh floor session]

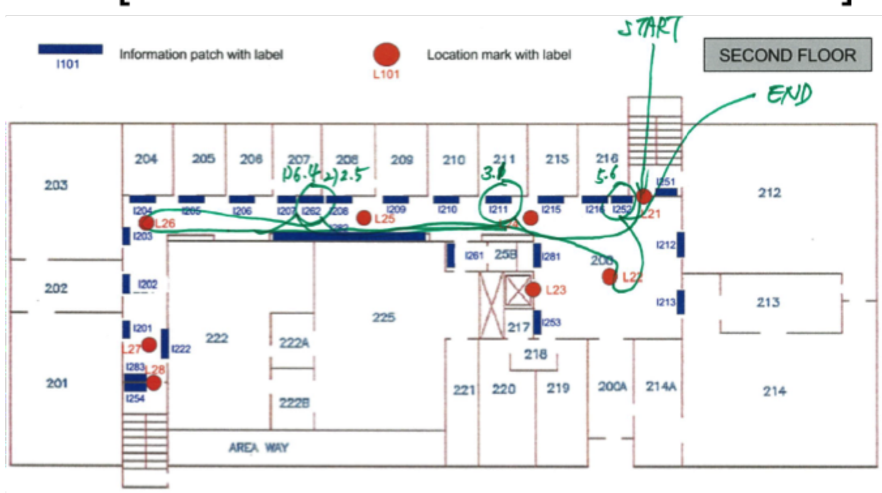


Figure D.8: Search paths of *user7* of the sixth *floor session* (2nd floor) and the seventh *floor session* (1st floor)

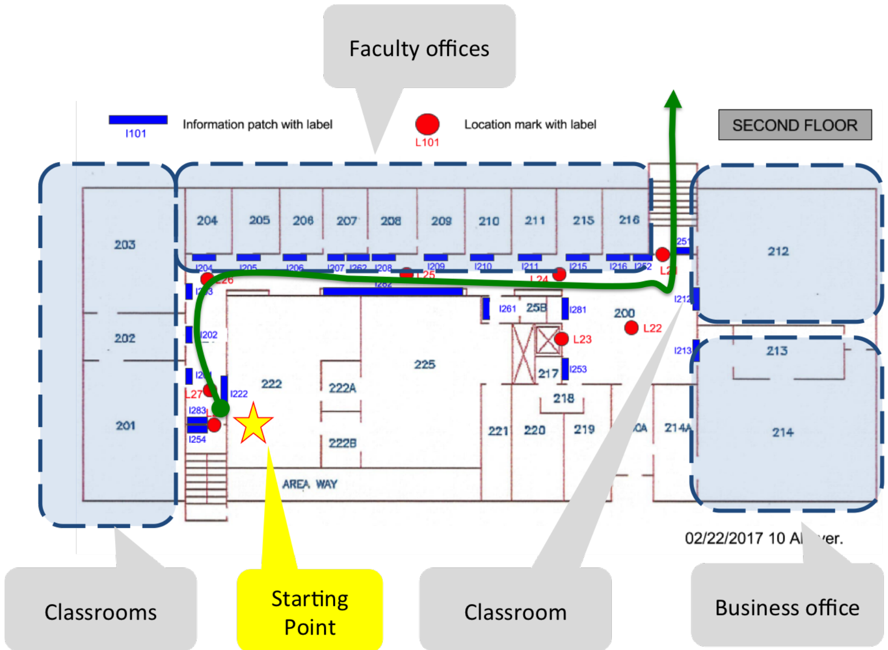


Figure D.9: Organization of 2nd floor of the building

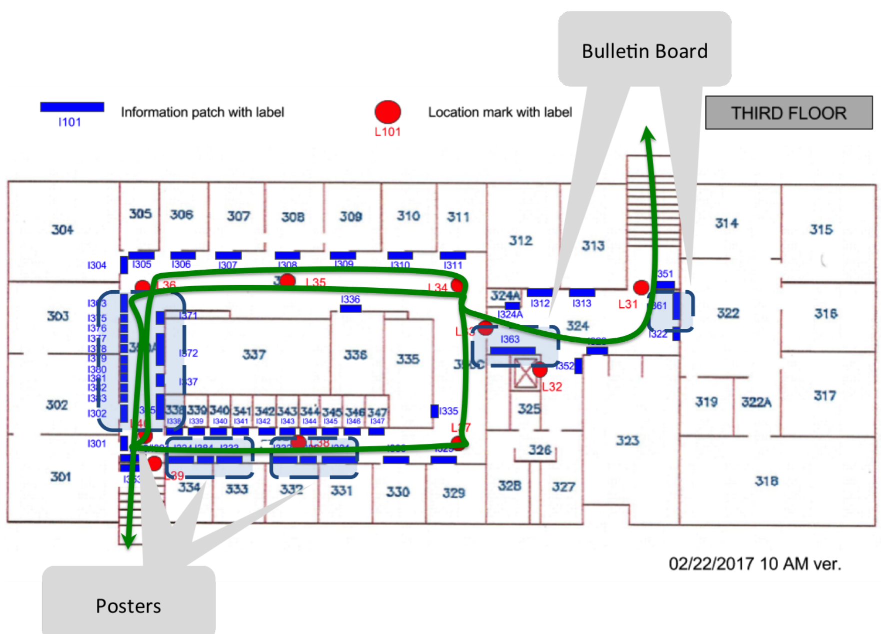


Figure D.10: Organization of 3rd floor of the building

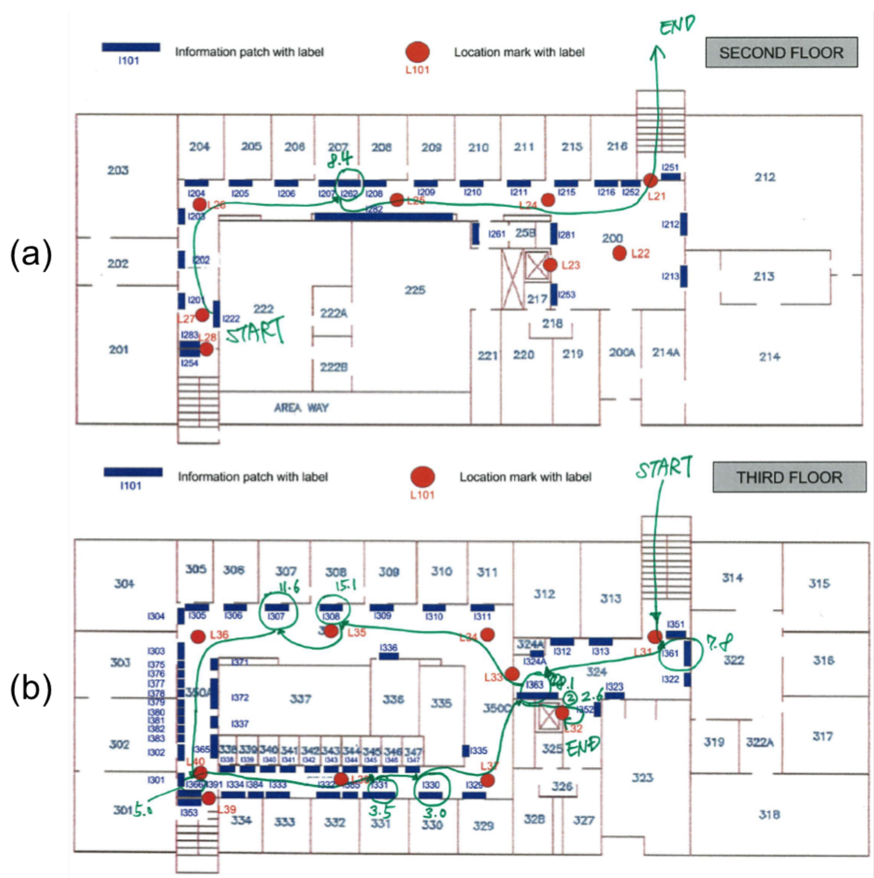


Figure D.11: Search paths of *user2* on 2nd floor and 3rd floor