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LongSAL: A Longitudinal Search as Learning Study With University Students

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LongSAL: A Longitudinal Search as Learning Study With University Students

by

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Abstract

LongSAL: A Longitudinal Search as Learning Study With University Students

Nilavra Bhattacharya নীলাভ্র ভট্টাচার্য্য, PhD
The University of Texas at Austin, 2023

Supervisor: Jacek Gwizdka

Learning today comprises navigation, discernment, induction, and synthesis of the wide body of information on the Internet present ubiquitously at every student's fingertips. Learning, or addressing a gap in one's knowledge, has been well established as an important motivator behind information-seeking activities. The Search as Learning research community advocates that online information search systems should be reconfigured to become educational platforms to foster learning and *sensemaking*. Modern search systems have yet to adapt to support this function. An important step to foster learning during online search is identifying behavioural patterns that distinguish searchers gaining more vs. less knowledge during search. Previous efforts have primarily studied searchers in the short term, typically during a single lab session. Researchers have expressed concerns over this ephemeral approach, as learning takes place over time, and is not fleeting. In this dissertation, an exploratory longitudinal study was conducted to observe the long-term searching behaviour of students enrolled in a university course, over the span of a semester. Our research aims were to identify if and how students' searching behaviour changes over time, as they gain new knowledge on a subject; and how individual traits such as motivation, metacognition, self-regulation, and other individual differences moderate their searching as learning behaviour. We found that differences in these traits create observable and quantifiable differences in information searching as a learning activity. Students with higher levels of metacognition, self-regulation, and motivation were more effective and efficient in

their search behaviours, reported better learning and search outcomes, and obtained better grades. We posit that learning environments should be designed to foster the effective use of metacognitive strategies to help learners develop and apply productive self-regulated learning. Moreover, learning technologies can be used to induce, track, model, and support learners' metacognition across tasks, domains, and contexts. The study recommends that understanding the complex relationship between motivation and metacognition is essential to designing effective searching as learning environments. Findings from this exploratory longitudinal study will help to build improved search systems that foster human learning and sensemaking, which are more equitable in the face of learner diversity.

সারসংক্ষেপ (Abstract in Bengali)

লংস্যাল: ইন্টারনেটে তথ্য অনুসন্ধানের মাধ্যমে শিক্ষার্থীদের জ্ঞানলাভের অভ্যাস বিশ্লেষণের জন্য একটি দীর্ঘ মেয়াদি গবেষণা

নীলাভ্র ভট্টাচার্য্য, পিএইচডি
টেক্সাস বিশ্ববিদ্যালয়, অস্টিন, মার্কিন যুক্তরাষ্ট্র, শ্রাবণ ১৪৩০ (আগস্ট ২০২৩)

অধীক্ষক: ডঃ ইয়াৎসেক গুইজদকা

বর্তমান যুগে শিক্ষালাভ এবং দৈনন্দিন জীবনযাপনের একটা বড় অংশ হলো ইন্টারনেট থেকে সঠিক তথ্য বা ইনফরমেশন খুঁজে বার করা, এবং তা থেকে জ্ঞান অর্জন করা। এই বিষয়ে সবচেয়ে অগ্রগামী গবেষণা সম্প্রদায়ের নাম হলো ``সার্চ অ্যাস লার্নিং'' (search as learning) বা ``তথ্য অনুসন্ধানের মাধ্যমে শিক্ষা''। ``সার্চ অ্যাস লার্নিং'' গবেষকরা মনে করেন যে আজকালকার সার্চ ইঞ্জিনগুলি (যেমন গুগল, বিং, ইয়াহু, ইত্যাদি) এখনো মানুষকে শিক্ষালাভ বা জ্ঞানলাভ করতে পুরোপুরি সাহায্য করতে পারে না। সার্চ ইঞ্জিনগুলি কেবল তথ্য অনুসন্ধানের নিমিত্ত মাত্র। তারা যে তথ্য গুলি খুঁজে বার করে, সেগুলো আমাদের কাজের জন্য প্রাসঙ্গিক, বিশ্বাসযোগ্য, বা সত্য কিনা, তার সিদ্ধান্ত নেওয়া সম্পূর্ণ আমাদের উপর নির্ভর করে; গুগল, বিং, বা ইয়াহু এটি তাদের দায়িত্ব হিসেবে দেখে না। তার উপর বিভিন্ন উৎস বা সার্চ রেজাল্ট থেকে যে সমস্ত তথ্য হাজির করে সার্চ ইঞ্জিনগুলি, সেই সমস্ত তথ্য একত্রিত করতেও আমাদের নিজস্ব বোধশক্তির প্রয়োগ করতে হয়; সার্চ ইঞ্জিনগুলি এখনো পর্যন্ত এ ব্যাপারে সম্পূর্ণ অক্ষম। অতএব ``সার্চ অ্যাস লার্নিং'' গবেষকরা প্রস্তাব করেছেন যে ভবিষ্যতের সার্চ ইঞ্জিনগুলিকে এই সমস্ত অক্ষমতা অতিক্রম করে মানুষের প্রকৃত জ্ঞানলানভের উপযোগী করতে হবে। এই বিষয়ে একটি গবেষণার দিক হলো শিক্ষার্থীদের ইন্টারনেটে তথ্য অনুসন্ধানের অভ্যাস গুলির বিশ্লেষণ করা, এবং সেখান থেকে কিছু অভ্যাসের প্যাটার্ন বা নমুনা সংগ্রহ করা। এই প্যাটার্ন গুলি থেকে বোঝা যেতে পারে যে কোন কোন অভ্যাসগুলি রপ্ত করলে ইন্টারনেটে তথ্য খুঁজে শিক্ষালাভ তাড়াতাড়ি হয়, আর কোন কোন অভ্যাসগুলি শিক্ষালাভের পথে বাধার সৃষ্টি করে। এই বিষয়ে অধিকাংশ পূর্ববর্তী গবেষকরা শিক্ষার্থীদের ইন্টারনেট ব্যবহার কেবলমাত্র কয়েক ঘণ্টার জন্য বিশ্লেষণ করেছেন। শিক্ষা এবং জ্ঞানলাভ একটি সময়সাপেক্ষ প্রক্রিয়া। ল্যাবরেটরিতে পড়ুয়াদের ডেকে এনে কয়েক ঘণ্টার জন্য তাদের ইন্টারনেট ব্যবহার পর্যবেক্ষণ করলে খুব সাময়িক একটা চিত্র পাওয়া যায়। ``সার্চ অ্যাস লার্নিং'' গবেষকরা এই ক্ষণস্থায়ী পদ্ধতির বিষয়ে বিশেষ উদ্বেগ প্রকাশ করেছেন: কারণ শিক্ষালাভ এত ক্ষণস্থায়ী নয়, তা দীর্ঘ সময়ের সাথে সংঘটিত হয়। এই পিএইচডি থিসিসে একটি ৫ মাস ব্যাপী দীর্ঘ মেয়াদী গবেষণা পরিচালনা

করা হয়েছে। এই গবেষণার মূল উদ্দেশ্য ছিলো বিশ্ববিদ্যালয়ের শিক্ষার্থীরা তাদের ইন্টারনেট ব্যবহারের অভ্যাস কেমন ভাবে নিয়ন্ত্রণ করে, এবং এই অভ্যাসগুলির সময়ের সাথে সাথে পরিবর্তন হয় কিনা, তার বিশ্লেষণ করা। এছাড়াও দেখা হয়েছে যে শিক্ষার্থীদের মনস্তাত্ত্বিক বৈশিষ্ট্যগুলি ---- তথা প্রেরণা বা মোটিভেশন (motivation), নিজস্ব চিন্তার বিষয়ে সচেতনতা বা মেটাকগনিশন (metacognition), এবং স্ব-নিয়ন্ত্রণ ক্ষমতা বা সেলফ-রেগুলেশন (self-regulation) ---- ইন্টারনেটে তথ্য অনুসন্ধানের মাধ্যমে জ্ঞানলাভের ক্ষেত্রে কোন প্রভাব সৃষ্টি করে কিনা। ২০২২ সালের জানুয়ারি থেকে মে মাস পর্যন্ত এই গবেষণাটি পরিচালনা করা হয়, এবং জুন ২০২২ থেকে জানুয়ারি ২০২৩ অবধি তার ফলাফল বিশ্লেষণ করা হয়। গবেষণার ফলাফলে দেখা গেছে যে মেটাকগনিশন, সেলফ-রেগুলেশন, এবং মোটিভেশন প্রকৃতপক্ষে শিক্ষার্থীদের ইন্টারনেট ব্যবহারের অভ্যাসের পার্থক্য সৃষ্টি করে। যে সমস্ত শিক্ষার্থীদের মেটাকগনিশন, সেলফ-রেগুলেশন, এবং মোটিভেশন বেশি ছিলো, তারা সুদক্ষ ভাবে ইন্টারনেটে তথ্য অনুসন্ধান করতে পেরেছে, এবং একই সাথে তারা ক্লাসে ভালো নম্বরও পেয়েছে। অন্যদিকে, যে সমস্ত শিক্ষার্থীদের মেটাকগনিশন, সেলফ-রেগুলেশন, এবং মোটিভেশন কম ছিলো, তাদের পক্ষে ইন্টারনেটে তথ্য অনুসন্ধান, এবং ক্লাসে ভালো নম্বর পাওয়া বিশেষ ভাবে কঠিন ও শ্রমসাধ্য হয়ে পড়ে। অতএব, এই গবষণার ফলাফল সুপারিশ করে যে ক্লাসরুম এবং অনলাইন শিক্ষার পরিবেশগুলি এমনভাবে তৈরি করা উচিৎ যাতে সেই পরিবেশগুলি শিক্ষার্থী তথা সাধারণ মানুষকে তাদের নিজস্ব চিন্তার বিষয়ে সচেতনতা বৃদ্ধি করতে সাহায্য করে, এবং মেটাকগনিটিভ কৌশলগুলির কার্যকর ব্যবহারকে উৎসাহিত করে। এর ফলে আমরা ভবিষ্যতে নতুন ধরণের তথ্য অনুসন্ধান এবং শিক্ষালাভের পরিবেশের সৃষ্টি করতে পারব, যেখানে প্রতিটি বৈচিত্র্যময় মানুষ তার নিজস্ব মতে সুদক্ষ ভাবে শিক্ষালাভ তথা জ্ঞানলাভ করতে পারবে, এবং যা বৈচিত্র্যময় শিক্ষার্থীদের জন্য আরও বেশি ব্যবহারোপযোগী, যথাযথ, এবং ন্যায়সঙ্গত হবে।

(বাংলা অনুবাদে সাহায্যের জন্য বিশেষ কৃতজ্ঞতা স্বীকার: রিফাত রহমান, শুচিস্মিতা ঘোষ, সাগ্নিকা দাস, ডঃ সৌরভ সিকদার, তিতিক্ষা সরকার, ও তপতী সরকার। Special thanks for help and guidance with the Bengali translation: Rifat Rahman, Suchismita Ghosh, Sagnika Das, Dr. Sourav Sikdar, Titiksha Sarkar, and Tapati Sarkar.)

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1 Introduction

1.1 Searching as Learning: Overview

Searching for information is a fundamental human activity. In the modern world, it is frequently conducted by users interacting with online search systems (e.g., web search engines), or more formally, **Information Retrieval** (IR) systems. As early as in 1980, Bertam Brookes, in his 'fundamental equation' of information and knowledge, had stated that an information searcher's current state of knowledge is changed to a new knowledge structure by exposure to information (Brookes, 1980, p. 131). This indicates that searchers acquire new knowledge in the search process, and the same information will have different effects on different searchers' knowledge states. Fifteen years later, Marchionini (1995) described information seeking as "a process, in which humans purposefully engage in order to change their state of knowledge". Thus, we have known for quite a while that search is driven by higher-level human needs, and IR systems are a means to an end, and not the end in itself. **Interactive information retrieval** (IIR), a.k.a. human-computer information retrieval (HCIR) (Marchionini, 2006) refers to the study and evaluation of users' interaction with IR systems and users' satisfaction with the retrieved information (Borlund, 2013).

Despite their technological marvels, modern IR systems falls short in several aspects of fully satisfying the higher level human need for information. In essence, IR systems are software that take, as input, some query, and return as output some ranked list of resources.

> *Within the context of information seeking, (search engines and IR systems)* ***feel*** *like they play a prominent role in our lives, when in actuality, they only play a small role: the* ***retrieval*** *part of information . . .*
>
> - *Search engines* ***don't help us identify what we need*** *– that's up to us; search engines don't question what we ask for, though they do recommend queries that use similar words.*
> - *Search engines* ***don't help us choose a source*** *– though they are themselves a source, and a heavily marketed one, so we are certainly compelled to choose search engines over other sources, even when other sources might have better information.*
> - *Search engines* ***don't help us express our query*** *accurately or precisely – though they will help with minor spelling corrections.*
> - *Search engines do help retrieve information—this is the primary part that they automate.*
> - *Search engines* ***don't help us evaluate the answers we retrieve*** *– it's up to us to decide whether the results are relevant, credible, true; Google doesn't view those as their responsibility.*
> - *Search engines* ***don't help us sensemake*** *– we have to use our minds to integrate what we've found into our knowledge.*
>
> — Ko (2021)

In recent years, the IIR research community has been actively promoting the **Search as Learning** (SAL) research direction. This fast-growing community of researchers propose that search environments should be augmented and reconfigured to foster learning, sensemaking, and long-term knowledge-gain. Various workshops and seminars have been organized to develop research agendas at the interaction of IIR and the Learning Sciences (Agosti et al., 2014; Allan et al., 2012; Collins-Thompson et al., 2017; Freund et al., 2013, 2014; Gwizdka et al., 2016). Additionally, special issues on Search as Learning have also been published in the *Journal of Information Science* (Hansen & Rieh, 2016) and in the *Information Retrieval Journal* (Eickhoff et al., 2017). Articles in these special issued presented landmark literature reviews (Rieh et al., 2016; Vakkari, 2016), research agendas, and ideas in this direction. Overall, these works generally advocate that future research in this domain should aim to:

- understand the contexts in which people search to learn
- understand factors that can influence learning outcomes
- understand how search behaviours can predict learning outcomes
- develop search systems to better support learning and sensemaking
- help searchers be more critical consumers of information
- understand the cognitive biases fostered by existing search systems
- develop search engine ranking algorithms and interface tools that foster long term knowledge gain

Parallelly, the Educational Science and the Learning Science research communities have also been organizing workshops and formulating research agendas to conceptualize forms of 'new learning' (Cope & Kalantzis, 2013; Kalantzis & Cope, 2012; New London Group, 1996) that are afforded by innovations in digital technologies and e-learning ecologies (Cope & Kalantzis, 2017). Higher education researchers have been increasingly studying how students' information search and information use behaviour affect and support their learning (Weber et al., 2018, 2019; Zlatkin-Troitschanskaia et al., 2021). Efforts are underway to conceptualize a theoretical framework around new forms of e-Learning that is aided and afforded by digital technologies (Amina, 2017; Cope & Kalantzis, 2017). In the community's own words: "learning today is more about navigation, discernment, induction, and synthesis" of the wide body of information present ubiquitously at every student's fingertips (Amina, 2017). Therefore, "knowing the source, finding the source, and using the information aptly is important to learn and know now more than ever before" (Cope & Kalantzis, 2013). All of these interests in the intersection of searching and learning goes to emphasize that understanding learning during search is critical to improve human-information interaction.

1.2 Problem Statement

A major limitation in the area of Search as Learning, Interactive IR (IIR), and more broadly, in Human-Computer Interaction (HCI) research is that, the user is examined in the short-term, typically over the course of a single experimental session in a lab (Karapanos et al., 2021; Kelly et al., 2009; Koeman, 2020; Zlatkin-Troitschanskaia et al., 2021). Very few studies exist in the search-as-learning domain that have observed *the same participant* over a longer period of time than a single search session (Kelly, 2006a, 2006b; Kuhlthau, 2004; Vakkari, 2001a; White et al., 2009; Wildemuth, 2004). This ephemeral approach has acute implications in any domain where learning is involved because "learning is a *process* that leads to *change* in knowledge ... (which) unfolds over time" (Ambrose et al., 2010), and "... does not happen all at once" (White, 2016b).

To the best of the author's knowledge, almost no new longitudinal studies were reported in major search-as-learning literature in the last five years, that systematically studied students' information search behaviour and information-use over the long term, in their *in-situ* naturalistic environment and contexts, and linked those behaviours quantitatively to the students' learning outcomes and individual differences.

Higher education students are increasingly using the Internet as their main learning environment and source of information when studying. Yet, the short term nature of research in this domain creates significant gaps in our knowledge regarding how students' information search behaviour and information use develop over time, and how it affects their learning (Zlatkin-Troitschanskaia et al., 2021).

> *When research in this area relies so heavily on (short-term) lab studies, can we realistically say we are comprehensively studying human-tech interactions – when many of those interactions take place over long periods of time in real-world contexts? ... An over-reliance on short studies risks inaccurate findings, potentially resulting in prematurely embracing or disregarding new concepts.*
>
> — Koeman (2020)

Current search engines and information retrieval systems "do not help us know what we want to know, ...do not help us know if what we've found is relevant or true; and they do not help us make sense of the retrieved information. All they do is quickly retrieve what other people on the internet have shared" (Ko, 2021). Unless we have more long-term understanding of the nature of knowledge gain during search, the limitations of current search systems will continue to persist. Increased knowledge and understanding of students', and more broadly searchers', information searching and learning behaviour over time will help us to overcome the limitations of current IR systems, and transform them into rich learning spaces where "search experiences and learning experiences are intertwined and even synergized" (Rieh, 2020). The internet and digital educational technologies offer great opportunities to transform learning and the education experience. Enabled by our increased comprehension of the longitudinal searching-as-learning process, improved and validated by empirical data, we can create a new wave of fundamentally transformative educational technologies and "e-learning ecologies, that will be more engaging for learners, more effective (than traditional classroom practices), more resource efficient, and more equitable in the face of learner diversity" (Cope & Kalantzis, 2017).

1.3 Purpose of this Dissertation

To address the gaps in our knowledge of how information searching influences students' learning process over time, this dissertation conducted a semester-long longitudinal study (approx. 16 weeks) with university student participants. The overarching research aim is to identify how students' online searching behaviour correlate with their learning outcomes for a particular university course. Building upon principles from the Learning Sciences (Ambrose et al., 2010; National Research Council, 2000; Novak, 2010; Sawyer, 2005), and empirical evidences from the Information Sciences (Rieh et al., 2016; Vakkari, 2016; White, 2016a), this dissertation aimed at:

- situating students as learners in their naturalistic contexts, and characterized by their individual differences
- measuring students' information search and information use behaviour over time

- correlating the information search behaviour with the learning outcomes for the university course

Learning, or addressing a gap in one's knowledge, has been well established as an important motivator behind information-seeking activities Section 1.1. Therefore, search systems that support rapid learning across a number of searchers, and a range of tasks, can be considered as more effective search systems (White, 2016a, p. 310). This dissertation takes a step in this direction. "It opens great expectations for many-sided, great contribution to our knowledge on the relations between search process and learning outcomes" (anonymous reviewer for Bhattacharya, 2021).

1.4 Outline

This dissertation document is structured as follows. First, principles of learning and relevant background from the domain of Educational Sciences are presented in Chapter 2. Next, relevant empirical evidences from the Information Searching Literature are discussed in Chapter 3. Chapter 4 presents the research questions, and discusses their rationale in the context of the existing research gaps. Chapter 5 describes the research methods, specifically the longitudinal study design and experimental procedures. Chapter 6 and 7 presents the data analyses framework, results, and discussions of the findings the study. Chapter 8 places the findings in terms of the research questions introduced in Chapter 4. Finally, Chapter 9 presents the conclusion, limitations, and future work.

2

Background: Knowledge and Learning

This first chapter on background literature discusses relevant concepts from the disciplines of Education and Learning Sciences. First, we introduce some relevant terminology, and the concepts of deep or meaningful learning. Then we discuss several research backed principles that have been shown to lead to meaningful learning. Next, we discuss how learning, sensemaking, and searching for information are related, and how modern technologies provide affordances for new forms of learning and knowledge work in the 21st century. We also discuss some concepts about individual differences of learners as well as techniques that can promote better learning. In the last section, we state what implications these findings have for shaping the longitudinal study in this dissertation.

2.1 Terminology

The Webster dictionary[1] defines **knowledge** in two ways. The first definition is "the range of one's information or understanding". Vakkari (2016) says it is "the totality what a person knows, that is, a **personal knowledge** or **belief system**. It may include both justified, true beliefs and less justified, not so true beliefs, which the person more or less thinks hold true." Webster's

[1] https://www.merriam-webster.com/dictionary/knowledge

second definition of knowledge is "the sum of what is known: the body of truth, information, and principles acquired by humankind". We can regard this as **universal knowledge**.

Learning is a *process*, that leads to a *change* in (personal) knowledge, beliefs, behaviours, and attitudes (Ambrose et al., 2010). Thus, learning always aims to increase one's personal knowledge, and can often draw from the body of universal knowledge. In some cases, the change in personal knowledge can also lead to change in universal knowledge, such as when new discoveries are made, or new philosophies are proposed. Human learning is an innate capacity. It is longitudinal and unfolds over time. Learning is lifelong and life-wide, and has a lasting impact on how humans think and act (Ambrose et al., 2010; Kalantzis & Cope, 2012). Learning can be informal or formal. **Informal learning** is the casual learning taking place in everyday life, and is incidental to the everyday life experience. **Formal learning** is the deliberate, conscious, systematic, and explicit acquiring of knowledge (Kalantzis & Cope, 2012).

Education is a form of formal learning. It is the systematic acquiring of knowledge. In today's world, the institutions of education are formally constructed places (classrooms), times (of the day and of life) and social relations (teachers and students); for instance, schools, colleges, and universities. The scientific discipline of Education concerns itself with the systematic investigation of the ways in which humans know and learn. It is the science of "coming to know" (Kalantzis & Cope, 2012).

Pedagogy describes small sequences of learner activities that promote learning in educational settings (Kalantzis & Cope, 2012). Traditional approaches to (classroom) pedagogy, especially the *didactic pedagogy*, primarily involves a teacher telling, and a learner listening. The teacher is in command of the knowledge, and their mission is to transmit this knowledge to the learners, in a one-way flow. It is hoped that the learners will dutifully absorb the knowledge laid before them by the teacher. The balance of agency weighs heavily towards the teacher. "There is a special focus on long-term memory, or retention, measurable by the ritual of closed-book, summative examination" (Cope & Kalantzis, 2017).

Cognitive scientists had discovered that learners retain material better, and are able to generalize and apply it to a broader range of contexts, when they learn **deep knowledge** rather

Learning Knowledge Deeply *Findings from Cognitive Science => Reflexive Pedagogy*	**Traditional Classroom Practices** *Didactic Pedagogy => Instructionism / Surface Learning*
Knowledge Integration and Sensemaking:	
• Learners relate new ideas and concepts to previous knowledge and experience • Learners integrate their knowledge into interrelated conceptual systems • Learners look for patterns and underlying principles	• Learners treat course material as unrelated to what they already know • Learners treat course material as disconnected bits of knowledge • Learners memorize facts and carry out procedures without understanding how or why
Active Knowledge Making and Multiliteracy	
• Learners understand the process of dialogue through which knowledge is created, and they examine the logic of an argument critically	• Learners treat facts and procedures as static knowledge, handed down from an all-knowing authority
• Learners are the also knowledge producers, and discerning knowledge discoverers / navigators	• Learner is the knowledge consumer, with passive knowledge acquisition and memorization
• Multiliteracies: learners interact with new forms of media; they consume and produce multimodal knowledge artefacts (images, videos, presentations, software, etc.)	• Academic literacies: learners interact with traditional textbooks, assignments, and tests
Metacognition and Self-regulation:	
• Learners reflect on their own understanding, and their own process of learning • Thinking about thinking, critical self-reflection on knowledge processes and disciplinary practices	• Learners memorize without reflecting on the purpose, or on their own learning strategies. • Focus on facts to be remembered, theories to be correctly applied.

Figure 2.1: Deep learning (of the human kind) versus traditional (also often online) classroom practices. Compiled from Cope & Kalantzis (2017) and Sawyer (2005).

than **surface knowledge**, and when they learn how to use that knowledge in real-world social and practical settings (Sawyer, 2005). Deep learning [2] takes place when "the learner chooses conscientiously to integrate new knowledge to knowledge that the learner already possesses" and involves "substantive, non-arbitrary incorporations of concepts into cognitive structure" (Novak, 2002, p. 549) and may eventually lead to the development of transferable knowledge and skills. A parallel terminology for deep learning (Marton & Säaljö, 1976; Marton & Säljö, 1976) is **meaningful learning** (Ausubel et al., 1968; Novak, 2002), and they are often contrasted with *surface learning* or *rote learning*. Figure 2.1 discusses some more details on deep or meaningful learning, and the limitations of traditional classroom practices to promote deep learning. Figure 2.2 describes (using a concept map) how meaningful learning can be achieved and sustained,

[2] of the human kind

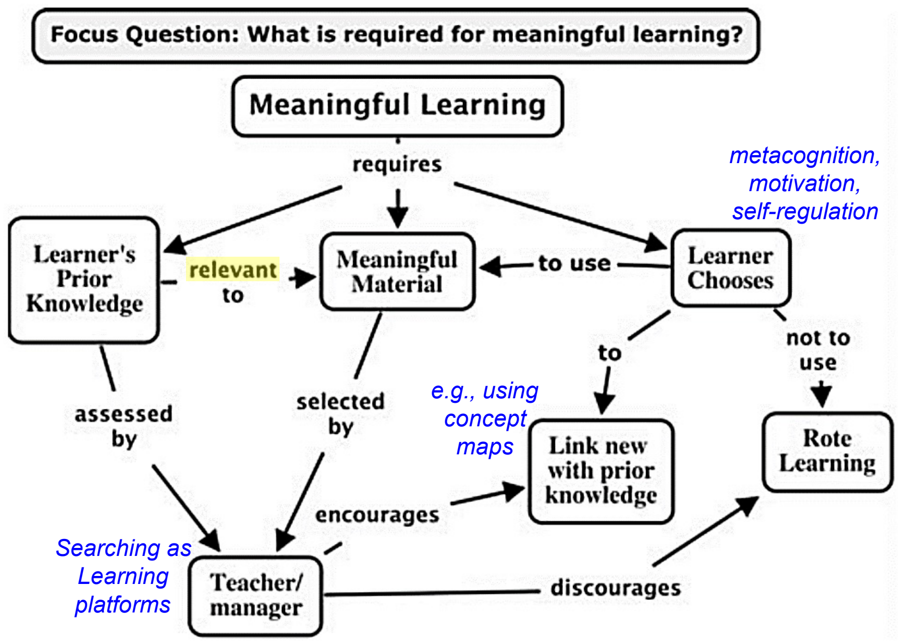


Figure 2.2: Meaningful learning (aka deep learning) as explained by Novak (2010, fig. 5.3) (annotations our own).

and our annotations highlight how Search-as-learning systems can foster the same.

2.2 Principles of Meaningful Learning

Ambrose et al. (2010) have proposed several principles of (student) learning that lead to creation of deeper knowledge in learners, and help educators understand why certain teaching approaches may help or hinder learning. These principles are based on research and literature from a range of disciplines in psychology, education, and anthropology, and the authors claim they are domain independent, experience independent, and cross-culturally relevant.

1. Students' **prior knowledge** can help or hinder learning.
2. How students **organize knowledge** influences how they learn and apply what they know.
3. Students' **motivation** determines, directs, and sustains what they do to learn.
4. Goal-directed practice coupled with **targeted feedback** enhances the quality of students' learning.

5. Students' current level of development interacts with the social, emotional, and intellectual **context** around the student to impact learning.
6. To become **self-directed** learners, students must learn to **monitor and adjust** their approaches to learning.

In line with the above, the US National Research Council identified several key principles about **experts' knowledge** (National Research Council, 2000), that illustrate the outcome of successful learning:

1. Experts notice features and **meaningful patterns** of information that are not noticed by novices.

2. Experts have acquired a great deal of content knowledge that is **organized** in ways that reflect a deep understanding of their subject matter.

3. Experts' knowledge cannot be reduced to sets of isolated facts or propositions but, instead, reflects contexts of **applicability**: that is, the knowledge is 'conditionalized' on a set of circumstances.

4. Experts are able to **flexibly retrieve** important aspects of their knowledge with little attentional effort.

5. Though experts know their disciplines thoroughly, this does not guarantee that they are able to teach others.

6. Experts have varying levels of flexibility in their approach to new situations.

The principles of learning illustrate that both the *context* of learning, and the *individual differences* of learners moderate the learning process. The findings about expert knowledge suggests that *incorporating new information into existing knowledge structures* in a meaningful manner is a key aspect of learning. We discuss these concepts in more detail in the following sections.

2.3 Meaningful Learning as Sensemaking

In this section, we discuss how meaningful learning can be further qualified using the concepts of sensemaking. **Sensemaking**[3] is a process that occurs when learners *connect* their *previously developed* knowledge, ideas, abilities, and experiences together to address the uncertainty presented by a newly introduced phenomenon, problem, or piece of information (Next Generation Science Standards, 2021). A significant portion of learning is sensemaking, especially those which use recorded information or systematic discovery to learn concepts, ideas, theories, and facts in a domain (such as science or history) (P. Zhang & Soergel, 2014). The phrase "figure something out" is often synonymous with sensemaking. Sensemaking is generally about actively trying to figure out the way the world works, and/or exploring how to create or alter things to achieve desired goals (Next Generation Science Standards, 2021). (Dervin & Naumer, 2010) distinguish work on sensemaking in four fields: "Human Computer Interaction (HCI) (Russell's sensemaking); Cognitive Systems Engineering (Klein's sensemaking); Organizational Communication (Weick's sensemaking; Kurtz and Snowden's sense-making); and Library and Information Science (Dervin's sense-making)".

Many theories of learning and sensemaking revolve around the concept of fitting new information into an existing or adapted knowledge structure (P. Zhang & Soergel, 2014). The central idea is that knowledge is stored in human memory as *structures* or *schemas*, which comprise interconnected concepts and relationships. When new information is encountered or acquired, the learner or sensemaker needs to actively construct a revised or entirely new knowledge structure. Examples of some such theories include: the *assimilation theory (theory of meaningful learning)* (Ausubel et al., 1968; Ausubel, 2012; Novak, 2002; Novak, 2010); the *schema theory* (Rumelhart & Norman, 1981; Rumelhart & Ortony, 1977); and the *generative learning theory* (Grabowski, 1996; Wittrock, 1989); all of which have their foundations in the Piagetian concepts of *assimilation* and *accommodation* (Piaget, 1936).

[3]"Brenda Dervin, one of the originators of the sense-making methodology, prefers the spelling with a hyphen, while the community in computer science and more technical people in information science (e.g., SIGCHI) use sensemaking without a hyphen" (P. Zhang & Soergel, 2014).

Assimilation means addition of new information into an existing knowledge structure. A "synonym" (Vakkari, 2016) for assimilation is **accretion**, which is the gradual addition of factual information to an existing knowledge structure, without structural changes. Accretion does not change concepts and their relations in the structure, but may populate a concept with new instances or facts. **Accommodation** means modifying or changing existing knowledge structures, by adding or removing concepts and their connections in the knowledge structure. Accommodation is subdivided into *tuning / weak-revision*, and *restructuring*, based on the degree of structural changes (P. Zhang & Soergel, 2014). **Tuning** or **weak revision** does not include replacing concepts or connections between concepts in the structure, but tuning of the scope and meaning of concepts and their connections. This may include, for example, generalizing or specifying a concept. **Restructuring** means radically changing and replacing concepts and their connections in the existing knowledge structure, or creating of new structures. Such radical changes often take place when prior knowledge conflicts with new information. New structures are constructed either to reinterpret old information or to account for new information (Vakkari, 2016; P. Zhang & Soergel, 2014). A comparison of these types of conceptual changes can be found in (P. Zhang & Soergel, 2014 Table 3).

2.3.1 Concept Maps to enhance Sensemaking

As we saw in the previous section, deep learning / meaningful learning / sensemaking is a process in which new information is connected to a relevant area of a learner's existing knowledge structure. However, the *learner must choose* to do this, and must actively seek a way to integrate the new information with existing relevant information in their cognitive structure (Ausubel et al., 1968; Novak, 2010). Learning facilitators (e.g., teachers) can encourage this choice by using the concept mapping technique.

A **concept-map** is a two-dimensional, hierarchical node-link diagram (a *graph* in Computer Science parlance) that depicts the structure of knowledge within a discipline, as viewed by a student, an instructor, or an expert in a field or sub-field. The map is composed of concept labels, each enclosed in a box (graph *nodes*); a series of labelled linking lines (*labelled edges*);

and an inclusive, general-to-specific organization (Halttunen & Jarvelin, 2005). Concept-maps assess how well students see the ''big picture", and where there are knowledge-gaps and misconceptions. A *mind map* is a diagram similar to a concept map, comprising nodes and links between nodes. However, mind maps emerge from a single centre, and have a more hierarchical, tree like structure. Concept maps are more free-form, allowing multiple hubs and clusters. Also, mind-maps have unlabelled links, and are subjective to the creator. There are no "correct" relationships between nodes in a mind map. Figure shows the key features of a concept map, with the help of a concept map.

Concept maps are therefore, arguably the most suited mechanism to represent the cognitive knowledge structures, connections, and patterns in a learner's mind. Conventional tests, such as multiple choice questions, are best at assessing students' recall of facts and guessing skills. Their format treats information as distinct and separate items, rather than interconnected pieces of a bigger picture. Concept maps on the other hand, encourage learners to identify and make connections between concepts that they know, and concepts that are new to them. Concept maps have been used for over 50 years to provide a useful and visually appealing way of illustrating and assessing learners' conceptual knowledge (Egusa et al., 2010, 2014a, 2014b, 2017; Halttunen & Jarvelin, 2005; Novak, 2010; Novak & Gowin, 1984).

Analysis of concept maps can reveal interesting patterns of learning and thinking. Some of these measures that have been used by (Halttunen & Jarvelin, 2005) are: addition, deletion, and differences in top-level concept-nodes; depths of hierarchy; and number of concepts that were ignored or changed fundamentally. In this regard, (Novak & Gowin, 1984) have presented well-established scoring schemes to evaluate concept-maps: 1 point is awarded for each correct relationship (i.e. concept–concept linkage); 5 points for each valid level of hierarchy; 10 points for each valid and significant cross-link; and 1 point for each example.

Having discussed how deep learning / meaningful learning / sensemaking involves creation of knowledge structures in the learner's mind, and suitably adding new pieces of information in the knowledge structure, we now discuss how these processes are influenced in the 21st century with the presence of new media, digital technologies, and information retrieval systems.

2.4 'New' Learning as Online Information Searching

Digital media technologies and e-learning 'ecologies' can enable new forms and models of learning, that are fundamentally different from the traditional classroom practices of didactic pedagogy (Cope & Kalantzis, 2017). Some key concepts associated with these forms of 'new learning' are described below. These concepts from the Educational Sciences domain tie back strongly to the issues, challenges, and research agenda being investigated by researchers in the Search as Learning and Information Retrieval domain (Section 1.1.

2.4.1 Active Knowledge Making

The Internet and new forms of media provide us the opportunity to create learning environments where learners are no longer mainly *consumers* of knowledge, but also *modifiers*, *producers*, and *exchangers* of knowledge. In **active knowledge making**, learners can, and often need to, find information on their own using online resources. They are not restricted to the textbook alone. The Internet is often a definitive resource for information on any given topic. A learner can search the web (to learn) at any time, from anywhere, on any web-enabled device.

As knowledge producers, learners search and analyze multiple sources with differing and contradictory perspectives, and develop their own observations and conclusions. In this process, they become researchers themselves and learn to collaborate with peers in knowledge production. Collaboration gives learners the opportunity to work with others as coauthors of knowledge, peer reviewers, and discussants to completed works. Because learners bring their own views, outlooks, and experiences, the knowledge artefact they create is often uniquely voiced instead of a templated "correct" response (Amina, 2017).

> *Learners become* ***active knowledge producers*** *(for instance, project-based learning, using multiple knowledge sources, and research based knowledge making), and not merely knowledge consumers (as exemplified in the 'transmission' pedagogies of traditional textbook learning or e-learning focused on video or e-textbook delivery). Active knowledge making practices underpin contemporary emphases on innovation, creativity and problem solving, which are quintessential 'knowledge economy' and 'knowledge society' attributes.* — Cope & Kalantzis (2017)

2.4.2 Artefacts for Learning Assessment

Traditionally, the focus of learning outcomes has been long term memory. Students and learners were expected to remember a collection of facts, definitions, proofs, equations, and other associated details. For a significant amount of modern knowledge-work today, **memory is actually less important**. Information is so readily accessible now that it is no longer necessary to remember the information. Because of the technological phenomenon, the mass of information is available ubiquitously [4] to a learner (or a knowledge worker), in every moment of learning. Empirical details such as facts, definitions, proofs, or equations do not need to be remembered today, because they can always be looked up again (Amina, 2017; Cope & Kalantzis, 2017).

This creates an interesting shift in the focus of learning and knowledge work today: *"if we are not going to measure and value long-term memory in education, what are we going to assess?"* Cope & Kalantzis (2017) suggest that **we assess the knowledge artefacts** that learners produce. In active knowledge making, the final work [5] can be proof of the learning outcome and represent a learner's ability to use the resources that are available (Amina, 2017). **Measure of learning can be measure of information quality and information use in artefacts.** This shows a shift in pedagogy and assessment and an increase in personalization and individualization of learning (Pea & Jacks, 2014). Memorizing the information on a topic is less important, compared to the writing, synthesizing, analyzing, and **sensemaking** of the available information that has been referenced in the work. This shifts the focus of assessment to the quality of the artefacts and the processes of their construction. Moreover, as technology increases the ability to capture detailed data from formal and informal learning activities, it can give us a new view of how learners progress in acquiring knowledge, skills, and attributes (DiCerbo & Behrens, 2014). Because learning is a continuous, longitudinal process, these advanced, technologically enhanced assessments are more useful in understanding the learning process and knowledge development (Amina, 2017).

[4] as long as there is internet connection

[5] be it a project report, poster, presentation, video, software,research paper, website, etc.

Assessing open-ended artefacts does come with its challenges and limitations. First, assessing and grading artefacts requires the development of detailed qualitative coding guides (M. J. Wilson & Wilson, 2013). This process involves defining grading criteria and measuring inter-coder agreement to ensure that the coding guide is reliable. Prior studies have scored summaries along dimensions such as the inclusion of facts, relationships between facts, and evaluative statements (Lei et al., 2015; Roy et al., 2021; M. J. Wilson & Wilson, 2013). Second, the quality of responses may be difficult to compare across learners. Since this type of assessment imposes very few constraints on the learners' responses, it may cause some learners to *satisfice*, and not convey everything that was learned. Additionally, writing skills are likely to vary across learners, and some may not be able to effectively articulate everything that was learnt.

2.4.3 'Information Search and Evaluation' as and for Learning

Learning today is more about **navigation, discernment, induction, and synthesis**, and less about memory and deduction (Cope & Kalantzis, 2013). However, knowing the source, finding the source, and using the information critically is important to learn and know now more than ever before (Amina, 2017). Learners must know the social sources of knowledge and understand and correctly use quotations, paraphrases, remixes, links, citations, and the like in the works that they develop. Searching and sourcing from the web entails a process of developing and completing a work that inevitably makes learners **knowledge producers**, as long as they can navigate and critically discern the value of multiple sources. This is a skill that must be learned, as many sources of information are not valid, reliable, or authentic (McGrew et al., 2018; Wineburg & McGrew, 2016). Understanding the different sources and identifying the more reliable ones are essential for effective teaching and learning (McGrew et al., 2017; McGrew, 2021). This is a critical aspect because the inability to cite properly or to use reliable resources provides learners with misconstrued information and ideas (Amina, 2017; Breakstone et al., 2021; McGrew et al., 2017).

The Stanford History Education Group (SHEG) conceptualised the **Civic Online Reasoning** (COR) curriculum [6] to enable students to effectively search for and evaluate online information (Breakstone et al., 2018; Breakstone et al., 2021; McGrew, 2020). The curriculum centres on asking three questions of any digital content: *(i)* who is behind a piece of information? *(ii)* what is the evidence for a claim? *(iii)* what do other sources say? The curriculum has lessons and assessments for information evaluation skills such as lateral reading (Wineburg & McGrew, 2017), identifying news versus opinions, checking domain names, identifying sponsored content, evaluating evidence, and practising click restraint (McGrew & Glass, 2021). The lessons were developed and piloted by the Stanford History Education Group (McGrew et al., 2018; McGrew, 2020; McGrew & Glass, 2021). Taken together, these strategies will allow academics and students to better evaluate digital content, from the perspectives of professional fact checkers.

The purview of the *Civic Online Reasoning* curriculum is more targeted than the expansive fields of media and digital literacy [7], (which can embrace topics ranging from cyberbullying to identity theft). Civic Online Reasoning focuses squarely on how to sort fact from fiction online, a prerequisite for responsible civic engagement in the twenty-first century (Breakstone et al., 2021; Kahne et al., 2012; Mihailidis & Thevenin, 2013).

2.5 Promoting Better Learning

> *It is not the technology that makes a difference; it is the pedagogy.*
>
> — Cope & Kalantzis (2017)

Having discussed how meaningful learning takes place, and how it is influenced by the presence of digital media and the mass of information on the Internet, let us now look deeper into the learners as persons themselves. In this section, we discuss how different cognitive and

[6] https://cor.stanford.edu

[7] *"Digital literacy describes a holistic approach to cultivating skills that allow people to participate meaningfully in online communities, interpret the changing digital landscape, understand the relationships between systemic -isms and information, and unlock the power of digital tools for good. This includes media literacy. Terms like critical media literacy, media literacy, news literacy, and more are not necessarily interchangeable."* – Collins (2021)

metacognitive practices and aspects of learners can promote better learning. These phenomena have important implications for any digital systems that aim to foster learning.

2.5.1 Externalization and Articulation

The learning sciences have discovered that when learners externalize and articulate their developing knowledge, they learn more effectively (National Research Council, 2000). Best learning takes place when learners articulate their unformed and still developing understanding, and continue to articulate it throughout the process of learning. This phenomenon was first studied in the 1920s by Russian psychologist Lev Vygotsky. Articulating and learning go hand in hand, in a mutually reinforcing feedback loop. Often learners do not actually learn something until they start to articulate it. While thinking out loud, they learn more rapidly and deeply than while studying quietly (Sawyer, 2005). The learning sciences community is actively researching how to support students in their ongoing process of articulation, and which forms of articulation are the most beneficial to learning. Articulation is more effective if it is scaffolded – channelled so that certain kinds of knowledge are articulated, and in a certain form that is most likely to result in useful reflection (Sawyer, 2005). Students need help in articulating their developing understandings, as they do not yet know how to think about thinking, or talk about thinking; their knowledge state is *anomalous* (Belkin et al., 1982).

2.5.2 Metacognition and Reflection

One of the reasons that articulation is so helpful to learning is that it promotes *reflection* or *metacognition*. **Metacognition**, commonly referred to as thinking about thinking, involves thinking at a higher level of abstraction, which in turn improves thinking and learning (Blanken-Webb, 2017). It is "the process of reflecting on and directing one's own thinking" (National Research Council, 2000, p. 78), and involves thinking about the process of learning, and thinking about knowledge. This ties forward to the self-regulation that effective learners exhibit (Section 2.5.4). Effective learners are aware of their learning process, and can measure how efficiently they are learning as they study.

Components of Metacognition	
Knowledge about Cognition	**Regulation of Cognition**
Declarative Knowledge: • knowledge about one's skills, intellectual resources, and abilities as a learner • the factual knowledge the learner needs before being able to process or use critical thinking related to the topic • students can obtain declarative knowledge through presentations, demonstrations, discussions **Procedural Knowledge:** • knowledge about *how* to implement learning procedures (e.g., strategies) • requires students know the process as well as when to apply process in various situations • students can obtain procedural knowledge through discovery, cooperative learning, and problem solving **Conditional Knowledge:** • knowledge about *when* and *why* to use learning procedures • the determination under what circumstances specific processes or skills should *transfer* • students can obtain conditional knowledge through simulation	**Planning:** • planning, goal-setting, and allocating resources *prior* to learning **Information Management:** • skills and strategy sequences used to process information more efficiently (e.g., organizing, elaborating, summarizing, selective focusing) **Monitoring:** • assessment of one's learning or strategy use **Debugging:** • strategies to correct comprehension and performance errors **Evaluation:** • analysis of performance and strategy effectiveness after a learning episode

Figure 2.3: Operational definitions and features of the metacognition components, adapted from Schraw & Dennison (1994) and Vancouver Island University (2021).

The literature on metacognition broadly identifies two fundamental components of metacognition: knowledge about cognition, and regulation of cognition. **Knowledge about cognition** includes three subprocesses that facilitate the *reflective* aspect of metacognition: declarative knowledge (knowledge about self and about strategies), procedural knowledge (knowledge about how to use strategies), and conditional knowledge (knowledge about when and why to use strategies). **Regulation of cognition** include a number of subprocesses that facilitate the *control* aspect of learning. Five component skills of regulation have been discussed extensively in the literature, including planning, information management strategies, comprehension monitoring, debugging strategies, and evaluation. The operational definitions of these components are described in Figure 2.3

Schraw & Dennison (1994) developed the **Metacognitive Awareness Inventory** (MAI) survey and a scoring guide to measure these self-reported components and subprocesses of

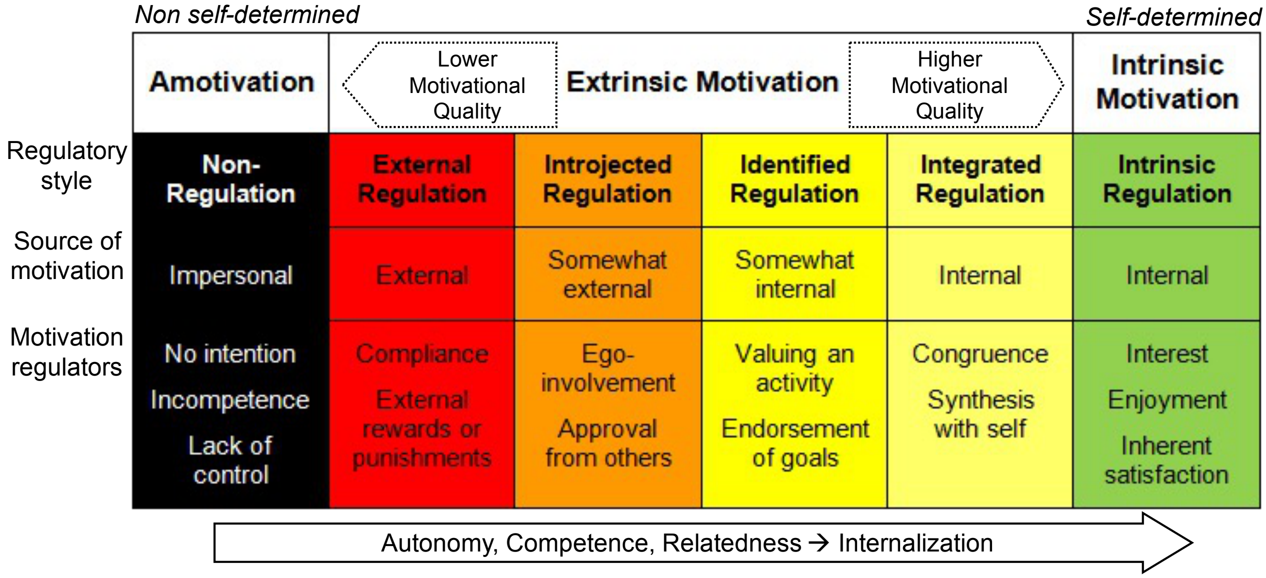


Figure 2.4: The motivation and self-determination continuum, as proposed by the Self-Determination Theory (SDT). Figure adapted from Ryan & Deci (2000a), Ryan & Deci (2000b), and Guyan (2013).

metacognition. The original survey consists of 52 true/false questions (Appendix B.5), such as "*I consider several alternatives to a problem before I answer*", "*I understand my intellectual strengths and weaknesses*", "*I have control over how well I learn", and "I change strategies when I fail to understand*". The instrument has been widely used in research, and has its reliability and validity measures available. Later, Terlecki & McMahon (2018) proposed a revised version of the MAI, using five-point Likert-scales, ranging from "*I never do this*" to "*I do this always*". They argue that when measuring change in metacognition over time, the Likert-scale based 'how often' questions are more effective than dichotomous 'Yes/No' questions (Terlecki, 2020; Terlecki & McMahon, 2018).

2.5.3 Motivation

Motivation is the process that initiates, guides, and maintains goal-oriented behaviours (Cherry, 2020). The **Self-Determination Theory** (SDT) represents a broad framework for the study of human motivation and personality (Ryan & Deci, 2017). SDT differentiates the types of motivation based on the reasons that give rise to behaviour: intrinsic motivation and extrinsic motivation. **Intrinsic motivation** is engaging in a task or behaviour for the rewards *inside* the task or behaviour, such the pleasure, enjoyment and satisfaction that the behaviour provides. It is a stable form of motivation. **Extrinsic motivation** is engaging in a task or behaviour for the rewards *outside* the task or behaviour, such as receiving rewards, avoidance of punishment, gaining social approval, or achievement of a valued result. Extrinsic motivation is on a continuum from less stable to more stable, as illustrated in Figure 2.4. Extrinsic motivation does not last unless the rewards and punishments are explicitly visible (Deci & Ryan, 2013; Ryan & Deci, 2000b; Tahamtan, 2019).

Ryan (1982) proposed the **Intrinsic Motivation Inventory** (IMI) (Appendix B.3), a multidimensional questionnaire intended to assess participants' subjective experience related to a target activity in laboratory experiments. The instrument assesses participants' interest/enjoyment, perceived competence, effort, value/usefulness, felt pressure and tension, and perceived choice while performing a given activity, yielding six subscale scores. The *interest/enjoyment* subscale is considered the most indicative self-report measure of intrinsic motivation. The *perceived choice* and *perceived competence* concepts are theorized to be positive predictors of both self-report and behavioural measures of intrinsic motivation. The *pressure/tension* is theorized to be a negative predictor of intrinsic motivation. *Effort* is a separate variable that is relevant to some motivation questions, so it is used if it is relevant. The *value/usefulness* subscale is used to measure internalization, with the idea being that people internalize and become self-regulating with respect to activities that they experience as useful or valuable for themselves.

2.5.4 Self-regulation

Self-regulation is the ability to develop, implement, and flexibly maintain planned behaviour in order to achieve one's goals. Self-regulation, and more broadly, self-direction, are critical to being an effective "lifelong" learner. Self-regulation becomes increasingly important at higher levels of education and in professional life, as people take on more complex tasks and greater responsibilities for their own learning. However, these metacognitive skills tend to fall outside the content area of most courses, and therefore, often neglected in instruction (Ambrose et al., 2010, p. 191). Building on the foundational work of Kanfer (1970b); Kanfer (1970a), Miller and Brown formulated a seven-step model of self-regulation (J. Brown, 1998; W. R. Miller & Brown, 1991). In this model, behavioural self-regulation may falter because of failure or deficits at any of these seven steps: *(i)* receiving relevant information, *(ii)* evaluating the information and comparing it to norms, *(iiii)* triggering change, *(iv)* searching for options, *(v)* formulating a plan, *(vi)* implementing the plan, and *(vii)* assessing the plan's effectiveness (which recycles to steps *(i)* and *(ii)*). Although this model was developed specifically to study addictive behaviours, the self-regulatory processes it describes are meant to be general principles of behavioural self-control. J. M. Brown et al. (1999) developed the **Self-Regulation Questionnaire** (SRQ) (Appendix B.4) to assess these self-regulatory processes through self-report. The items were developed to mark each of the seven sub-processes of the W. R. Miller & Brown (1991) model, forming seven subscales of the SRQ. The 63-item scale elicits responses in the form of 5-point Likert scale, ranging from strongly disagree to strongly agree. Based on clinical and college samples, the authors tentatively recommend a score of 239 and above as high (intact) self-regulation capacity (top quartile), 214-238 as intermediate (moderate) self-regulation capacity (middle quartiles), and 213 and below as low (impaired) self-regulation capacity (bottom quartile).

2.5.4.1 Self-directed and Self-regulated Learning

As we saw in the previous sections, self-regulation, motivation, and metacognition are key concepts that moderate the learning process. These terms are couched in the concepts of self-regulated learning and self-directed learning.

Self-directed learning (SDL) is a "process in which individuals take the initiative, with or without the help from others, in diagnosing their learning needs, formulating goals, identifying human and material resources, choosing and implementing appropriate learning strategies, and evaluating learning outcomes"(Knowles, 1975, p. 18). **Self-regulated learning** (SRL) can be described as the degree to which students are "metacognitively, motivationally, and behaviourally active participants in their own learning process" (Zimmerman, 1989, p. 329).

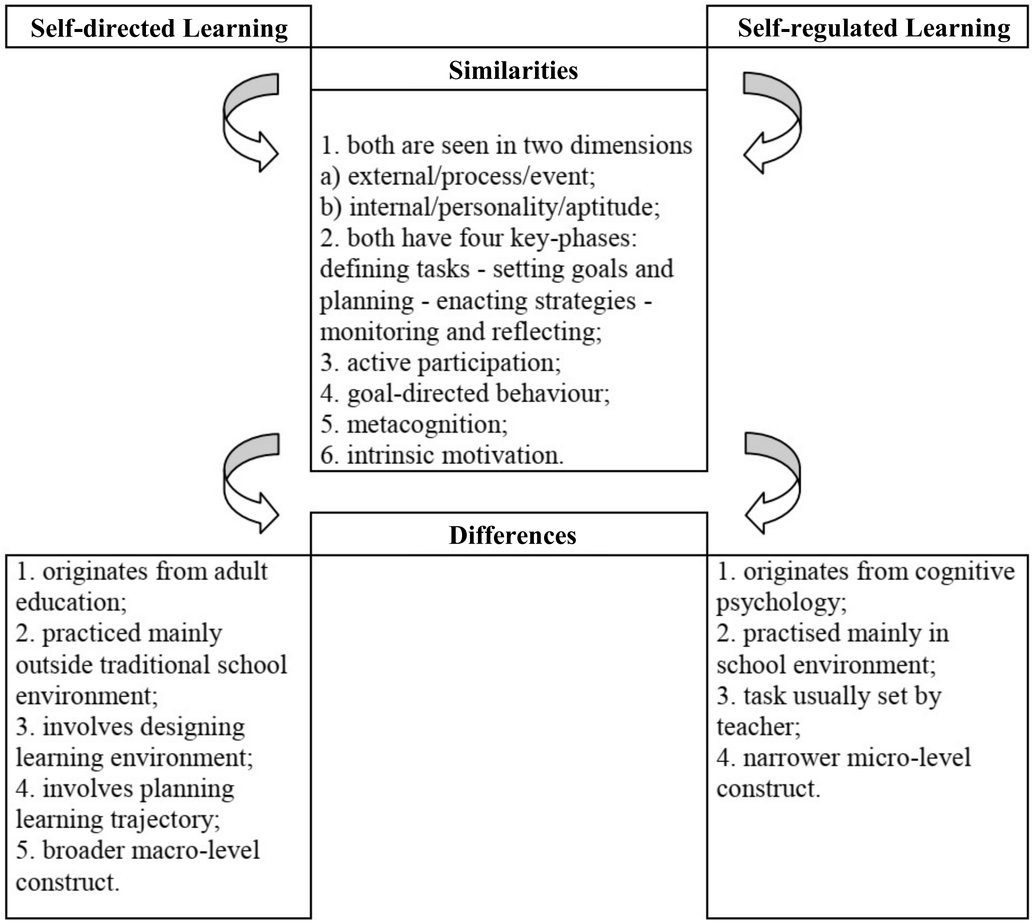


Figure 2.5: Self-directed learning vs. self-regulated learning, as illustrated by Saks & Leijen (2014).

Often used interchangeably, self-directed learning (SDL) and self-regulated learning (SRL) have some important similarities and differences (Figure 2.5) (Saks & Leijen, 2014). SDL, originating from adult education, is a broader, macro-level construct, and is usually practised outside the traditional school environment. The self-directed learner is free to design their own learning environment, and free to plan and set their own learning goals. SRL, on the other hand, is a narrower, micro-level construct, originating from educational and cognitive psychology, and is mostly utilized in the school environment. Learners do not have as much freedom as in SDL. The instructor or facilitator often defines the learning task and the learning goals. Self-directed learning may include self-regulated learning, but the converse is not true (Jossberger et al., 2010; Loyens et al., 2008). In other words, *"a self-directed learner is supposed to self-regulate, but a self-regulated learner may not self-direct"* (Saks & Leijen, 2014). Despite their differences, SDL and SRL share key similarities (Saks & Leijen, 2014). First, both can be seen in two dimensions: *(i) external* to the learner, as a process or series of events, and *(ii) internal* to the learner, arising from the learner's personality, aptitude, and individual differences. Second, both the learning processes have four key phases: *(i)* defining tasks, *(ii)* setting goals and planning, *(iii)* enacting strategies, and *(iv)* monitoring and reflecting. Third, both SDL and SRL require active participation, goal-directed behaviour, metacognition, and intrinsic motivation.

In summary, metacognition is monitoring and controlling what is in the learner's head; self-regulation is monitoring and controlling how the learner interacts with their environment; self-regulated learning is the application of metacognition and self-regulation to learning (Mannion, 2020); and the whole learning process is sustained by motivation, which is desirable to be intrinsic.

2.6 Summary and Implications for this Dissertation

In this first chapter of the background literature review, we discussed *(i)* what is meaningful learning, a.k.a. deep learning, or sensemaking; *(ii)* how meaningful learning updates the learner's cognitive knowledge structure; *(iii)* how the learning process is influenced by digital technologies, mass of information on the Internet, and IR systems; and *(iv)* what principles and practices learners and educators must realize and follow to promote meaningful learning. These findings are from the domains of Educational Sciences, Learning Sciences and Cognitive Sciences. We argue that these are important aspects to be considered when designing future IR or educational information systems that aim to combine and improve the searching and learning experience.

Guided by these findings, we made some important decision choices for the longitudinal study conducted in this dissertation. We aimed to situate learners in their context, and incorporate their individual differences using metacognition, motivation, and self-regulation characteristics. Additionally, we aimed to assess learning using artefacts and concept maps. We chose not use traditional tests like question-answers, and multiple choice assignments, since they are often not the preferred choice of knowledge-work output in real world scenarios.

In the next chapter, we look at relevant literature from the Information Sciences and Interactive Information Retrieval disciplines.

3

Background: Information Searching

This second chapter on background literature discusses relevant concepts from the disciplines of Information Sciences, and more specifically Interaction Information Retrieval. First, we introduce some terminology around information behaviour, information need, and information relevance. Then we discuss relevant findings various empirical studies, from the lens of three-stage interactions in the information search process. Then we discuss some overall generic characteristics of information search behaviour, and how they are linked to expertise and working memory. Next we discuss how learning has been assessed in recent search-as-learning studies. We also discuss some limitations of current search systems to foster learning, including the lack of sufficient number of longitudinal studies. In the last section, we state what implications these findings had for shaping the longitudinal study conducted for this dissertation.

3.1 Terminology

Information retrieval (IR) is the process of obtaining *information objects*, that are *relevant* to an *information need*, from a collection of those objects (Wikipedia). **Information objects** are entities that can potentially convey information. They can take many forms, such as documents, webpages, facts, music, spoken words, images, videos, artefacts, and other forms of

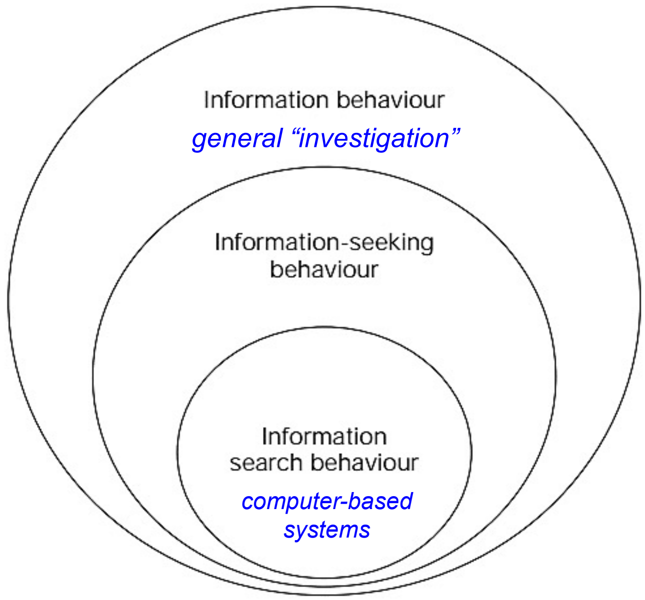


Figure 3.1: Nested model of information behaviour by T. D. Wilson (1999).

human expression. Areas where information retrieval techniques are employed include search engines, such as web search, social search, and desktop search; media search, as in image, music, video; digital libraries and recommender systems, as well as domain specific applications like geographical information systems, e-Commerce websites, legal information search, and others.

Multiple perspectives exist around how users interact with information, and IR systems. In the **Search Engine application view**, the interactions are restricted to the search engine interface. In the **Human-computer interaction** (HCI) view, interactions are between a person and a system; but the system can go *beyond* supporting only retrieval, to supporting more complex tasks. In the **cognitive view of IR**, which is the broadest, the interactions for obtaining information can be between a person and a system, as well as between people, for retrieval of information.

People's behaviour around information can be modelled as a nested Venn diagram as proposed by T. D. Wilson (1999) (Figure 3.1). **Information behaviour** is the more general field of investigation. **Information-seeking behaviour** can be seen as a sub-set of the field, particularly concerned with the variety of methods people employ to discover, and gain access to information objects. **Information search behaviour** is yet a sub-set of information-seeking, concerned with the interactions between the user and computer-based information systems. In this dissertation, we focus on information search rather than the other two higher hierarchical concepts. This is because online IR systems, such as search engines or digital libraries, have become the primary source for people to obtain information in modern times, and web search is becoming ever more pervasive and ubiquitous in our day-to-day lives.

The field of **interactive information retrieval** (IIR) posits that IR systems should operate in the way that good libraries do. Good libraries provide both the information a visitor needs, as well as a *partner* in the learning process — the information professional — to navigate that information, make sense of it, preserve it, and turn it into knowledge. As early as in 1980, Bertram Brookes stated that searchers acquire new knowledge in the information seeking process (Brookes, 1980). Fifteen years later, Gary Marchionini described information seeking, as *"a process, in which humans purposefully engage in order to change their state of knowledge"* (Marchionini, 1995). So we have known for quite a while that search is driven by the higher-level human need to gain knowledge. Information Retrieval is thus a means to an end, and not the end in itself. Thus, the ideal IR system should not only help users to locate information, but also help them to **bridge the gap between information and knowledge**.

This brings us to the concept of information need. **Information Need** is the desire to locate and obtain information to satisfy a conscious or unconscious human need. Most search systems of today assume that the search query is an accurate representation of a user's information need. However, Belkin et al. (1982) observed that in many cases, users of search systems are unable to precisely formulate what they need. They miss some vital knowledge to formulate their queries. As humans, we have difficulty in asking questions about what we do not know. Belkin called this phenomenon as **Anomalous State of Knowledge**, or ASK. Later, Huang & Soergel (2013) identified an exhaustive set of criteria that should be considered in order to ideally represent a user's information need. These criteria for information need are highly dependent on the user context: user attributes, tasks or goals, as well as the situation the user is embedded in. This brings us to another closely related concept: information relevance.

Relevance is a fundamental concept of Information Science and Information Retrieval, and perhaps the most celebrated work in this area has been done by Tefko Saracevic (Saracevic, 1975, 2007a, 2007b, 2016). Webster dictionary define relevance as "a relation to the matter at hand". In most circumstances, relevance is a "y'know" notion. People apply it effortlessly, without anybody having to define for them what "relevance" is. This creates one of the most fascinating challenges in the information field: humans understand relevance intuitively, while it is an open research problem to represent relevance effectively for use by algorithmic systems. The situation becomes more interesting because relevance always depends on context, and the context is ever dynamic, as the matter at hand changes.

3.2 Three-stage Interactions with Online Search Systems

As we saw in the previous section, information search behaviour is the (study of) interactions between a user, and digital Information Retrieval (IR) systems. The field of Information Science/Studies has developed multiple models explaining how information search works (T. D. Wilson, 1999). A few of them are presented in Figure 3.2. Across many of these models, we observe that most major Information Retrieval (IR) systems have three fundamental ways of letting users interact with the system, and the underlying information: *(1)* an interface for entering search **queries**; *(2)* an interface for viewing and evaluating a **list** of retrieved information-objects, or search results; *(3)* an interface for viewing and evaluating **individual information-objects**. For instance, Marchionini (1995)'s ISP model hints at these three interfaces in the fourth, sixth and seventh stages, namely "formulate query", "examine results", and "extract info". Spink (1997)'s model of the IR interaction process consists of sequential steps or cycles, and each cycle comprises one or more interactive feedback occurrences of user input (query), IR system output (list), and user interpretation and judgement (of individual information-objects). Consequently, findings from the large body of empirical research in interactive IR (especially those with web based search systems) can be grouped around these thee stages of interactions with search systems:

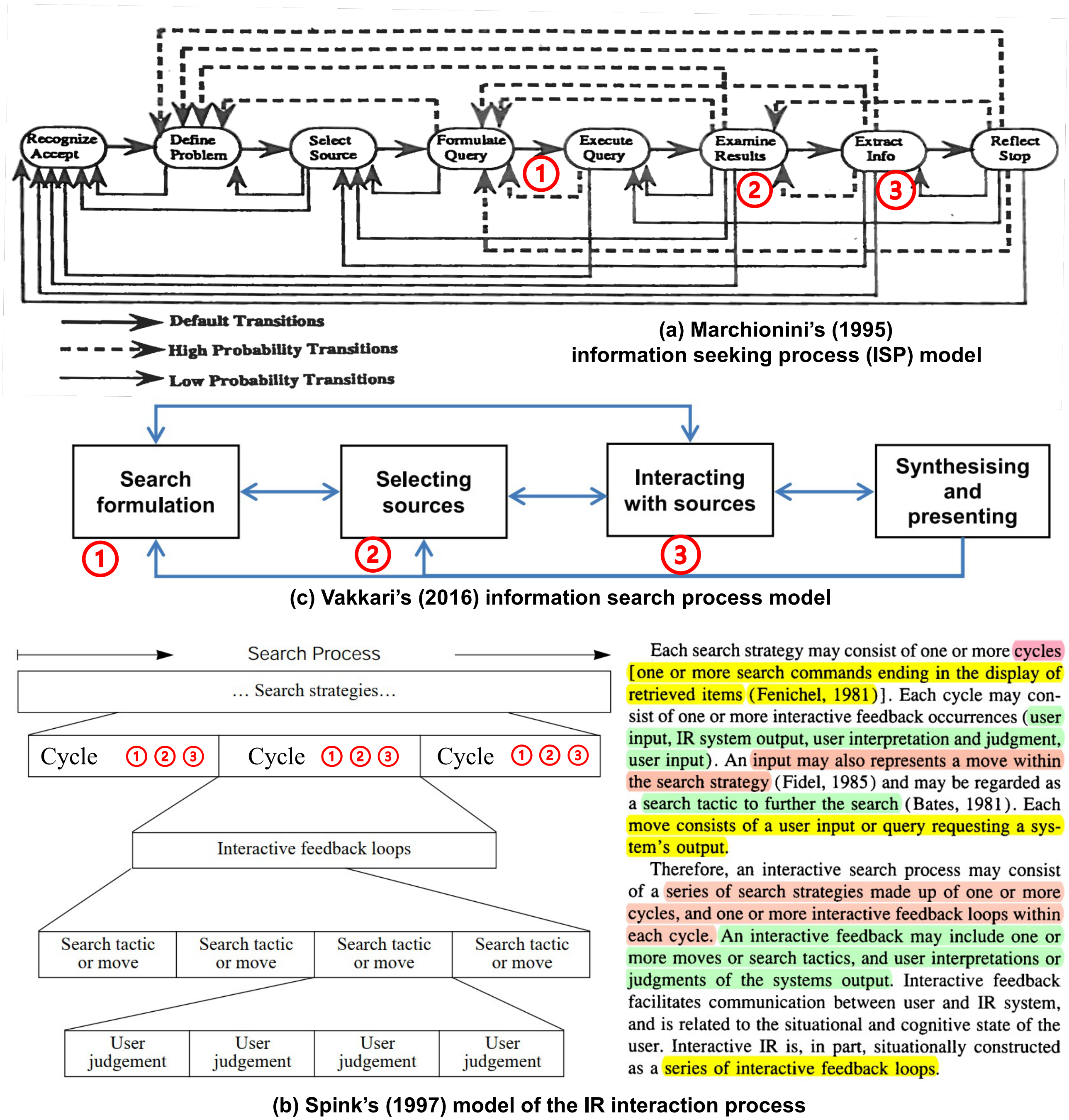


Figure 3.2: Models of information search process, with our coloured annotations identifying the three stages: (1) query formulation, (2) list-item selection, and (3) item examination.

1. *Stage 1:* search query (re)formulation
2. *Stage 2:* list-item selection: search results evaluation (aka source selection)
3. *Stage 3:* item examination: content page evaluation (aka interacting with sources)

The discussions in the following subsections are based around these three stages of interactions. The empirical studies discussed below generally follow some common principles of user studies in Interactive IR (IIR) (Borlund, 2013; Kelly, 2009): participants are presented with a search task or search topic, and then they are asked to search the internet (or a simulation of the open web) for information. During the search, the various interactions (queries, clicks, webpages opened etc.) are recorded, and these are analysed and correlated with other sources of data to answer research questions.

3.2.1 Stage 1: Query (Re)formulation

How do users behave when submitting search queries (to an IR system)?

Query formulation is the process of composing a search query that describes the information need of a searcher. **Query reformulation** refers to the act of either modifying a previous query, or creating a new query. Query reformulation typically occurs due to a searcher's improved understanding of how to better translate their information need into a search query. The relationship between two successively issued queries have been classified in a number of ways. These classifications are called *Query Reformulation Types*, or QRTs. Amongst many other, Boldi et al. (2009) used cognitive aspects of the searchers issuing the query to propose a taxonomy of QRTs, while C. Liu et al. (2010) proposed a similar taxonomy focusing more on the linguistic properties of the two successive queries. These are compared and contrasted in Figure 3.3.

Task-type, task-topic, task-goal, and domain-expertise were found to influence query reformulation patterns of searchers (Eickhoff et al., 2015; Jiang et al., 2014; Mao et al., 2018). At first glance, a significant portion of the query reformulation terms ($\sim 86\%$) seemed to be coming from the task-description itself (Jiang et al., 2014; Mao et al., 2018). This was characterized by

Boldi et al. (2009)	**Liu et al. (2010)**
Used cognitive aspects of searchers issuing the query:	Used linguistic properties of two successive queries:
Generalization: user wants broader information than was obtained from the current search	**Generalization:** successive queries contain at least one term in common; second query contains fewer terms than first query
Specialization: user narrows down the current search	**Specialization:** successive queries contain at least one term in common; second query contains more terms than first query
Mission Change: user changes the search topic to an entirely different one	**Word Substitution:** successive queries contain at least one term in common; second query has same length as first query, but contains some terms that are not in first query
Parallel Move: user modifies the current query to change the search aspect with the same context Learners are the also knowledge producers, and discerning knowledge discoverers / navigators	**Repeat:** successive queries contain exactly the same terms, but the format or ordering of these terms may be different
Error Correction: user's search intent does not change in the period before and after reformulation; examples are correcting a misspelled term and/or performing a query paraphrase	**New:** successive queries do not contain any common terms

Generalization and *Specialization* are identical in both taxonomies. *Parallel Move* can contain *Word Substitution*, *Repeat*, or *New* QRTs. *Mission Change* will generally have *New* QRTs. *Error Correction* will possibly have *Repeat* or *Word Substitution*.

Figure 3.3: Comparison of Query Reformulation Types (QRTs) proposed by Boldi et al. (2009) and C. Liu et al. (2010).

significantly more fixations on the task-description, rather than other SERP elements. Jiang et al. (2014) and Mao et al. (2018) investigated this phenomenon further. Jiang et al. (2014) controlled for the task-type and task-goal, using the faceted-framework by Li & Belkin (2008). Mao et al. (2018) controlled for the task-topic and the domain-expertise of the searchers.

If search tasks had *factual* goals, searchers relied heavily on the task-description for reformulating their queries (Jiang et al., 2014). For *interpretive* tasks (intellectual tasks with specific goals), users spent more time reading search result surrogates, before reformulating their queries. This was observed by increased eye-fixations (indicative of visual attention) and dwell time on search result snippets (surrogates). For exploratory tasks, searchers fixated the longest on query-autocompletion (QAC) suggestions, indicating that they were possibly looking for help and suggestion based on their specific query, as the search-task had non-specific (amorphous) goals.

Searchers also relied on the task-description for reformulating queries, when the search-task was outside their domain of expertise (Mao et al., 2018). For in-domain tasks, they used query terms from their own knowledge, that were not fixated on in visited SERPs and content pages. Eickhoff et al. (2015) reported that a significant share of new query terms came from visited SERPs and content pages, and query reformulation (specialization) often did not literally re-use previously encountered terms, but highly related ones [1] instead. These observations can possibly be explained by Mao et al. (2018)'s findings: when exploring a new domain, the searcher may accumulate vocabulary and learn how to query during the search; when performing in-domain search-tasks, the searcher may have enough prior knowledge to come up with effective query terms. It was also seen that searchers from medicine domain used more unread query terms for their in-domain search-tasks, compared to politics and environment domains (Mao et al., 2018). This suggested that domain knowledge and expertise is more important for formulating good search queries in highly technical disciplines (e.g., medicine), compared to less technical domains (e.g., politics).

Query Auto Completion (QAC) is a technological feature that suggests possible queries to web search users from the moment they start typing a query. It is nearly ubiquitous in modern search systems, and is thought to reduce physical and cognitive effort when formulating a query. QAC suggestions are usually displayed as a list (Figure 3.4(b) and (c)), and users interact in a variety of ways with the list. Hofmann et al. (2014) observed a strong position bias among searchers who examined the QAC list: the top suggestions received the highest visual attention, even when the ordering of the suggestions were randomized. Average fixation time decreased consistently on suggested items from top to bottom. Even when the ranking of suggestions were randomized, time taken to formulate queries did not significantly differ.

Search topics were found to have a large effect on QAC usage (Jiang et al., 2014; Smith et al., 2016). Search was easiest for the topics with the highest QAC usage. Total eye-gaze duration was longest when visual attention was shared between the QAC suggestions and the actual search query input box. Some additional time was probably due to decision making on whether to use a QAC suggestion. Typing was faster when a QAC was not used. However, the IR system's retrieval performance (measured using NDCG@3), was greater when QAC was

[1] measured using Leacock-Chodorow semantic similarity metric (Leacock & Chodorow, 1998)

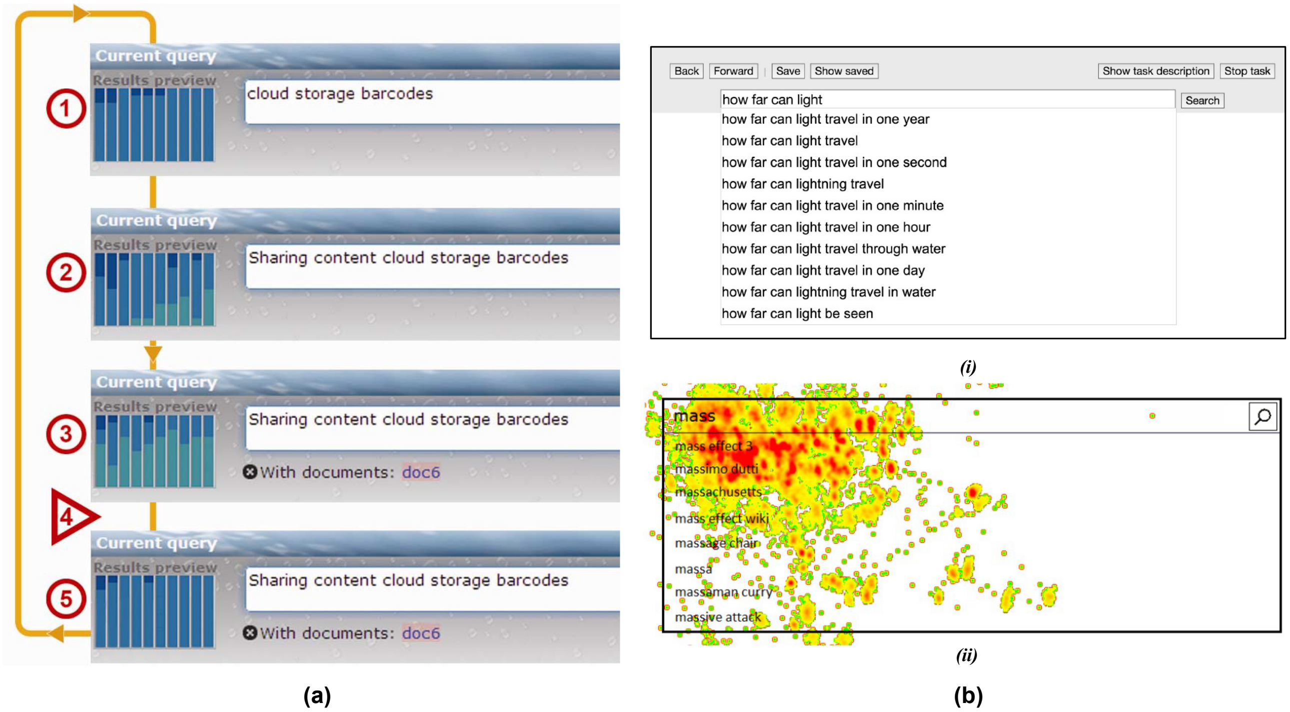


Figure 3.4: Investigating user-interactions with queries: **(a)** Visualizing the distribution of retrieved search results prior to running a query, for helping searchers understand their queries' effectiveness (Qvarfordt et al., 2013). The visualization is a stacked column chart with ten columns. Each column represents ten search results: first column represents results ranked 1-10, second column represents results 11-20, etc. Individual columns have three divisions, indicating the counts of results that: are already seen by the searcher (dark blue, top), will be re-retrieved, but have not been seen by the searcher (medium blue, middle), and will be newly-retrieved (bright teal blue, bottom). The system evaluates the searcher's query continuously as it is being typed, and updates the visualization in real-time. **(b)** Interfaces for examining interactions with query auto-completion (QAC), by ***(i)*** Smith et al. (2016), and ***(ii)*** Hofmann et al. (2014) (overlaid with heatmaps of eye fixations for all participants). This figure is best viewed in colour.

used. So Smith et al. (2016) speculated that the value of using QAC suggestions was realized later in the search session by users, when they saw a reduction in the number of additional queries needed, or an increase in the value of the information found.

Several user behavioural profiles were identified by exploring associations between visual attention from eye-tracking, search interactions from mouse and keyboard activity, and the use of QAC suggestions (Hofmann et al., 2014; Smith et al., 2016). These profiles are described in Figure 3.5. An interesting, yet common-sense observation was that participants' touch-typing ability greatly influenced their interactions with QAC suggestions.

Hofmann et al. (2014) From 331 search 'episodes' (*N* = unmentioned)	**Smith et al. (2016)** From 707 queries submitted in 232 topic sessions (*N* = 29)
A: monitoring: frequent fixations on QAC, and on the top-ranked suggestions in particular (hypothesized that QAC played a role in confirming to the user that they were typing the query correctly)	**A: Fast Boxers:** worked quickly, submitted queries in the query input box, using the enter key almost exclusively, with very little attention to the screen other than to the query input box
	B: Touch Typists: similar to A, worked quickly and mostly using the query input box and the enter key, but not to the exclusion of queries from the QAC suggestions and clicking on them. They looked at the QAC suggestions very rarely, but they did focus on the query input box, as they rarely have a missing fixation.
B: searching: user actively scanned and engaged with the QAC list from top to bottom; two distinct types of searching were identified:	**C: Slow and Methodical Typists:** worked slowly to create many long queries in the query input box. Although they tended to focus a great deal of attention to all parts of the screen, they were likely to focus on the query input box alone for many queries, and rarely focused only on the QAC suggestions list.
1) *seeking spelling support* for difficult words (e.g. 'schwarzenegger') while entering a query they have in mind;	**D: Agnostic Mousers:** used both the query input box and the QAC suggestions list, but put more time focus on QAC list than the query box. Queries were submitted by clicking the mouse, to the near exclusion of the enter key. A high visual attention to the screen could be explained by the reliance on the mouse and the need to track the mouse cursor visually.
2) not seeking spelling support, but rather *looking for a complete query* that appropriately expressed their information need;	
C: ignoring: non-touch-typists largely ignored the QAC suggestions because they primarily looked at the keyboard while typing, and typically only looked up from the keyboard when they had finished typing.	**E: Fast and Unfocused Agnostics:** worked quickly to submit a lot of queries using QAC suggestions, but they also typed some queries fully in the query input box. Although a lot of their visual attention was on QAC suggestions list and very little elsewhere, they had a lot of missed fixations, and may have focused on the keyboard.
	F: Fast QACers: also worked quickly, but created very short queries that were likely to be queries from the QAC suggestions. Their attention often focused on the QAC suggestions list only, and rarely on the query input box.

Figure 3.5: Comparison of User behaviour profiles identified around Query Auto-Completion (QAC), from eye-tracking data, by Hofmann et al. (2014) and Smith et al. (2016).

The native language of searchers was found to influence their overall querying and searching behaviour. Ling et al. (2018) explored this space using four variations of a multi-lingual search interface. They observed that participants strongly preferred to issue queries in their first or native language. A second or non-native language was the next preferred choice. Mixing of first and second-languages occurred very rarely. In 80% of the total 300 tasks (25 users $\times$ 4 interfaces $\times$ 3 task-types), participants used a single language for querying. In the rest 20% of the tasks, participants switched languages for querying, with a transition from first language to second language being the most common.

3.2.2 Stage 2: Search Results Evaluation / List-Item Selection

How do users behave when examining a list of information-objects (returned by an IR system)?

After a user submits a query to an IR system, the next action they generally perform is examining and evaluating the list of search results returned by the IR system. In this section, we discuss empirical studies which investigated information-searching behaviour around a list of information-objects, or a representation of information-objects (also called *surrogates*). We identified some common themes in the research questions investigated. The discussion below is grouped along these themes, as relationships between search behaviour and: *(i)* ranking of search results; *(ii)* information shown in search results; *(iii)* individual user characteristics; and *(iv)* relevance judgement and feedback.

3.2.2.1 Ranking of search results

Most search engines display results in a rank ordered list, with the highest *algorithmically* relevant results placed at the top, and others results ordered below. Granka et al. (2004; Lorigo et al., 2008) studied eye-movement behaviour of searchers examining SERPs, and reported observations from three user studies. They saw that in 96% of the queries, participants looked at only the first result page, containing the top 10 results. No participant looked beyond the third result page for a given query. Participants looked primarily at the first few results, with nearly equal attention (dwell time) given to the first and the second results. However, despite equal attention, the first result was clicked 42% of the time, while the second was clicked only 8% of the time. If none of the top three results appeared to be relevant, then users chose not to explore further results, but issued a reformulated query instead. When the ranking of the search results were reversed (i.e. placing less relevant results in the higher ranked positions), participants spent considerably more time scrutinizing and comparing results (more fixations and regressions) before making a decision to click or reformulate.

Some effects of gender were found to influence SERP examination (Lorigo et al., 2008). Females clicked on the second result twice as often, and made more regressions or repeat viewings of already visited abstracts, compared to males. Males were more likely to click

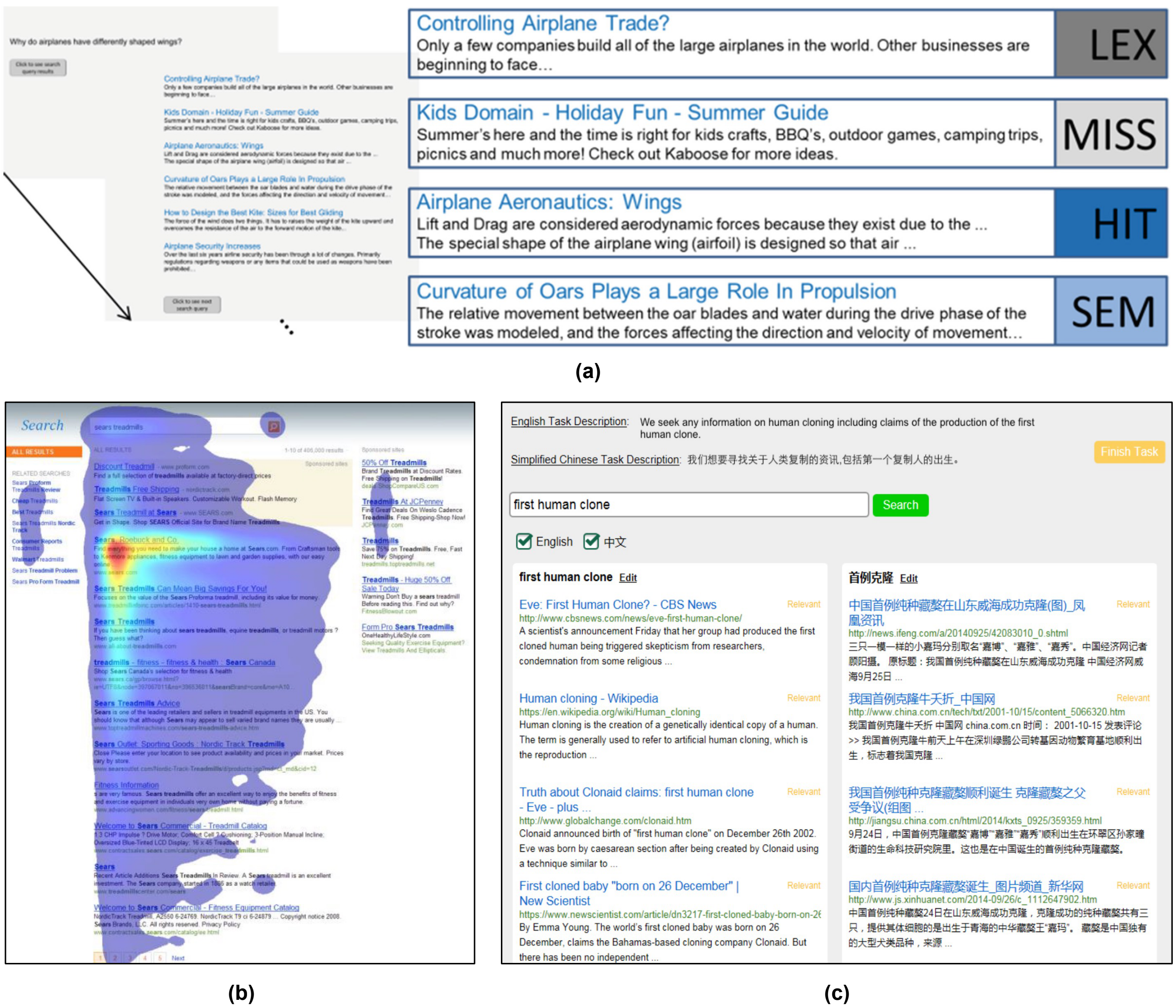


Figure 3.6: Example interfaces for studying user-interactions with a search-engine results page (SERP): **(a)** a simplified SERP without query input facility, to judge relevance of search results (on a 4-level scale) for pre-determined search queries (in this case 'why do airplanes have differently shaped wings?'), from Scharinger et al. (2016); **(b)** eye-tracking heatmap on an organic SERP from Buscher et al. (2010; Dumais et al., 2010), showing the F-shaped pattern of visual attention; **(c)** a multilingual SERP from Ling et al. (2018). This figure is best viewed in colour.

on lower ranked results, from entries 7 through 10, and also look beyond the first 10 results significantly more often than women. Males were also more linear in their scanning patterns, with less regressions. Pupil dilation did not differ significantly between gender groups.

Effects of task-type and task-goals also influenced SERP examination behaviour. Guan & Cutrell (2007) used Broder (2002)'s taxonomy of navigational vs. informational searches. The authors reported that when users could not find the target results for navigational searches, they either selected the first result, or switched to a new query. However, for informational searches, users rarely issued a new query and were more likely to try out the top-ranked results, even when those results had lower relevance to the task. This illustrated possible strong confidence of searchers in the search engine's relevance ranking, even though searchers clearly saw target results at lower positions. Thus, people were more likely to deprecate their own sense of objective relevance and obeyed the ranking determined by the search engine. Jiang et al. (2014) used Li & Belkin (2008)'s framework of search-tasks, and saw that in tasks having specific goals, searchers fixated more on lower ranked results after some time. On the other hand, for tasks having amorphous goals, there was a wider breadth in viewing the SERP, and less effort spent in viewing the content pages. Fixations tended to decrease as search session progressed, indicating decreased interest and increasing mental effort, which could demonstrate *satisficing* behaviour (Simon, 1956). A comprehensive overview of various behavioural traits associated with task-types and task-goals can be found in (Jiang et al., 2014 Table 8).

3.2.2.2 Information Shown in Search Results (Surrogates)

The amount and quality of different kinds of information shown on SERPs also affected user's information searching behaviour. Cutrell & Guan (2007) saw that as the length of the surrogate information (result snippets) was increased, user's search performance improved for informational tasks, but degraded for navigational tasks (Broder, 2002). Analyzing eye-tracking data, they posited that the difference in performance was due to users paying more attention to the snippet, and less attention to the URL located at the bottom of the search result. This led to performance deterioration in navigational searches. Buscher et al. (2010) studied the effects of the quality of advertisements placed in the SERPs (Figure 3.6(b)). Similar to findings discussed above, a strong position bias of visual attention was found towards the top few organic result entries — the well known F-shaped pattern of visual attention — which was stronger for informational than for navigational tasks. However, a strong bias *against* sponsored links was observed in general. Even for informational tasks, where participants generally had a harder time finding a solution, the ads did not receive any additional attention from the participants. Lorigo et al. (2008) compared the visual attention patterns of searchers using two different search engines: Google, and Yahoo!. Behavioural trends followed similar patterns for both search engines, even though Google was rated as the primary search engine of all but one of the participants. They found slight variations in some eye-tracking measures (reading time of surrogates, time to click results, and query reformulation time), and some self-reported measures (perceived ease of use, perceived satisfaction, and success rate). However, none of these differences were statistically significant.

The novel query-preview interface by Qvarfordt et al. (2013) was discussed in Section 3.2.1 and in Figure 3.4(a). The authors also reported several observations about user behaviour on SERPs. They saw that the presence of the preview visualization enabled participants to look deeper into the results lists. Participants tried to use the preview as a navigation tool, although it was not designed as such. The tool increased the rates at which participants examined documents at middle ranks in query results, and thus helped discover more useful documents in those middle ranks than without the preview widget. The preview tool also helped to increase the diversity of documents found in a search session, which could in turn lead to better performance in terms of recall and precision. Thus, the tool helped searchers overcome the strong position bias towards top-ranked results, as observed by other studies discussed previously.

3.2.2.3 Individual User Characteristics

Individual traits of searchers also influence their pattern of interactions with a SERP, and these patterns can be revealed by analyzing eye-tracking data. For instance, searchers have been classified as *economic* vs. *exhaustive*, based on their style of evaluating SERPs (Aula

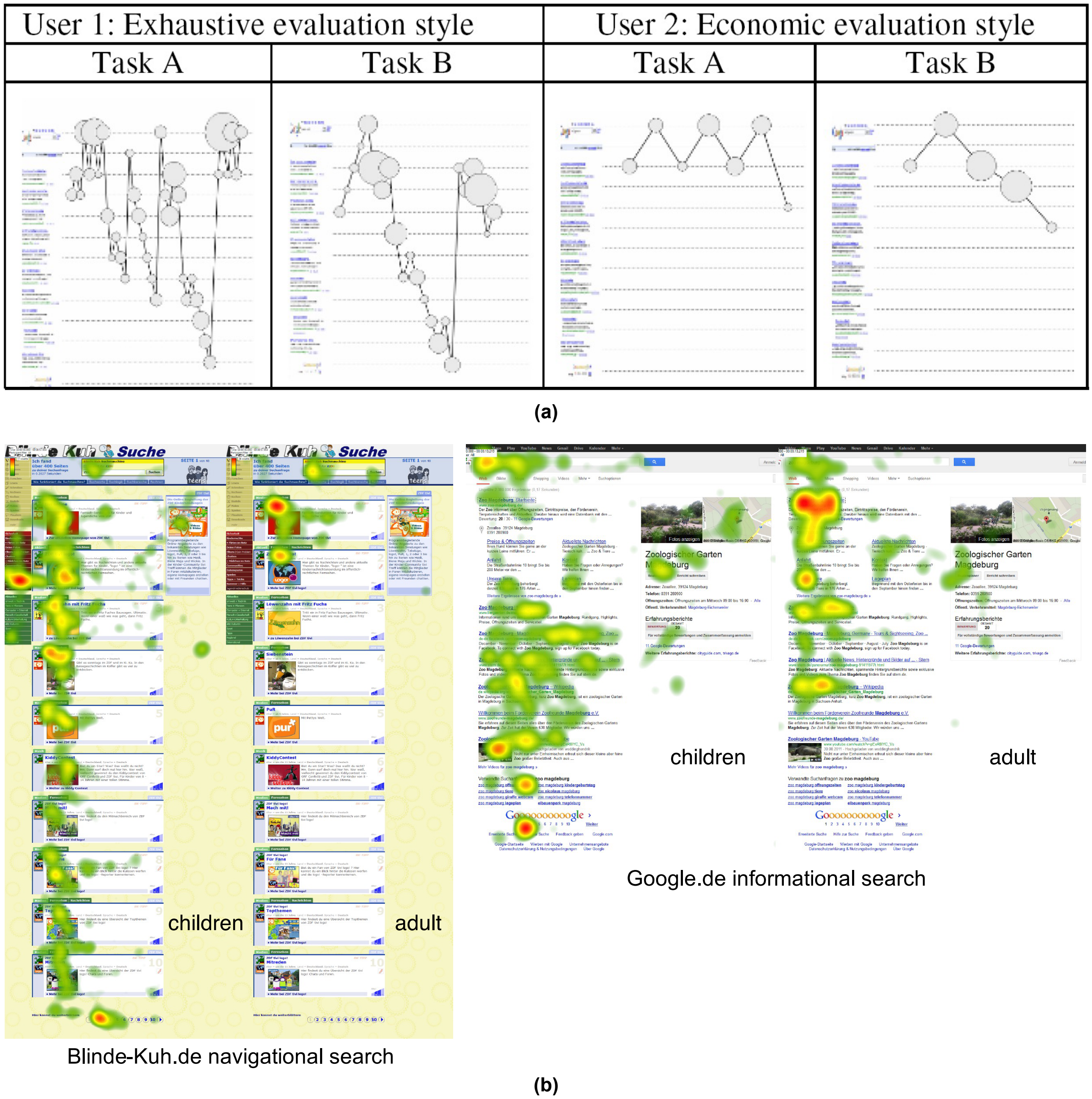


Figure 3.7: Effects of differences in user characteristics on interactions with SERPs: **(a)** exhaustive or *depth-first* user (User 1), vs. economic or *breadth-first* user (User 2), examining mostly irrelevant results in Task A, and mostly relevant results in Task B (both users followed the second link in Task B); vertical axis denotes vertical location on SERP, and horizontal axis denotes temporal ordering of result examination; from Aula et al. (2005); (similar patterns were identified by Bilal & Gwizdka (2016), in the SERP examination behaviour of children) **(b)** children vs. adults examining SERPs from a German search engine for children (left), and Google (right); differently from adults, children exhaustively explored all search results, paid more attention to thumbnails and embedded media, and read less text-only snippets; from Gossen et al. (2014). Similar observations as with children were reported for searchers with dyslexia (Palani et al., 2020). This figure is best viewed in colour.

et al., 2005). *Economic* searchers were found to scan less than half (three) of the displayed results above the fold, before making their first action (query re-formulation, or following a link). *Exhaustive* searchers evaluated more than half of the visible results above the fold, or even scrolled the results page to view all of the results, before performing the first action. Thus, economic searchers demonstrated depth-first search strategy, while exhaustive users favoured the breadth-first approach (Figure 3.7(a)). Dumais et al. (2010) demonstrated the use of unsupervised clustering to re-identify the *economic-exhaustive* user groups, based on differences in total fixation impact [2], scanpaths, task outcomes, and questionnaire data. The *economic* cluster was further broken down by users who looked primarily at results (*economic-results* cluster), and users who viewed both results and ads (*economic-ads* cluster). All three groups spent the highest amount of time on the first three results, with the *exhaustive* group being substantially slower than the other two groups. The *exhaustive* and *economic-results* groups spent the second-highest amount of time on results four through six, while the *economic-eds* group spent this time on the main advertisements. This group spent more than twice as much time on the main ads as the *economic-results* group, and even more time on main ads than the *exhaustive group*. This observation is incongruent to Buscher et al. (2010)'s findings, as they observed a generally strong bias *against* viewing sponsored links. Abualsaud & Smucker (2019) conducted further analysis using these user types, and, in general, reconfirmed the previous findings. They found that the results above the fold, especially, ***the first three search results are special***, more so for economic users. On submitting a 'weak' query, if economic users did not find a correct result within the first three results, they abandoned examination, and reformulated their query.

Age of searchers also influence SERP evaluation behaviour. Gossen et al. (2014) demonstrated differences in SERP evaluation for children and adults (Figure 3.7(b)). When answers were not found within the top search results, the adults reformulated the query starting a new search, while young users exhaustively explored all the ten results, and used the navigation buttons between results pages to continue further examination. Children also paid more

[2] a measure derived from eye fixation durations, proposed by Buscher et al. (2009)

attention to thumbnails and embedded media, and focused less on textual snippets. Children saw the query suggestions at the bottom of the Google SERP (because they navigated to the bottom), while the adults did not. Bilal & Gwizdka (2016; Gwizdka & Bilal, 2017) investigated this phenomenon further, and observed that even within children, age plays a role in SERP evaluation behaviour. Younger children (grade six, age 11) clicked more often on results in lower-ranked positions than older children (grade eight, age 13). Older children's clicking behaviour was based more often on reading result snippets, and not just on the ranked position of a result in a SERP. Whereas, younger children made less deliberate choices in choosing which result to click, and were more exhaustive in the exploration of results. Thus, using Aula et al. (2005)'s classification and Dumais et al. (2010)'s observations, it can be posited that (younger) children start out as *exhaustive* searchers. With increase in age and maturity, older children and adults evolve into *economic* searchers. Interestingly, very similar behaviour patterns as with children (scrolling further down on SERPs, exhaustive exploration, etc.) were also observed recently for searchers with dyslexia (Palani et al., 2020).

Searcher's native language also influenced SERP interaction behaviour (Ling et al., 2018) (Figure 3.6(c)). We discussed in Section 3.2.1 that users strongly preferred issuing queries in a single language, especially their native language. However, while examining SERPs, they marked search results in both their first language and second language to be relevant, to an equal degree. This confirms the usefulness of search result pages that integrate results from multiple languages. However, a clear separation in the language of the search results was strongly preferred, and an 'interleaved' presentation (e.g. odd numbered results in one language and even numbered results in another language) was least preferred.

3.2.2.4 Relevance Judgement

Balatsoukas & Ruthven (2010, 2012) proposed a list of relevance criteria for understanding how searchers evaluate search results, or perform *relevance judgement*. These criteria were developed based on literature reviews and their empirical findings from eye-tracking studies.

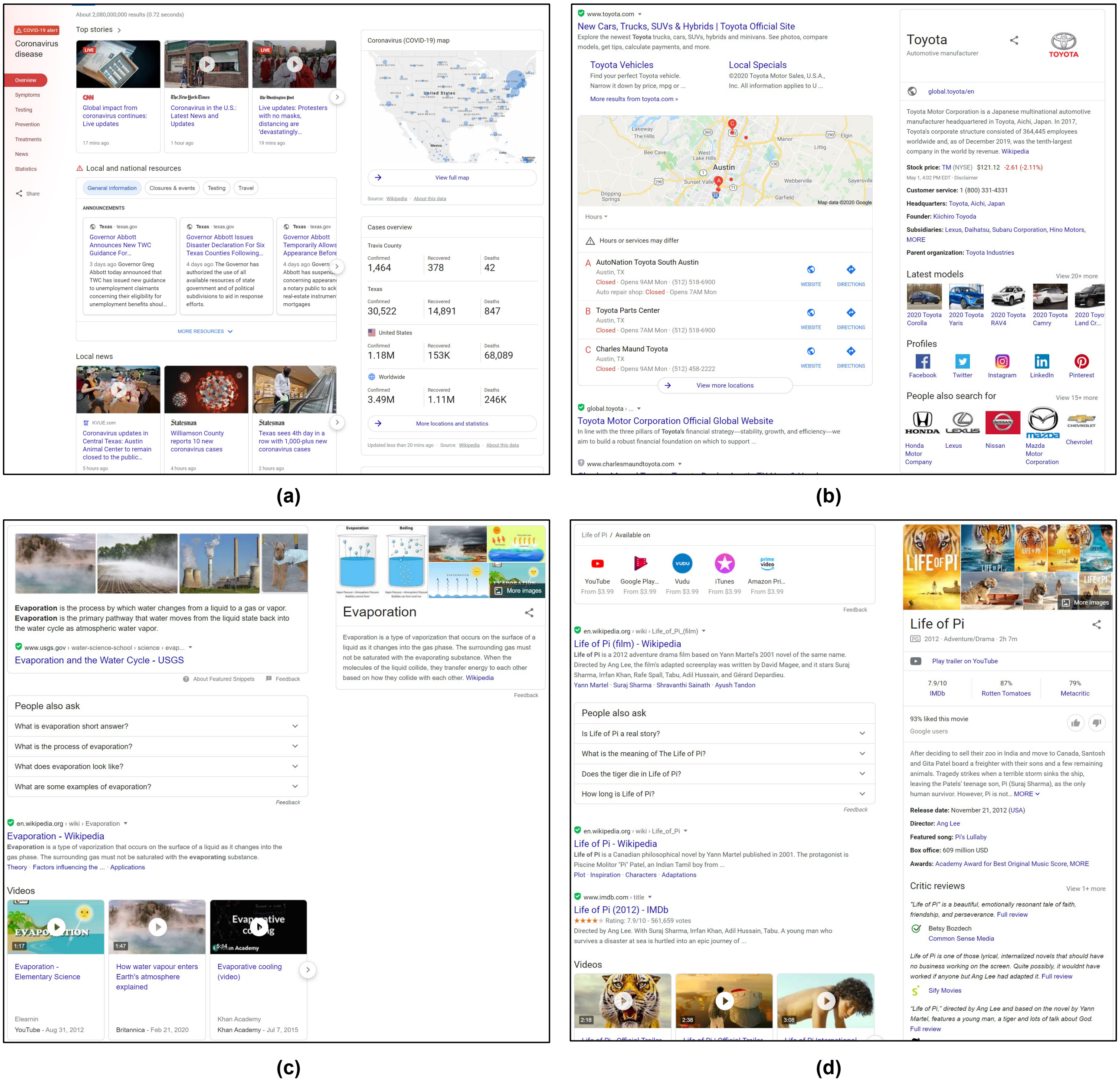


Figure 3.8: Google search engine result page (SERP) for the queries: **(a)** "coronavirus" **(b)** "toyota" **(c)** "evaporation", and **(d)** "life of pie". All screenshots are from 'above-the-fold', viewed on a 2560 × 1440 monitor. These examples highlight that modern SERPs have come a long way from a list of "ten blue links". SERPs are becoming consumable information-objects in their own right, and thus require different kinds of cognitive processing and interactions, than from the early days of the internet. Inspired and adapted from Wang et al. (2018). Accessed on May 5, 2020. This figure is best viewed in colour.

The final list contains 15 relevance criteria (e.g., *topicality*, *quality*, *recency*, *scope*, *availability*, etc.) and can be found in (Balatsoukas & Ruthven, 2012 Appendix B).

Search engines are increasingly adding different modalities of information on the SERP, besides the "ten blue links". These include images, videos, encyclopaedic information, and maps (Figure 3.8). Z. Liu et al. (2015) studied the influence of these different forms of SERP information – called 'verticals' – on searcher's relevance judgements. A general observation was that if verticals were present in a SERP, they created strong attraction biases. The attraction effect was influenced by the type of verticals, while the vertical quality (relevant or not) did not have a major impact. For instance, 'images' and 'software download' verticals had higher visual attention, while news verticals had equal attention as the "ten blue links" search results.

3.2.3 Stage 3: Content Page Evaluation / Item Examination

> *How do users behave when examining a single information-object (e.g., a a non-search-engine webpage, aka content page) obtained from an IR system?*

In online information searching, searchers repeatedly interact with individual webpages, a.k.a. 'content pages' in IR terminology. These webpages can be visited by following links from a search engine, following links between different webpages, or directly typing the URL in the browser.

The first group of papers we discuss investigated users' **visual attention** and **reading behaviour** on webpages. Pan et al. (2004) studied whether eye-tracking scanpaths on webpages varied based on task-type, webpage type (business, news, search, or shopping), viewing order of webpages, and gender of users. The found significant differences for all factors, except for task-type, which seemed to have no effect on scanpaths. They used weak task-types: remembering what was on a webpage vs. no specific task. In a later work on using informational vs. navigational search-tasks, they again saw limited effect of task-type on visual attention (Lorigo et al., 2006). Findings from Josephson & Holmes (2002)'s study suggested that users possibly follow habitually preferred scanpaths on a webpage, which can be influenced by factors like webpage characteristics and memory. However, they used only three webpages, making the findings difficult to generalize. Goldberg et al. (2002) studied eye movements on Web portals during search-tasks, and saw that header bars were typically not viewed before focusing the main part of the page. So they suggested placing navigation bars on the left side of a page. Beymer et al. (2007) focused on a very specific feature on webpages: images that are placed next to text content and how they influence eye movements during a reading task. They found significant influence on fixation location and duration. Those influences were dependent on how the image contents related to the text contents (i.e., whether they showed ads or text-related images). Buscher et al. (2009) presented findings from a large scale study where users performed information-foraging and page-recognition tasks. They observed that in the first few moments, users quickly scanned the top left of the page, presumably looking for clues about the content, provenance, type of information, etc. for that page. The elements that were normally displayed in the upper left third of webpages (e.g., logos, headlines, titles or perhaps an important picture related to the content) seemed to be important for recognizing and categorizing a page. After these initial moments, influence of task-type set in. For page-recognition tasks, the attention remained in the top-left corner of the webpage. However, for information-foraging tasks, fixations moved to the center-left region of the webpage, where the user was possibly trying to find task-specific information. The right third of webpages attracted almost no visual attention during the first one-second of each page view. Afterwards as well, most users seemed to entirely ignore this region, or only occasionally look at it. This suggested that users had low expectations of information-content or general relevance on the right side of most webpages. As many webpages display advertisements on the right side, this was a plausible observation, and are in line with the observed “F-shaped-patterns” [3] on webpages.

Buscher et al. (2009) also proposed an eye-tracking measure called *fixation impact*. This measure first appends a circular Gaussian distribution around each fixation on a webpage element, to create a fuzzy area of interest. This is called the *distance impact* value. If a webpage element completely covers the fixation circle (Gaussian distribution), it gets a *distance impact* value of 1. If the element partially covers the fixation circle, its *distance impact* value is smaller.

[3] https://www.nngroup.com/articles/f-shaped-pattern-reading-web-content

Multiplying the *distance impact* value with the fixation duration gives the fixation impact for the given webpage element. Thus, an element that completely covers the fixation circle gets the full fixation duration as *fixation impact* value. Elements which are partially inside the circle get a value proportional to the Gaussian distribution. The authors posited that the rationale behind creating the fixation impact measure was motivated by observations from human vision research, which indicates that fixation duration correlates with the amount of visual information processed; the longer a fixation, the more information is processed around the fixation centre. Using the fixation impact measure, Buscher et al. (2009) proposed a model for predicting the amount visual attention that individual webpage elements may receive (i.e. visual salience).

Another group of studies investigated how users judged **relevance of webpages** w.r.t. an assigned search-task or information need. (Gwizdka, 2018; Gwizdka & Zhang, 2015a, 2015b) observed that when relevant pages were revisited, the webpages were read more carefully. Pupil dilations were significantly larger on visits and revisits to relevant pages, and just before relevance judgements were made. Certain conditions of visits and revisits also showed significant differences in EEG alpha frequency band power, and EEG-derived attention levels. Relevance of individual webpage elements were also assessed as *click-intention*: whether users would click on an element they were looking at. Slanzi et al. (2017) used pupillometry and EEG signals to predict whether a mouse click was present for each eye fixation. EEG features included simple statistical features of signals (mean, SD, power, etc.), as well as sophisticated mathematical features (Hjorth features, Fractal Dimensions, Entropy, etc.). A battery of classifier models were tested. However, the results were not promising. Logistic Regression had the highest accuracy (71%), but very low F1 score (0.33), while neural network based classifiers the had highest F1 score (0.4). The authors suspected that the low sampling rate of their instruments (30 Hz eye-tracker and 128 Hz 14-channel EEG) impacted their classifier performances. González-Ibáñez et al. (2019) compared relevance prediction performances in the presence and absence of eye-tracking data, and argued that when eye-tracking data collection is not feasible, mouse left-clicks can be used a good alternative indicator of relevance.

The '*Competition for Attention*' theory states that items in our visual field compete for our attention (Desimone & Duncan, 1995). Djamasbi et al. (2013) studied web search and browsing from the perspective of this theory. Theoretical models suggest that in goal-directed searches, information-salience and/or information-relevance drives search behaviour (i.e. competition for attention does not hold true), whereas exploratory search behaviour is influenced by competition among stimuli that attracts a user's attention (i.e. competition for attention holds true). However, in practice, information search behaviour often becomes a combination of both types of visual search activities (Groner et al., 1984). Djamasbi et al. (2013) found that, despite the goal directed nature of their search-task (finding the best snack place in Boston to take their friends) *competition for attention* had some effect at the content page level. Some of the users' attention was diverted to non-focal areas on content pages. However, there was little effect of *competition for attention* on how the results were viewed on SERPs. Users exhibited the familiar top-to-bottom pattern of viewing (Section 3.2.2), paying the most attention to the top two entries.

3.3 Effects of Expertise and Working Memory on Search Behaviour

Our focus of discussion in this dissertation is information searching and learning. As we saw in Chapter 2, learning and expertise are closely connected: expertise is an evolving characteristic of users that reflects learning over time, rather than being a static property (Rieh et al., 2016; Sawyer, 2005). (White, 2016a, Chapter 7) considers three types of expertise, that are relevant in information seeking settings: *(i)* domain or subject-matter expertise; *(ii)* search expertise; and *(iii)* task expertise. **Domain or subject-matter expertise** describes people's knowledge in a specialised subject area such as a domain of interest. **Search expertise** refers to people's skill level at performing information-seeking activities, both in a Web search setting and in other settings such as specialised domains. **Task expertise** describes people's expertise in performing particular search tasks, potentially independent of domain. Although considered distinctly, the boundaries between these expertise types are quite blurred, and therefore difficult to estimate at the time of search, and model it in a way that can be consumed by search systems.

Search Stage	Search behaviours indicative of learning, or increasing domain expertise
Query (re)formulation	- Increase in the *number* and *specificity* of query terms - Increase in number of synonyms - Decrease in number of reformulated queries
Search Engine Results Page (SERP) examination *(Source Selection)*	- Increased clarity in relevance criteria = increased ability to distinguish between relevant and non-relevant results - Decrease in the number of search results viewed (supported by Mao et al. (2018), contrasted by White et al. (2009)) - Decrease in the proportion of partially relevant results viewed, and increase in the number of relevant results viewed - Average time for assessing a search result decreases
Content Page examination *(Interaction with sources)*	- Increase in the amount of information-use from viewed content pages in the learning outcome artefact (summary, project report, exam answers, etc.) Knowledge Assimilation: addition of new information to existing knowledge structure - Focus on factual and specific information - Refining output with factual information - Revisiting content pages for information initially overlooked Knowledge Restructuring: large changes or replacement of concepts and their relations in knowledge structure - Focus on background and conceptual information; notes taken on themes and ideas - Ideas are related and combined for a focus, in the outcome Knowledge Tuning: small changes in scope and meaning of concepts and their relations in knowledge structure; no replacements - Focus on procedural and specific information - Identification of information to support and refine focus
Overall search session	- Decreased time per search session - Decrease in variability of search tactics - Increase in the diversity of websites visited within a subject area (increase in the average number of unique top-level websites on a SERP or across clicked documents) - Increase in focus of exploration (e.g., the degree to which a SERP is covered by a single topic) - Search path is more ‘branchy’ – returning to a previously visited point and then following a new unexplored direction) (White et al., 2009)

Figure 3.9: Literature reviews by Rieh et al. (2016) and Vakkari (2016) identified the following search behavioural traits as indicative of domain experts, or novices undergoing learning to become experts.

Previous work on domain knowledge and expertise have linked [4] domain expertise and search behaviour in terms of metrics, behavioural patterns, and criteria (M. J. Cole et al., 2013; Mao et al., 2018; O'Brien et al., 2020; White et al., 2009). A representative summary is presented in Figure 3.9, and is adapted from literature reviews by (Rieh et al., 2016) and (Vakkari, 2016). Briefly, (Wildemuth, 2004) showed that novices converge toward the same search patterns as experts, as they are exposed to a topic and learn more about it. (X. Zhang et al., 2011) found that features such as document retention, query length, and the average rank of results selected could be predictive of domain expertise. (M. J. Cole et al., 2013) showed that eye-gaze patterns could be used to predict an individual's level of domain expertise using estimates of cognitive effort associated with reading. (White et al., 2009) showed that measures such as diverse website visitation, more narrow topical focus, less diversity (or entropy), more 'branchiness' of search sessions, less dwell time, and higher query and session complexity are indicative of expert knoweldge and/or search behaviour.

As a stark contrast, (Zlatkin-Troitschanskaia et al., 2021) reviewed literature on higher education **students' information search behaviour**. Students can be considered as novices in all three respects: domain/subject-matter, search skills, and task. The authors report that across literature, higher education students' information search behaviour tends to follow some general general patterns: *(i) foraging:* no explicit (task-specific) research plan and little understanding of the differences (pros/cons) between various IR systems; *(ii) Google dependence:* no intention to use any search tool other than Google, causing students to struggle to understand library information structures and engage with scholarly literature effectively; *(iii) rudimentary search heuristic:* reliance on one and the same simple search strategy, regardless of search context; *(iv) habitual topic changing:* students change the search topic after rather superficial skimming, and before evaluating all search results; and *(v) overuse of natural language:* students type questions into the search box that are phrased as if posing them to a person. Highly ranked online sources accessed via a well-known search engine were perceived as trustworthy.

[4] and continue to link

Effects of memory span and working memory capacity have also been found to influence search effort and search behaviour (Arguello & Choi, 2019; Bhattacharya & Gwizdka, 2019a; L. Cole et al., 2020; Gwizdka, 2013, 2017). **Working memory** (WM) is considered a core executive function is defined as someone's ability to hold information in short-term memory when it is no longer perceptually present (Diamond, 2013; G. A. Miller, 1956). (Bailey & Kelly, 2011) showed that the amount of effort was a good indicator of user success on search tasks. (Smith & Kantor, 2008) studied searcher adaptation to poorly performing systems and found that searchers changed their search behaviors between difficult and easy topics in a way that could indicate that users are satisficing. Differences in search effort between different types systems (higher effort invested in searching library database vs. web) were found by (Rieh et al., 2012). A couple of studies showed that mental effort involved in judging document relevance is lower for irrelevant and higher for relevant documents (Gwizdka, 2014; Villa & Halvey, 2013). (Gwizdka, 2017) found that that higher WM searchers perform more actions and that most significant differences are in time spent on reading results pages. Behaviour of high and low WM searchers were also found to change differently in the course of a search task performance.

3.4 Assessing Learning during Search

In order for IR systems to foster user-learning at scale, while respecting individual differences of searchers, there is a need for measures to represent, assess, and evaluate the learning process, possibly in an automated fashion. Consequently, a variety of assessment tools have been used in prior studies. These include self reports, close ended factual questions (multiple choice), open ended questions (short answers, summaries, essays, free recall, sentence generation), and visual mapping techniques using concept maps or mind maps. Each approach has its own associated advantages and limitations. Urgo & Arguello (2022) compare and contrast these assessment techniques extensively in their very comprehensive literature review.

Self-report asks searchers to rate their self-perceived pre-search and post-search knowledge levels (Ghosh et al., 2018; O'Brien et al., 2020). This approach is the easiest to construct, and can be generalised over any search topic. However, self-perceptions may not objectively represent true learning. **Closed ended questions** test searchers' knowledge using factual multiple choice questions (MCQs). The answer options can be a mixture of fact-based responses (*TRUE*, *FALSE*, or *I DON'T KNOW*), (Gadiraju et al., 2018; Xu et al., 2020; Yu et al., 2018) or recall-based responses (*I remember / don't remember seeing this information*) (Kruikemeier et al., 2018; Roy et al., 2020). Constructing topic-dependant MCQs may take time and effort, since they are topic dependant. Recent work on automatic question generation may be leveraged to overcome this limitation (Syed et al., 2020). Evaluating close ended questions is the easiest, and generally automated in various online learning platforms. Multiple choice questions, however, suffer from a limitation: they allow respondents to answer correctly by guesswork. **Open ended questions** assess learning by letting searchers write natural language summaries or short answers (Bhattacharya & Gwizdka, 2018; O'Brien et al., 2020; Roy et al., 2021). Depending on experimental design, prompts for writing such responses can be generic (least effort) (Bhattacharya & Gwizdka, 2018, 2019b), or topic-specific (some effort) (Syed et al., 2020). While this approach can provide the richest information about the searcher's knowledge state, evaluating such responses is the most challenging, and requires extensive human intervention (Kanniainen et al., 2021; Leu et al., 2015; M. J. Wilson & Wilson, 2013) (as discussed in Section 2.4.2). **Visual mapping** techniques such as mind maps and concept maps have also been used to assess learning during search (Egusa et al., 2010, 2014a, 2014b, 2017; Halttunen & Jarvelin, 2005). Concept maps have been discussed at length in Section 2.3.1. Learning has also been measured in **other ways**, such as user's familiarity with concepts and relationships between concepts (Pirolli et al., 1996), gains in user's understanding of the topic structure, e.g., via conceptual changes described in pre-defined taxonomies (P. Zhang & Soergel, 2016), and user's ability to formulate more effective queries (Chen et al., 2020; Pirolli et al., 1996).

3.5 Limitations of Current Search Systems in Fostering Learning

3.5.1 Longitudinal studies

Learning is a longitudinal process, occurring gradually over time (Sections 2.3 and 2.2). Therefore, information researchers have studied participant's search behaviour in prior, **albeit few**, longitudinal studies. Examples include studies by (Kelly, 2006a, 2006b; Kuhlthau, 2004; Vakkari, 2001a; White et al., 2009; Wildemuth, 2004).

(Wildemuth, 2004) examined the search behaviour of medical students in microbiology. In this experiment, students were observed at three points of time (at the beginning of the course, at the end of the course, and six months after the course), under the assumption that domain expertise changes during a semester. Some search strategies, most notably the gradual narrowing of the results through iterative query modification, were the same throughout the observation period. Other strategies varied over time as individuals gained domains knowledge. Novices were less efficient in selecting concepts to include in search and less accurate in their tactics for modifying searches. (Pennanen & Vakkari, 2003; Vakkari, 2000, 2001a, 2001b) also examined students at multiple points in time, as they were developing their thesis proposal. One important change in behaviour was the use of a more varied and more specific vocabulary as students learned more about their research topic. (Weber et al., 2019) examined a large sample of German students from all academic fields in a two wave study and found that the more advanced they are in their studies, the more students show a more advanced search behaviour (e.g., using more English queries and accessing academic databases more frequently). **Advanced search behaviour predicted better university grades.** (Weber et al., 2018) also provide mixed evidence on the potential long-term effects of such interventions, as some of their participants reverted to their previous habits two weeks after the study and therefore exhibited only short-term changes in their information-seeking behaviour.

Overall, results regarding the promotion of user' search and evaluation skills are encouraging. But there is a clear need for more longitudinal studies. The general body of search-as-learning literature examines the learner in the short-term, typically over the course of a single lab session (Kelly et al., 2009; Zlatkin-Troitschanskaia et al., 2021). The trend is similar in other Human-Computer Interaction (HCI) research venues. A meta-analysis of 1014 user studies reported in the ACM CHI 2020 conference revealed that more than 85% of the studies observed participants for a day or less. To this day, "longitudinal studies are the exception rather than the norm" (Koeman, 2020). "An over-reliance on short studies risks inaccurate findings, potentially resulting in prematurely embracing or disregarding new concepts" (Koeman, 2020).

3.5.2 Supporting sensemaking and reflection

As we saw in Section 2.3, learning *is* sensemaking. Yet, modern search systems are still quite far from supporting sensemaking and learning, and rather, at best are good *locators* of information. (Rieh et al., 2016) says that modern search systems should support sensemaking by offering more interactive functions, such as tagging for annotation, or tracking individuals' search history, so that a learner could return to a particular learning point. In addition, a system could provide new features that allow learners to reflect upon their own learning process and search outcomes, thus facilitating the development of critical thinking skills.

> *It's easy to be impressed by the scientific and engineering feats that have produced web search engines. They are, unquestionably, one of the most impactful and disruptive information technologies of our time. However, it's critical to remember their many limitations: they do not help us* ***know what we want to know****; they do not help us* ***choose the right words*** *to find it; they do not help us know if what we've found is* ***relevant or true****; and they do not help us* ***make sense of it****. All they do is quickly retrieve what other people on the internet have shared. While this is a great feat, all of the content on the internet is far from everything we know, and quite often a poor substitute for expertise.*
>
> — Ko (2021) (emphasis our own)

3.6 Summary

In this second chapter of the background literature review, we discussed *(i)* how searchers interact with three stages / interfaces of modern information retrieval system: query formulation, search results evaluation, and content page evaluation; *(ii)* how expertise and working memory influence overall search behaviour; *(iii)* how learning or knowledge gain during search has been assessed in recent search as learning literature; and *(iv)* what are the limitations of current search systems to foster learning, including gaps in literature about long term search behaviour and learning outcomes, as well as lack of support for sensemaking.

We saw that while we have a plethora of studies investigating search behaviour searchers in the short term, we have merely a handful of studies observing the same participant for more than a day. To the best of the author's knowledge, most of these studies were conducted over a decade ago. Thus, while we have excellent knowledge of short term nature of influence of searching on learning, we do not know what are the longer term effects. Furthermore, we we have gaps in our knowledge of *(i)* how practices like articulation and externalization, and user attributes like metacognition, motivation, and self regulation moderate the searching as learning process; *(ii)* how these moderator variables change over time; and *(iii)* what these phenomena collectively entail for the design of future learning-centric IR systems. In the next chapter, we take these gaps in knowledge and use them to inform our research questions and hypotheses.

4 Research Questions

Combining empirical findings and gaps in the literature from the disciplines of Education (Chapter 2) and Information (Chapter 3), we saw that:

- searching for information online is an integral part of new learning (Section 2.4.3)
- learning happens when students connect new pieces of information to their existing knowledge structures via assimilation, restructuring, or tuning (Section 2.3), and this process is influenced by the learner's individual traits (Section 2.5)
- modern knowledge-work requires less of long term memory, and more of creation of knowledge-artefacts, which should be treated as better assessors and outcomes of learning (Section 2.4.2)
- domain expertise and search behaviour are strongly linked (Section 3.3)
- learning is a process that takes place longitudinally over time (Sections 2.3 and 2.2), yet only a handful of studies (mostly over a decade ago) have investigated the intertwined process of searchers' learning and their information searching behaviour over time (Section 3.5.1)
- this creates acute gaps in our knowledge about long term information searching and learning behaviour, which is crucial for building learning-centric search systems of the

future, which can support sensemaking and knowledge-gain

Guided by the above insights, we ask the following research questions in this dissertation, and aim to answer them via an exploratory longitudinal study of students' information search behaviour and learning outcomes over the course of a university semester (Section 5.1).

RQ1: *How do (changing) individual differences of students affect their longitudinal information search behaviour?*

RQ2: *What are the similarities and differences in information search behaviours for tasks where the learning goals are new (non-repeated search tasks), versus those where the learning goals are repeated (repeated search tasks)?*

RQ3: *How do (longitudinal) information search behaviour of students relate to their (self-perceived) learning outcomes?*

The study was purposefully planned to be exploratory in nature (Stebbins, 2001). Therefore, the research questions are exploratory as well, meant at discovering interesting patterns, and aiming to illuminate new concepts through quantitative observation.

Students' motivation, self-regulation and metacognition capabilities determine, direct, and sustain the approaches they take to learn (Section 2.5). Effective searching for learning is affected by students' search tactics and information evaluation capabilities (Section 2.4.3) as well as cognitive capabilities, such as memory span (Section 3.3). We (weakly) hypothesize that students showing sustained or increasing values of metacognition, self-regulation, and motivation over the duration of the semester will put more effort into their searches, and demonstrate better learning and search outcomes.

Learning and expertise are closely connected: expertise is an evolving characteristic of learners that reflects learning over time, rather than being a static property (Rieh et al., 2016). Domain expertise and search behaviour has been studied, albeit mostly during single lab sessions, and sometimes longitudinally (Section 3.3). Therefore, there is a clear gap in understanding how higher education students search for information in the long term, how their information use behaviour develop over time, and how it affects their learning (Zlatkin-Troitschanskaia et al., 2021). The three research questions presented in this chapter aim to address some of these gaps.

5

Method: LongSAL - the Longitudinal Study

To investigate the research questions and hypotheses discussed in Chapter 4, we conducted the LongSAL study. The following sections discuss the study design, apparatus and procedure.

5.1 Study Design and Participants

LongSAL (Longitudinal Search as Learning study) is a remote, exploratory, longitudinal study that was conducted between January and June 2022 (Spring semester) at the School of Information, University of Texas at Austin (UT Austin). The study was approved by The University of Texas at Austin Institutional Review Board (Submission ID: `STUDY00002136`, Date Approved: December 8, 2021).

Participants were recruited from the student pool enrolled in the required undergraduate core-course: *Ethical Foundations for Informatics* (Fleischmann et al., 2022). 18 participants originally signed up for the study; 10 participants fully completed all the phases of the study, and the remaining 8 dropped off at different points during the semester. Students enrolled in the course had to submit a research paper of 2,000-2,500 words as the final project for the course. There were has four checkpoints spread across the semester to submit the drafts in progress: (i) paper proposal, (ii) outline, (iii) rough draft, and (iv) final paper. Writing the research paper required choosing an informatics ethical dilemma, and applying three ethical perspectives covered in the course to explore potential solutions to the selected dilemma. This involved searching and navigating information online, finding at least 20 relevant external sources, combining ideas, and weaving a narration around the information found in the selected sources.

The study design was informed by running a pilot study during Summer 2021 semester, in partnership with two courses at UT Austin School of Information: *Information in Cyberspace*, and *Academic Success in the Digital University*. More details of the pilot study are presented in Appendix A.

5.2 Apparatus

5.2.1 YASBIL Browsing Logger

The YASBIL browsing logger (Bhattacharya & Gwizdka, 2021) was utilised for this study. YASBIL (Yet Another Search Behaviour and Interaction Logger)[1] is a two-component logging solution for ethically recording a user's browsing activity for Interactive IR user studies. It was developed by the author in early Spring 2021, and was employed in the pilot study for data collection and testing. YASBIL comprises a Firefox browser extension and a WordPress plugin. The browser extension logs browsing activity in the participants' machines. The WordPress plugin collects the logged data into the researcher's data server. YASBIL captures participant's behavioural data, such as webpage visits, time spent on pages, identification of popular search engines and their SERPs, tracking mouse clicks and scrolls, and the order and sequences of these events. The logging works on any webpage, without the need to own or have knowledge about the HTML structure of the webpage. To protect the privacy of participants, the logger software can be switched on or off by the participant. Participants received regular reminders to turn YASBIL on only when they were searching for information related to the course.

YASBIL offers ethical data transparency and security for participants, by enabling them to view and obtain copies of the logged data, as well as securely upload the data to the researcher's

[1] https://github.com/LongSAL/yasbil

	ENTRY QSNAIRE [QSNR1]	INITIAL PHASE [PHASE1]	LONGITUDINAL TRACKING PHASE [PHASE2A, 2B, 2C, 2D]	MID-TERM QSNAIRE [QSNR2]	FINAL PHASE [PHASE3]	EXIT QSNAIRE [QSNR3]
Why	Record individual-differences	Establish baseline search behaviour and initial knowledge	Understand change in search behaviour and knowledge acquisition over time	Track changes in individual differences	Record "evolved" search behaviour, and "final" knowledge	Final state of individual differences
When	Week 1-2 of semester	Weeks 1-2 of semester; after QSNR1	Four different points over the semester	Semester mid-point	After last day of classes	After PHASE3
Where	Asynchronous	**Synchronous**: Remote	Async	Async	**Sync:** Remote	Async
What	Only in QSNR1: −Consent Form Repeated in QSNR2 and QSNR3: −Motivation −Self-regulation −Metacognition	**Two search tasks:** for each task, participants searched to find at least three unique, good quality online resources relevant to a given topic. • Pre-search self reporting: existing knowledge, interest, perceived difficulty • Post-search self reporting: perceived learning, perceived search success, interest and motivation, decision making	Participants recorded browsing activity when they worked on **final project assignment:** writing a research paper, at four different points in the semester (PHASE2). − 2A: Proposal − 2B: Paper Outline − 2C: Rough Draft − 2D: Final Paper Participants also shared (anonymized) assignment submission	Similar to QSNR1, with repeated components	**Two search tasks:** one task-topic repeated from PHASE1, one new; same format as PHASE1	Similar to QSNR2 Participants self-reported scores and grades they received for different parts of the final project
Approx. Time Reqd.	10 - 15 mins	60 - 90 mins	No time limit for working on assignments. Sharing data with researchers took 1-5 minutes.	10 - 15 mins	60 - 90 mins	10 - 15 mins
Comp: (USD) $150	$5	$25	$5, $5, $10, $15 (total $35)	$10	$30	$15
	Bonus $30 paid in the end, if participant completed all parts of the study.					

Figure 5.1: Longitudinal study procedure.

server over an HTTPS connection. Although developed using the cross-browser WebExtension API [2], YASBIL currently works in the Firefox Web Browser. So participants were instructed to install Firefox and YASBIL on their machines when they volunteered to participate in the study.

5.3 Procedure

The longitudinal study consisted of six data collection components, as illustrated in Figure 5.1. They comprise three asynchronous **questionnaires** (`QSNR1`, `QSNR2`, `QSNR3`), two **remote synchronous study phases** over Zoom video conferencing software (`PHASE1`, `PHASE3`), and a set of four asynchronous **longitudinal tracking phases** (`PHASE2a`, `PHASE2b`, `PHASE2c`, `PHASE2d`). These phases are discussed in detail in the following sections.

[2] https://developer.mozilla.org/en-US/docs/Mozilla/Add-ons/WebExtensions/Build-a-cross-browser-extension

5.3.1 `QSNR0`: Recruitment Questionnaire (Appendix B.1)

Participants were recruited for the study via the recruitment questionnaire (`QSNR0`). The questionnaire contained questions about demographic information of the participant pool. The description of the study and the link to the questionnaire was posted in the Canvas Learning Management System used for the I303 course.

5.3.2 `QSNR1`: Entry Questionnaire

After recruitment, participants completed the entry questionnaire (QSNR1). The purpose of QSNR1 was to capture their individual-differences, or moderating variables, at the beginning of the semester. Details of the data captured in SUR1 are described below, with references to sections in the Appendix, where the full-text of the questionnaire can be found.

5.3.2.1 Consent Form (Appendix B.2.1)

The first page of QSNR1 was online consent form for participating in the study. Participants were able to proceed with the study once they provided informed consent.

5.3.2.2 Motivation (Appendix B.3)

Adapted from the *Intrinsic Motivation Inventory (IMI)* by (Ryan, 1982), which is a multi-dimensional measurement device intended to assess participants' subjective experience related to a target activity (the assignments for the course they are taking). The instrument assesses participants' interest/enjoyment, perceived competence, effort/importance, pressure/tension, perceived choice, and value/usefulness, while performing a given activity, thus yielding six sub-scale scores. The pressure/tension and the perceived choice components were not included in the entry questionnaire QSNR1, and were present in the mid-term (QSNR2) and exit (QSNR3) questionnaires.

5.3.2.3 Self-regulation (Appendix B.4)

Adapted from the *Self-Regulation Questionnaire (SRQ)* by (J. M. Brown et al., 1999), which assess seven self-regulatory processes through self-report: receiving relevant information, evaluating the information and comparing it to norms, triggering change, searching for options, formulating a plan, implementing the plan, and assessing the plan's effectiveness (Section 2.5.4).

5.3.2.4 Metacognition (Appendix B.5)

Adapted from the *Metacognivite Awareness Inventory (MAI)*, originally proposed by (Schraw & Dennison, 1994) as a 52-item true / false questionnaire, and later revised by (Terlecki & McMahon, 2018) to use five-point Likert scales. The instrument measures two components of cognition through self-report: knowledge about cognition, and regulation of cognition (Section 2.5.2).

After completing QSNR1 offline, participants were instructed to prepare for the initial synchronous phase, `PHASE1`, by installing Firefox web browser and the YASBIL extension on their machines. This was a one-time step. If a participant could not find the time for this step, they were informed that an extra 5-10 minutes would be taken in the beginning of `PHASE1` to complete this step.

The entry questionnaire and the software installation took about 10-15 minutes to complete. Participants were compensated with USD 5 for their time for completing this step. The questionnaire was published to the I-303 course students in the first week of the Spring 2022 semester.

5.3.3 `PHASE1`: Initial Phase

The `PHASE1` of the data collection took place in the beginning of the semester. The data-collection took place over a Zoom video call combined with YASBIL browsing logger installed in the participants' machines. Participants were asked to share their screen for the whole duration of the phase. Their screens and audio were recorded for the entire duration. They had the freedom to turn off their video. The total time for `PHASE1` was expected to not exceed

1.5 hours (90 minutes). Participants were compensated with USD 25 for this phase. The different components of `PHASE1` are described below.

5.3.3.1 Training Search Task

Participants performed a training search task to familiarize themselves with how to operate the YASBIL browser extension to log their browsing activity. The training task took around 2-5 minutes.

5.3.3.2 `PHASE1-FINANCE` and `PHASE1-UBUNTU`: Two Actual Search Tasks

Participants performed two search tasks: `PHASE1-FINANCE`, and `PHASE1-UBUNTU`. The `PHASE1-FINANCE` task was repeated at the end of the semester as `PHASE3-FINANCE` task. The `PHASE1-UBUNTU` task was not repeated, and instead the `PHASE3-BIAS` task tooK its place. This helps to answer the research question RQ2 (Chapter 4). The order of the two search tasks were randomized.

The repeated search task `FINANCE` was on the topic of financial literacy, a topic that we posit can be considered as universally important to college students, and part of lifelong learning. The prompts for the `PHASE1-FINANCE` and `PHASE3-FINANCE` tasks are presented in Figure 5.2. The non-repeated search tasks were on topics that were taught in the I303 course: Ubuntu ethics (for `PHASE1`) and Algorithmic Bias (for `PHASE3`). The prompts for these tasks are present in Figure 5.3.

Each search task began with a pre-task questionnaire (Appendix C.1), which asked participants to self-rate their pre-search knowledge-level and interest on the topic. Then participants turned on the YASBIL browsing logger and started searching. The deliverable for each search task was a written summary (artefact). After participants are satisfied with the quality of the deliverable, they turned off YASBIL browsing logger, and proceeded to the post-task questionnaire.

<table>
<tr><th colspan="2">Repeated Search Task: Financial Literacy</th></tr>
<tr><th>Prompt for Initial Phase
[PHASE1-FINANCE]</th><th>Prompt for Final Phase
[PHASE3-FINANCE]</th></tr>
<tr><td>Money management and financial literacy are essential life skills, and what better time to learn about them than in college?

Write a note to your future self, about essential money-related advice and skills that college students should know and practice.

<u>What to do</u>:
• Find <u>at least three (3)</u> unique, good quality online resources that are relevant to this topic
• Look for resources that help establish connections and develop a narrative

<u>What to deliver</u>:
• Write a summary of the lessons, advice, and/or tips you found across the different resources. This is a note to your future self, so the narrative can be in a format that is most useful and interesting to YOU :)
• Paste the links of ALL the resources that you finally selected to develop your narrative, in the second text box, one link per line

Please turn YASBIL ON before starting to search.

Write the summary (note to your future self) here: _____

Paste the links of the resources that you finally selected (at least 3), one per line: _____</td><td>At the start of the semester, you wrote a note to your future self, about essential money-related advice and skills that college students should know and practice.

Here is what you wrote:
[… dynamic content showing participant's PHASE1 response …]

Here are the resources you took help from:
[… dynamic content …]

Now you have a chance to update or revise the note with more information. You can either choose to write afresh, or copy-paste the note from above into the first textbox below and add to it /edit it.

Feel free to search the web if you need to, <u>after turning YASBIL on</u> .

You can choose NOT to search, as well.

If you do choose to search, please paste the links of ALL the resources that you finally selected for updating your note, one link per line, in the second textbox. The links can be the same ones you visited earlier, or different.

Please turn YASBIL ON before starting to search (if you choose to search).

Write the updated summary (note to your future self) here: _____

Paste the links of the resources that you used to update your note here, one per line. If you did not search this time, type "N/A": _____

Did you need to search the web for updating the note? Why?
Yes: _____ No: _____ Other: _____</td></tr>
</table>

Figure 5.2: Prompts for the search task that was repeated in the final phase, on the topic of financial literacy.

The post-task questionnaire (Appendix C.2) asked participants to self-rate their perceived learning and search outcomes, search experience, interest and motivation, and overall perceptions. The pre-task and post-task questionnaires are adapted from (Collins-Thompson et al., 2016; Crescenzi, 2020).

Non-Repeated Search Tasks	
Prompt for Initial Phase: Ubuntu Ethics [PHASE1-UBUNTU]	**Prompt for Final Phase: Algorithmic Bias [PHASE3-BIAS]**
The term Ubuntu originates in Africa, and refers to the idea that our individual lives are intricately tied to the lives of others, and we all need to cherish these interconnections. Such interconnections should be guided by kindness, openness, accommodation, and willingness to work for others' interest. Do you think the Ubuntu philosophy can be used to mitigate the social, physical, and mental isolation that people may be facing during the COVID-19 pandemic? **What to do**: • Find **at least three (3)** unique, good quality online resources that are relevant to this topic • Look for resources that help establish connections and develop a narrative **What to deliver**: • Write a short summary of the content that you found across the different resources. • In the summary, briefly mention your thoughts about each resource - do you agree or disagree with the content in the resource? Anything else? • Paste the links of ALL the resources that you finally selected to develop your narrative, in the second text box, one link per line Please **turn YASBIL ON** before starting to search. Write the summary here: _____ Paste the links of the resources that you finally selected (at least 3), one per line: _____	In the I303 course, you studied about **Algorithmic Bias and its implications**. Therefore, for answering the questions below, **you may choose NOT to search the web**, if you feel you can answer the questions reasonably well. If you need to search the web, feel free to do so, **after turning YASBIL ON**. Paste the links of ALL the resources that you finally selected to develop your narrative, in the second text box, one link per line Please **turn YASBIL ON** before starting to search (if you choose to search). As you understand these concepts, briefly explain (with examples if necessary) 1. What is algorithmic bias? 2. How does algorithmic bias originate? 3. What are some implications of algorithmic bias? Response: _____ Paste the links of the resources that you used to write your answers, one per line. If you did not need to search, type "N/A": _____ Did you need to search the web for this task? Why? Yes: _____ No: _____ Other: _____

Figure 5.3: Prompts for the non-repeating search tasks. Topics were selected from the I-303 course content.

5.3.3.3 Memory Span Test

PHASE1 concluded with the assessment of the participant's working memory capacity (WMC) using a memory span task (Francis et al., 2004). Memory span assessment was kept in the synchronous phase because it is a timed task, and needs to conducted in a controlled (experimenter observed) condition. The task has 25 trials. On each trial participants saw a list of items presented one at a time in random order and were asked to recall the items in the same order in which they were presented. If they got a list correct, the list length increased by

Final Project Description: Ethical Dilemma Research Paper

Throughout the semester, you will choose an ***informatics ethical dilemma*** and apply ***three ethical perspectives*** covered in the class to explore potential solutions to your selected dilemma. You are required to apply readings from the course as well as readings from outside of the course, including incorporating the three ethical theories as part of your analysis. This final project is broken down into several components that you will complete throughout the semester.

<u>Proposal (week 3)</u>: must include the proposed ***title*** of your research paper as well as a one-page description of the ***informatics ethical dilemma***. At this stage, you are not required to have settled on your ethical theories yet. Please make sure to include your ***strategy*** for finding appropriate outside readings. **[PHASE2A]**

<u>Outline (week 6)</u>: will typically include bulleted lists, filling in as much detail as you have ready at this point; must include the three planned ethical theories; must **list** of at least **10** potentially relevant references / scholarly readings, with **5** of them coming from beyond the course syllabus (external sources). **[PHASE2B]**

<u>Rough Draft (week 10)</u>: must be at least a half-complete version of your final paper; should be 1,000-2,500 words; must **cite** at least **10** sources, including **5** from external sources. **[PHASE2C]**

<u>Final Paper (week 15)</u>: must be complete, coherent, and easy to read; must incorporate feedback from all previous stages; should be 2000-2500 words; must cite at least **20** sources, including **10** external sources. **[PHASE2D]**

<u>Peer Reviews of Rough Draft (week 10-11)</u>: peer-review the rough draft of two of your peers; prepare a one page peer review for each of them; must include: a brief summary of the purpose and content of the paper as you understood it, the strengths of the paper, and constructive feedback on how to improve it

<u>Final Presentation (week 15)</u>: record a 5-min video presentation of your paper.

Figure 5.4: Final project description, setting up the longitudinal tracking phase of the study throughout the duration of the Spring 2022 semester. Text taken from I-303 course syllabus (Fleischmann et al., 2022); emphasis and annotations our own.

1 for that type of material. If they got a list incorrect, the list length decreased by 1.

The type of material participants were asked to recall were: digits, letters that sound dissimilar, letters that sound similar, short words, and long words. The outcome score was the list length of the last list that participants could correctly recall.

5.3.4 PHASE2A - PHASE2D: Longitudinal Tracking Phase

The four-part longitudinal tracking phases PHASE2A - PHASE2D were conducted asynchronously over the duration of the semester, to understand the change (or lack thereof) of participants' search behaviour and knowledge gain over time. Whenever participants worked on different parts of their final project (Ethical dilemma research paper for the I-303 course), as described in Figure 5.4, they used Firefox web browser, and logged their browsing activity using YASBIL browsing logger. To protect their privacy, participants were regularly instructed to turn YASBIL on only when they were searching for information related to coursework. After each checkpoint assignment, participants self-uploaded an anonymized version of the working-draft of their research paper, and answered a post-task questionnaire. The post-task questionnaire were similar to those used in the PHASE1 and PHASE3 search tasks, where participants self-reported, among other things, their perceived learning outcome and perceived search outcome (Collins-Thompson et al., 2016). Participants received reminder emails before the deadline of each assignment, to remind them to use Firefox, turn YASBIL on, and upload the anonymized working-draft. To prevent participant drop-off, a staggered payment model was adopted during PHASE2. Participants received USD 5 each when they completed PHASE2A and PHASE2B, USD 10 for PHASE2C, and USD 15 for PHASE2D, for a total of USD 35 for entire PHASE2.

5.3.5 QSNR2: Mid-Term Questionnaire

The mid-term questionnaire QSNR2 took place around the mid-point of the semester (Week 8-9). The purpose was to track whether any of the participants' individual difference measures (motivation, metacognition, and self-regulation) changed during the first half of the semester. This questionnaire was essentially a replica of the Entry Questionnaire QSNR1, with two modifications. First, the consent form and the demographics sections were absent. Second, the Intrinsic Motivation Inventory (IMI) included the 'pressure/tension' and the 'perceived choice' subscales, as these scales are more meaningful after an activity has taken place (Ryan, 1982). The IMI was also be reworded to reflect the mid-point of the semester. Participants were compensated with USD 10 for completing this step.

5.3.6 PHASE3: Final Phase

The Final Phase PHASE3 was similar in structure to the Initial Phase (PHASE1), and took place at the end of the semester, after all the course related tasks were completed by the participant. The purpose of the session is to record the 'evolved' search behaviour, and final knowledge state. Participants performed two search tasks: PHASE3-FINANCE and PHASE3-BIAS.

At the end of PHASE3, a semi-structured interview was conducted. The questions were aimed to collect the participants' reflections on their searching and learning experience throughout the semester, w.r.t. to the I303 course. While a full-scale qualitative analysis of the interview responses is beyond the scope of this dissertation, some preliminary qualitative quotes are presented in the results and discussion sections, to support the quantitative results as necessary.

5.3.6.1 PHASE3-FINANCE and PHASE3-BIAS: Two Actual Search Tasks

Of the two search tasks, the topic of one was repeated from PHASE1 (financial literacy, Figure 5.2), while the topic of the other came from the course material: algorithmic bias (Figure 5.3). In both search tasks, participants were given the option of ***not searching*** if they felt confident enough to answer the search task questions from their prior knowledge (Crescenzi, 2020). The deliverables for each search-task, as before, was a written summary (artefact).

Similar to PHASE1, participants were asked to share their screen for the whole duration of the phase. Their screen and audio was recorded for the same. They had the freedom to turn off their video. The total time for PHASE3 was expected to not exceed 1.5 hours (90 minutes). Participants were compensated with USD 30 for PHASE3. At the end of PHASE3, participants were instructed to complete the Exit Questionnaire QSNR3 as soon as convenient.

5.3.7 QSNR3: Exit Questionnaire

The exit questionnaire QSNR3 took place after the Final Phase PHASE3. The purpose was to record the final state of the participants' individual difference measures (motivation, metacognition, self-regulation), and whether these characteristics changed during the second half of the semester. As before, QSNR3 questionnaire was essentially be a replica of QSNR2, with the Intrinsic Motivation Inventory (IMI) reworded to reflect the end-point of the semester Participants were be compensated with USD 15 for their time for completing this step.

After QSNR3 was complete, participants received a bonus compensation of USD 30, if they completed all the phases of the LongSAL study without missing anything.

5.4 Measures to Address Ethical Concerns

- Participation in the study (which was voluntary and compensated separately) and participation in the I303 course (which was required for graduation from the Informatics major) were sufficiently disentangled. The course instructors were never aware of which students participate in the course, and did not share any student data with the researchers. This avoided any undue pressure or expectation on the students.

- Participants logged their browsing activity using a Firefox browser extension YASBIL, which was been developed by the authors. The extension has an ON-OFF button, which put the participants in full control of when they wished to start and stop the logging. Participants had been sufficiently trained to use the browser extension, and were repeatedly reminded to log data only when they were working on the research paper assignments for the course, and not at other times.

- This study has been approved by The University of Texas at Austin Institutional Review Board (Submission ID: STUDY00002136, Date Approved: December 8, 2021).

After data collection for all the phases was complete, data analysis was performed on the collected data, which is discussed in the next chapter.

6

Data Analysis, Results, and Discussion: Longitudinal Tracking Phase

The longitudinal phase of the LongSAL study involved understanding students' searching as learning behaviour for the research paper writing task. The aim was to investigate how students' information search behaviours and learning outcomes change over time. This chapter presents participant information, the timeline of data collection, and data analysis steps, followed by the results of the longitudinal phase of the study. The findings from the initial and final phases are presented in the next chapter for better narration.

6.1 Participants and Timeline of Collected Data

Figure 6.1 shows the timeline of the data collected in the LongSAL study, spread across the Spring 2022 semester at the University of Texas at Austin, USA. Eighteen participants enlisted their names in the Recruitment Questionnaire, `QSNR0`. Sixteen showed up for the initial phase and remained in the study till the mid-point of the semester (mid-term questionnaire, `QSNR2`). Then six participants dropped off, and ten participants fully completed the study (who stayed until the exit questionnaire, `QSNR3`.) In Figure 6.1, participant names in **bold** (bottom 10) indicate those who fully completed the longitudinal study, while participant names in *italics*

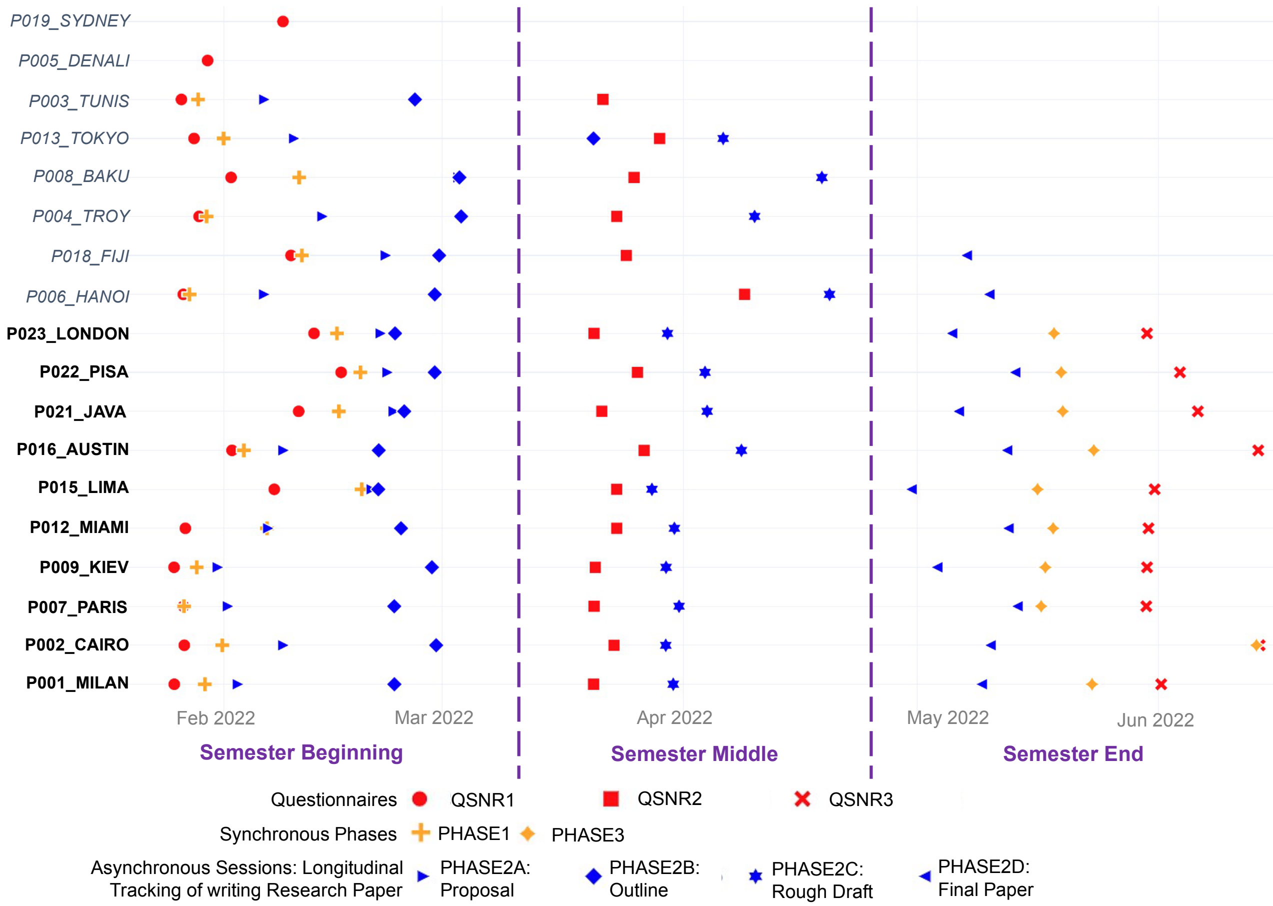


Figure 6.1: Timeline of collected data.

(top 8) indicate those who dropped off at various stages along the way. For data analysis, we partitioned the semester duration into three phases along the green vertical dotted lines: beginning, middle, and end of the semester. Inspired by the Spanish TV series *La Casa de Papel* (English name: *Money Heist*)[1], participants were assigned code-names which were aliases of geographic locations.

6.2 Data Analysis Framework

The general framework for analysing the data collected in the *LongSAL* study is described in Figure 6.2. Primarily, two categories of data were collected in the study: explicit responses via

[1] https://en.wikipedia.org/wiki/Money_Heist

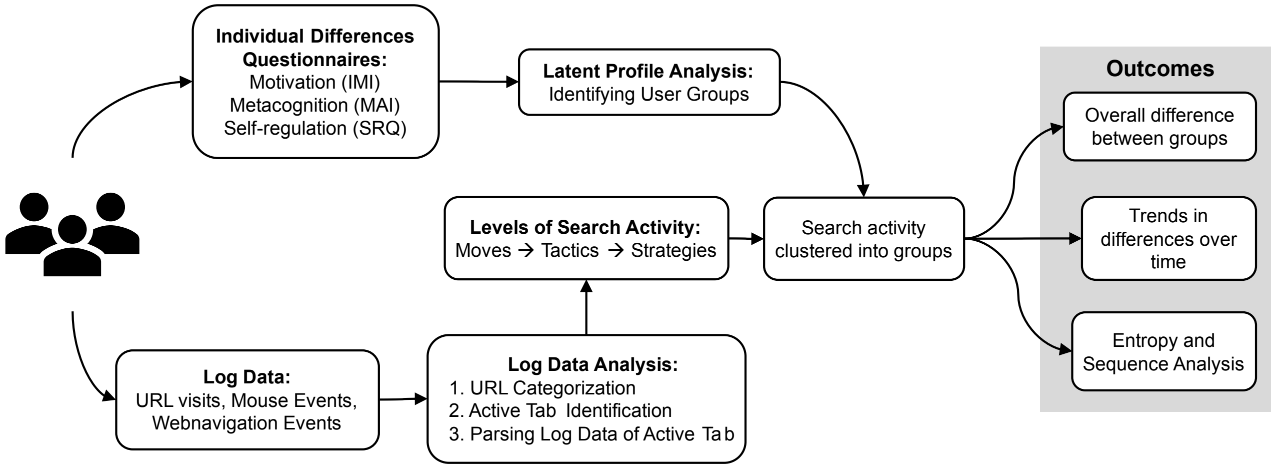


Figure 6.2: Data analysis framework followed in this dissertation.

Qualtrics survey platform, and implicit search behaviours via YASBIL browsing logger. The data collected from Qualtrics were primarily search task written responses, as well as responses to the individual difference questionnaire instruments for motivation, metacognition, and self-regulation. Data from the questionnaires were used to divide participants into groups, which is discussed in Section 6.3. Log data from YASBIL was cleaned, processed, categorized (Section 6.6) and analysed, to examine (differences in) search behaviour of different participant groups.

For examining statistical differences between groups, we employed the non-parametric **Mann-Whitney U test** for null-hypothesis significance testing (Mann & Whitney, 1947). This choice was due to several reasons: the sample sizes were often small, the groups were imbalanced, and / or the data did not satisfy the assumptions of parametric tests such as ANOVA. Employing one statistical test allows for easy comparison between different categories of results.

Additionally, we also report **Common Language Effect Size (CLES)** for each statistical test result. The common language effect size is the proportion of pairs where x from the first group is greater than y from the second group. In other words, it is the probability that a score sampled at random from the first distribution will be higher than a score sampled from the second distribution. CLES was first introduced by McGraw & Wong (1992). The Python statistical library employed in the data analysis – Pingouin (Vallat, 2018) – uses a brute-force version of the formula given by Vargha & Delaney (2000). The advantage is of this method

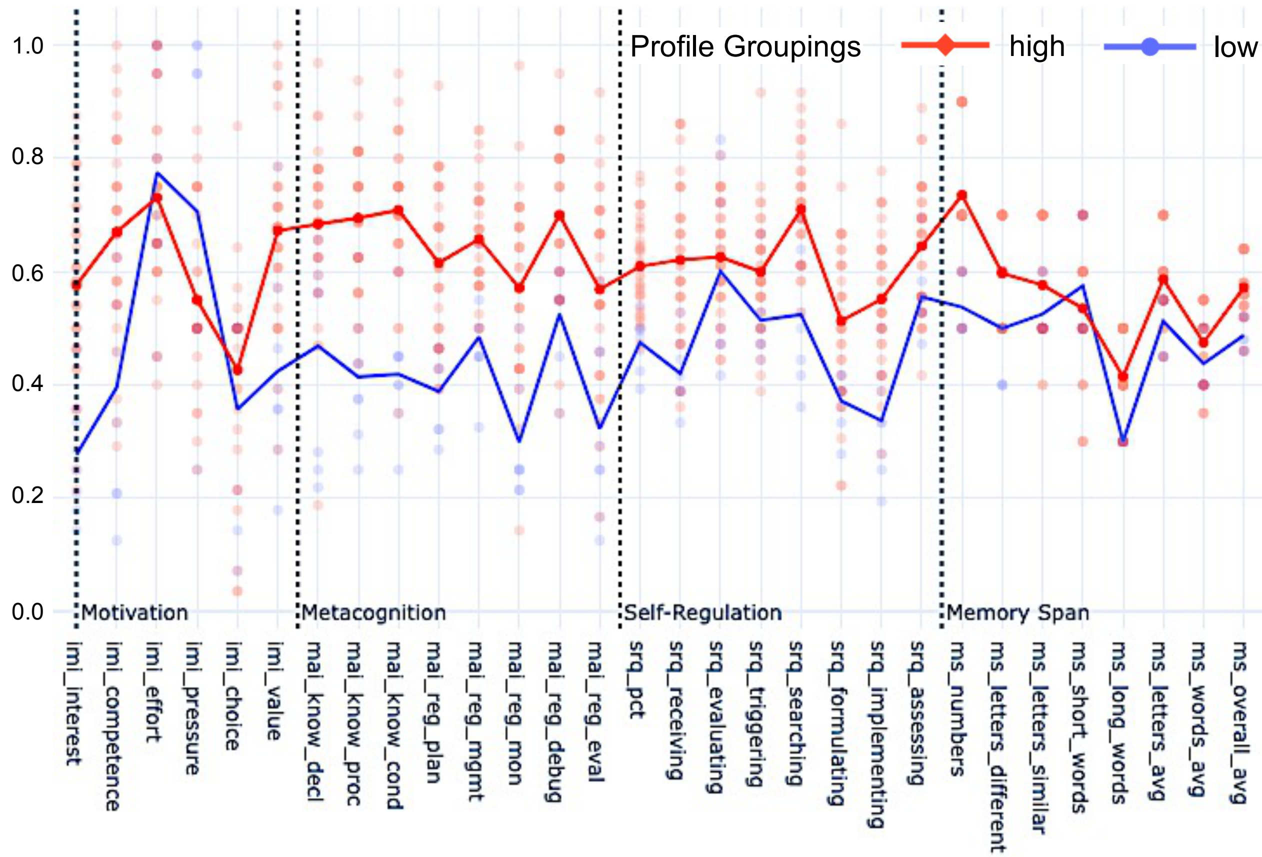


Figure 6.3: Mean Values of Indicator Variables for the two identified groups via Latent Profile Analysis (LPA). The grouping was based on the self-reported values of motivation (IMI), metacognition (MAI), self-regulation (SRQ), and a Memory Span task.

are twofold: first, the brute-force approach pairs each observation of x to its y counterpart, and therefore does not require normally distributed data; second, the formula takes ties into account and therefore works with ordinal data [2].

6.3 Latent Profile Analysis

According to Ambrose et al. (2010), students' motivation, metacognition, and self-regulation are critical factors that determine, direct, and sustain what they do to learn. Given our interest in understanding how these traits impact students' searching as learning behaviour, we collected self-perceived reports of all three constructs, via the IMI, MAI, and SRQ questionnaires (Section

[2] https://pingouin-stats.org/build/html/generated/pingouin.mwu.html

5.3.2). However, it is important to note that these constructs are not single binary variables that can be used to easily group individuals. Rather, they are complex and multidimensional data that serve as observable indicators of a person's underlying latent characteristics.

To cluster participants into meaningful groups based on these multiple constructs, we turned to the educational psychology literature. **Latent Profile Analysis (LPA)** is an increasingly popular statistical approach falling under the umbrella of person-centred techniques used in organizational psychology and child development research. It provides a framework for characterizing population heterogeneity in terms of differences across individuals on a set of behaviours or characteristics, as opposed to describing the variability of a single variable. By identifying latent subgroups within a population, LPA enables researchers to gain a more nuanced understanding of the complexity of human behaviour.

The **person-centred approach** underlying LPA is a departure from traditional variable-centred approaches such as multiple regression analysis. Instead of quantifying the role of particular variables in a study, LPA organizes a population into a finite number of mutually exclusive and exhaustive profiles, each comprising individuals who are similar to one another. In this way, LPA identifies distinct profiles of individuals who exhibit similar patterns of behaviour across multiple variables.

The identification and description of these latent profiles is a crucial step in LPA. Each profile represents a subgroup of individuals who share similar patterns of responses on a set of variables, which can provide insights into the underlying mechanisms driving their behaviour. Furthermore, the identification of the optimal number of profiles to represent a population is a critical issue in LPA. This involves balancing the complexity of the model with its ability to capture meaningful variability in the data, and requires careful consideration of both statistical and substantive criteria.

LPA has several advantages over traditional variable-centred approaches. It allows for a more nuanced understanding of the complexity of human behaviour, particularly in cases where individuals exhibit multiple and diverse patterns of behaviour across different sets of variables.

In the context of information search behaviour, LPA can help to identify distinct groups of individuals who engage in different search strategies or have different search motivations. This can be useful for understanding how people search for information online, what factors influence their search behaviour, and how search behaviour relates to other variables such as task performance, satisfaction, and learning outcomes.

The purpose of this study was to investigate the relationship between individual differences in motivation, metacognition, and self-regulation and search behaviour. To classify participants into high and low groups based on their scores on these questionnaires, we employed LPA. LPA is particularly useful when the relationship between variables is not well understood or when it is difficult to determine which variables should be used to classify individuals into groups. We employed LPA to identify latent profiles of participants based on their scores on the IMI, MAI, and SRQ questionnaires. LPA is particularly useful when the relationship between variables is not well understood, or when it is difficult to determine which variables should be used to classify individuals into groups.

The results of the LPA showed that there were two distinct groups (latent profiles) of participants based on their scores on the IMI, MAI, SRQ, and MS: a high group and a low group (Figure 6.3). The high group had generally higher average scores on the IMI, MAI, SRQ, and MS compared to the low group, indicating that they were more intrinsically motivated, more aware of their metacognitive processes, and had higher levels of self-regulation.

Figure 6.4 illustrates the memberships in the two groups at different points in time, and how one participant (`P016_AUSTIN`) changed group membership at the end of the semester. 12 participants started off the semester (`QSNR1`) in the high group, while 4 in the low group. The group membership remained the same in the middle of the semester (`QSNR2`). At semester end, 4 participants from the high group and 2 participant from the low group dropped off. One participant transitioned from high group to low group. This resulted in 7 participants in the high group and 3 participant in the low group, with no data for 6 participants at the semester end timepoint (`QSNR3`)

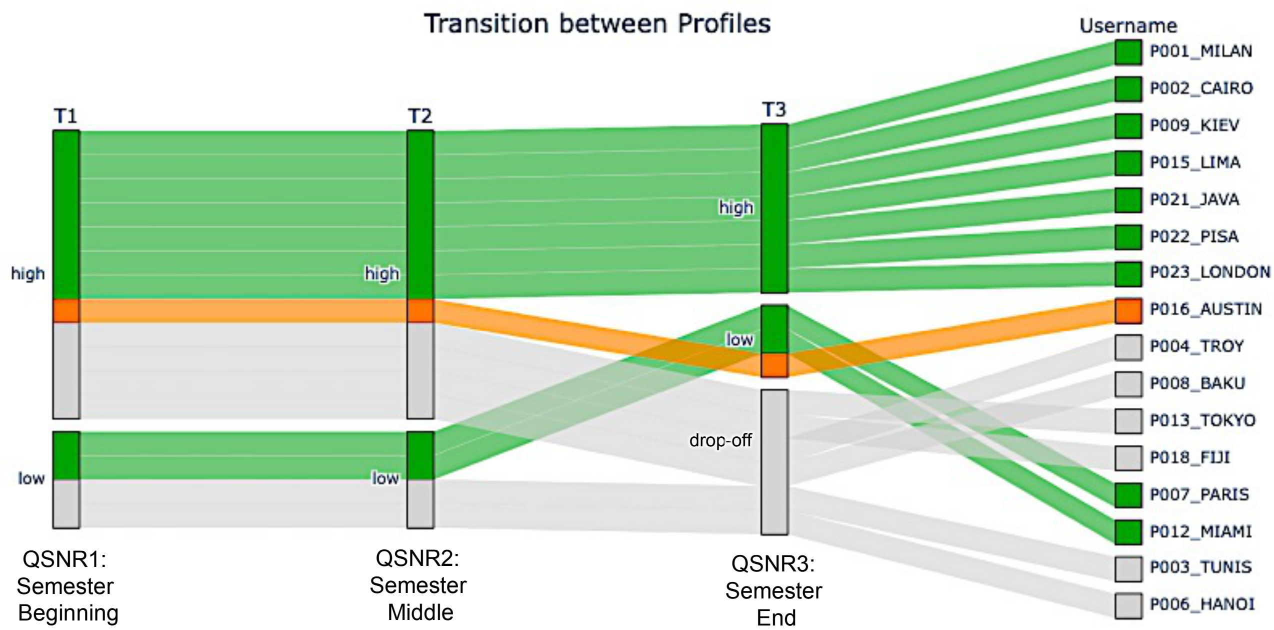


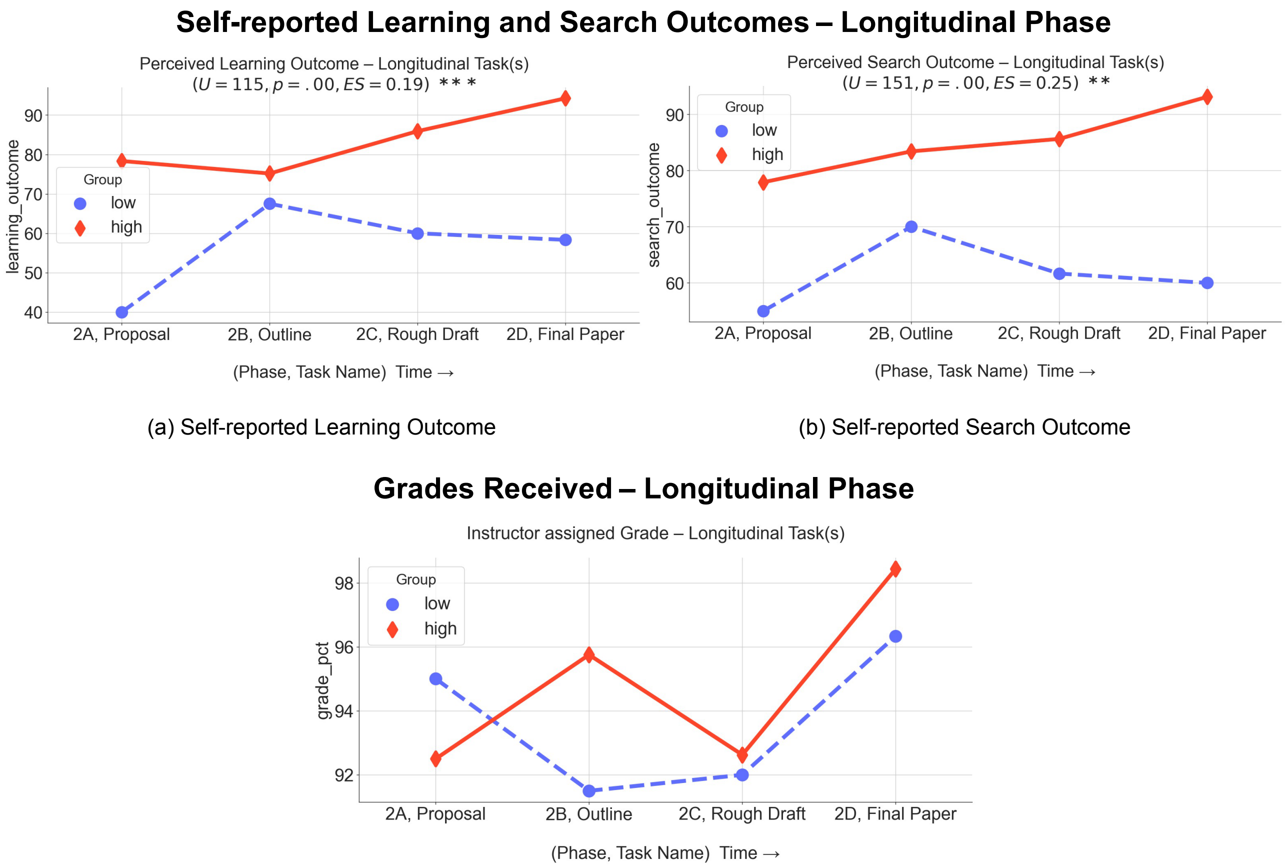
Figure 6.4: Diagram illustrating, at different timepoints, how participants stayed within their same high/low LPA profiles (green) or changed profiles (orange). Grey trajectories indicate participants who dropped off and did not complete the study.

In the discussion that follows, all the **Effect Sizes (ES)** reported as part of Mann Whitney U tests, compare the scores of the low group (first distribution) with those of the high group (second distribution). In other words, an example effect size $ES = 0.19$ means that there is a 19% chance that a score from the low group will be greater than the corresponding score from the high group.

6.4 Learning and Search Outcomes

Figure 6.5 shows the mean values of the self-reported (perceived) learning outcomes (a), self-reported search outcome (b), and instructor assigned grades (c) for the Ethical Dilemma research paper writing task over the semester. The self-reported learning and search outcomes are inspired from work by Collins-Thompson et al. (2016).

We see that the high group had higher levels of perceived learning outcome and perceived search outcome compared to the low group, and these differences were statistically signifi-



(c) Instructor Assigned Grade

Figure 6.5: Self-reported learning and search outcomes (a, b), and instructor assigned grades for the high and low groups (c).

cant: ($U = 115.0, p = .0005, ES = 0.19$) for the learning outcome, and ($U = 151.0, p = .005, ES = 0.25$) for the search outcome. (The effect sizes indicate the probability that a value chosen at random from the low group's scores will be greater than a value chosen at random from the high group's scroes.)

The fact that the high group had statistically significant higher self-reported learning outcomes and self-reported search outcomes suggests that these students had a higher level of motivation, self-regulation, and better time management skills than the low group. This is because students who are motivated and self-regulated tend to be more efficient and effective in their information searching behaviours, which in turn may lead to better learning outcomes.

Additionally, students in the high group were better at managing their time and resources, allowing them to engage in more thorough and comprehensive information-searching activities. This is corroborated by interview responses as well. For instance, when asked "How did you keep track of the sources you found?", a participant in the low group responded:

> *...in the reference list, I put all the links that I found. I did [save the articles] at one point. And then before I knew it, **I had 10 tabs (open)**, and I feel extremely unmotivated. I said, no, I can't do this anymore. **So I just closed all of them**.*
>
> *And I decided, okay, everything's in the reference list, **Whatever seems like its relevant. I'll click on it, and I'll see it later**. So I don't have to read 10 different papers. **I relied too much on the reference list. I throw everything in there**, like okay, I'll deal with you later.*
>
> — P007_PARIS

In contrast, a participant in the high group responded:

> *I have a **separate document** with a table and **three columns**, one for the **in-line citation**, so I could just easily copy and paste it. And then the middle was **direct quotes**. And then the (last column) was **notes** that are like sentences, what I wanted to say. And so that's how I organize my (sources).*
>
> — P021_JAVA

The response from the participant in the low group suggests a less organized approach to tracking sources. They mentioned initially saving articles and opening multiple tabs but eventually feeling overwhelmed and unmotivated, leading them to rely heavily on the reference list. This indicates a lack of systematic organization and a reliance on the reference list as a means of keeping track of sources, potentially leading to challenges in managing and accessing relevant information. In contrast, the participant from the high group described a more structured and organized method for tracking sources. They mentioned using a separate document with a table consisting of three columns for in-line citations, direct quotes, and notes. This approach demonstrates a deliberate and systematic way of organizing and capturing information from sources, allowing for efficient referencing and easy retrieval of relevant content during the writing process. These qualitative responses align with the quantitative findings of higher perceived learning outcome and perceived search outcome in the high group. The more organized and structured approach to tracking sources in the high group is likely to have contributed to their enhanced perception of learning and search outcomes.

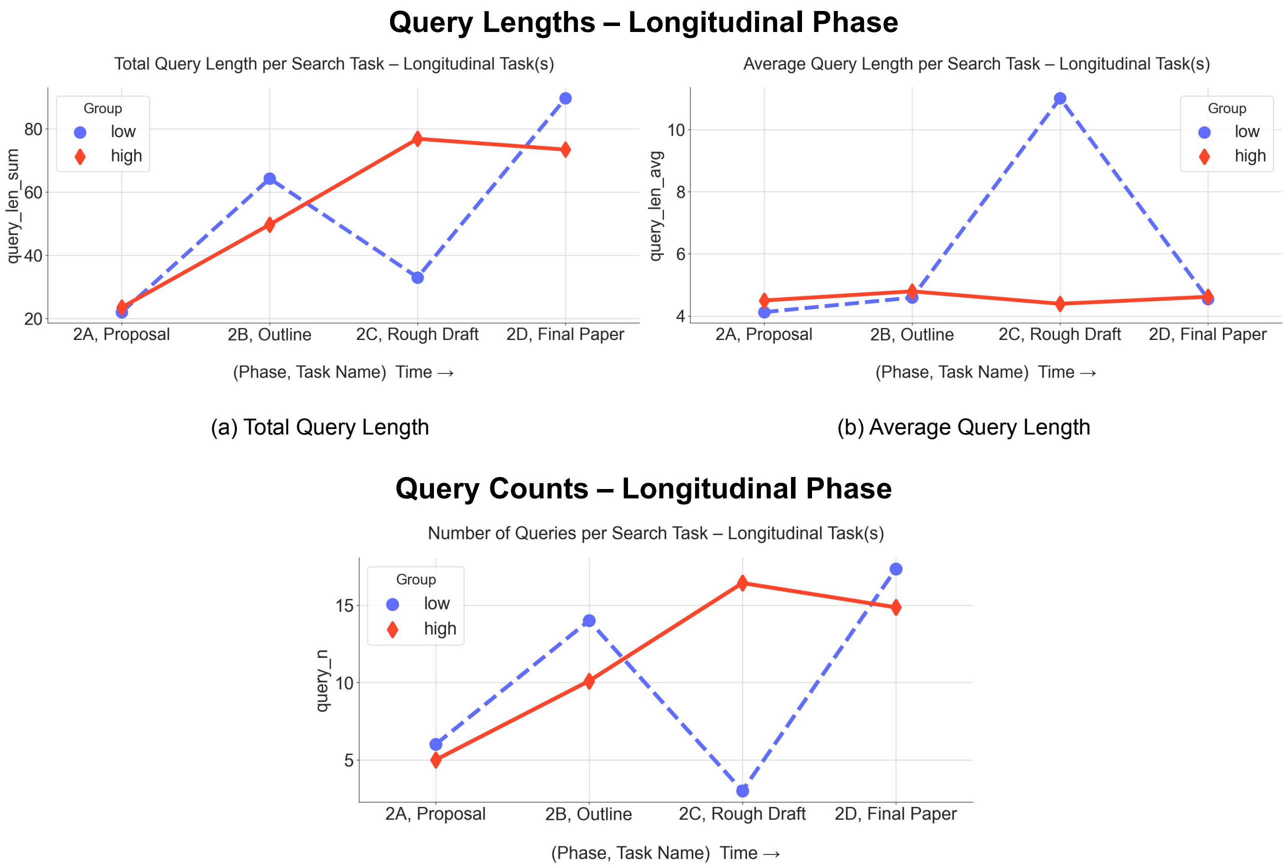
The instructor-assigned grades for the high group also generally stayed higher than the low group (except for the Proposal stage). However, the differences were small. This may indicate that the instructors' grading criteria may not have fully captured the impact of information-searching behaviours on learning outcomes. This is because the instructor's grading criteria may have been focused more on the content of the research paper, rather than the process of information searching. As a result, students who were more effective in their information-searching behaviours may not have received a higher grade, even if their research paper was of higher quality. Another possibility is that the grading process may have been liberal towards the students.

Collins-Thompson et al. (2016) reported that "searchers' perceived learning outcomes closely matched their actual learning outcomes" and this was also indirectly correlated with their information search behaviours in terms of dwell time on documents. Let us examine in the following sections how the findings from the LongSAL study compare and contrast with those reported by Collins-Thompson et al. (2016) and others.

6.5 Q: Query Formulations

6.5.1 Length and Count of Queries per Search Task

Query length was operationalized as the number of terms (words separated by spaces) in the search query that participants submitted to the search engines or other information retrieval sites. Query length can vary from a single word to several phrases or a complete sentence. Longer search queries may indicate a more specific or complex information need, while shorter search queries may be more general or broad in scope. **Queries count** per search task refers to the number of separate queries or search attempts that a participant issued in order to complete a task. This measure may vary depending on the complexity of the information need, the user's level of expertise with the search system, and other factors.



(a) Total Query Length

(b) Average Query Length

(c) Number of Queries

Figure 6.6: Lengths and count of queries for each search task in the Longitudinal Phase.

Figure 6.6 (a) and (b) shows the differences in total and average query length of the high and low groups, while Figure 6.6 (c) illustrates the number of queries issued, at different stages of writing the research paper. The low group demonstrated a zig-zag pattern in their **total query length** and query count over the semester, with a low start at proposal, followed by a peak at outline, a dip at rough draft, and a peak at Final Paper. The high group had a steady increase in total query length and query count, from proposal to outline to rough draft, and took a very gentle dip (or remained steady) at final paper stage. Comparing the total query length and query count to the **average query length** (Figure 6.6 (b)), we see that the high group maintained a steady 4-5 terms per query throughout the semester, whereas the low group had a jump to more than 10 terms per query in the rough draft stage.

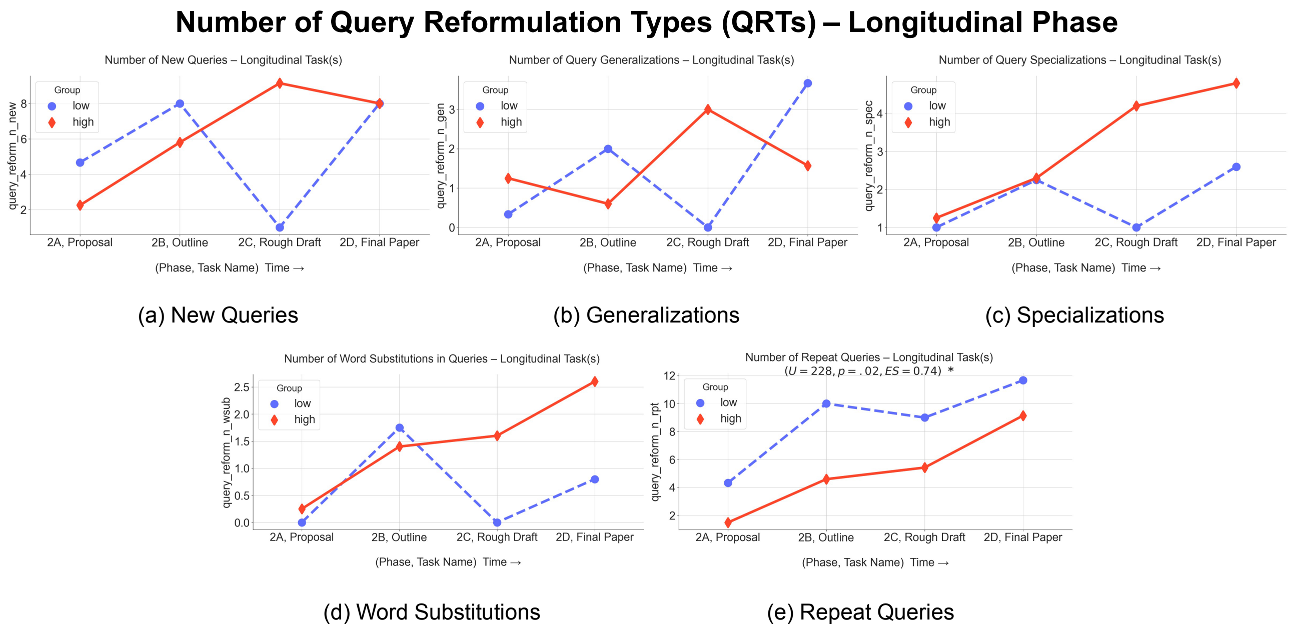
The low group issued few short queries during the proposal, many short queries during the outline, very few long queries during the rough draft, and again many short queries during the final paper phase. On the other hand, the high group kept issuing a steadily increasing count of similar-length (short) queries throughout the semester.

Combining these results we can posit that the low group demonstrated signs of struggling throughout the semester (Hassan et al., 2014). These students may have struggled to effectively search for information at the beginning of the semester, but then increased their search efforts as the deadlines approached. The fact that they issued few long queries during the rough draft phase may indicate that they were not able to effectively refine their search strategies to find more relevant and valuable information. In contrast, the high group's pattern of issuing a steadily increasing count of similar-length (short) queries throughout the semester suggests that these students may have had a more consistent and effective search strategy. They may have been better able to refine their search strategies over time, which allowed them to find more relevant and useful information throughout the different stages of the research paper writing process.

6.5.2 Query Reformulation Types (QRTs)

Query reformulation refers to the process of modifying or refining a search query in order to improve the relevance of search results and better match the user's information needs (Section 3.2.1). Query reformulation typically occurs due to a searcher's improved understanding of how to better translate their information need into a search query. Using the taxonomy proposed by C. Liu et al. (2010) (Figure 3.3), we classified each previous-next query pair issued by participants into one of the five query reformulation types (QRTs): New, Generalization, Specialization, Word Substitution, and Repeat.

We faced a challenge in disentangling **Repeat** queries from "hub-and-spoke" behaviour, where the user goes back and forth between a SERP and different content page by using



(a) New Queries (b) Generalizations (c) Specializations

(d) Word Substitutions (e) Repeat Queries

Figure 6.7: Number of different query reformulation types (QRTs) as per taxonomy proposed by C. Liu et al. (2010).

the browser's forward and back buttons [3]. Each back button press on the browser (to go back to the SERP from a content page) meant a fresh HTTP GET request was sent to the search engine. This resulted in YASBIL logging the move as a resubmission of the query. So for the discussions that follows, **"Repeat" refers to repeat queries combined with hub-and-spoke behaviour.**.

The counts of the five QRTs are presented in Figures 6.7 (a) through (e). For the low group, the trend of counts followed similarly from their trends of query counts and total query lengths (Figures 6.6 (a) and (c)), with varying intensities: alternating between high and low values at successive points in the semester. For the high group, except Query Generalizations – which followed a zig-zag pattern – all the other QRTs showed an overall increase in count throughout the semester.

[3]The SERP is the hub, which represents the initial point of inquiry, while the spokes represent the subsequent branches of exploration along different content pages. This search behaviour is often used when users have a general idea of the topic they are interested in, but need to explore different facets of the topic to narrow down their search and find relevant information.

The high group issued the most new queries and generalized queries while writing the rough draft. In contrast they had the highest counts of specializations and word substitutions while writing the final paper. The low group, on the other hand, had their lowest counts of all QRTs, except repeat, while writing the rough draft. The most interesting tresnd is that of Query Generalizations (Figure 6.7(b)), where the high group and low group demonstrated diametrically opposite behaviour: maxima at outline and final paper for the low group, whereas minima at those stages for the high group. The high group also issued significantly fewer repeat queries (aka hub and spoke behaviour) throughout the semester, compared to the low group ($U = 228.0, p = .02, ES = 0.74$).

The low group's fewer counts of all QRTs while writing the rough draft suggests that they may have struggled to effectively reformulate their queries throughout the different stages of the research paper writing process, perhaps due to the complexity and depth of the research required for the tasks. The low group may have had more difficulty refining and targeting their search queries, resulting in more new and repeated queries at the final stage of the paper writing process. They may also have had more difficulty with the conceptualization of their research question or topic, leading to more generalizations and fewer specializations in their queries. Additionally, their higher use of repeat queries (or hub and spoke behaviour) may indicate that they were relying on a limited set of sources or search terms, which may have limited their ability to find new and relevant information.

The high group, however, had a different pattern of query reformulation compared to the low group. They had their highest counts of new queries and query generalizations in the Rough Draft Phase, and most specialization, word substitutions, and repeat queries while writing the Final Paper. This indicates that their queries were more exploratory in the early part of the semester, and became more precise and refined in the later parts of the semester. They may have been more proactive in identifying new avenues for research earlier in the semester. The highest count of query generalizations during the writing of the rough draft may suggest that they were better able to synthesize and generalize information from their sources at an earlier stage in the writing process. The high group may also have been better able to refine their search queries through word substitutions, which peaked while writing the final paper, indicating a greater level of precision and focus in their information seeking behaviour. In contrast, the low group had their highest count of repeat queries during the outline and final paper, indicating that they may have had more difficulty finding and retaining relevant information throughout the research process.

Interview responses from the participants also support these quantitative results. When asked which stage of the project needed the most amount of searching – the proposal, the outline, the rough draft, or the final paper – a participant in the low group responded:

> *Definitely the **final one**. Not only do I have to find the extra 10 source material, because in the rough draft, I only need 10. So not only do **I have to find 10 new ones**, I need to go back to look at the old 10 sources that I had before because **I don't remember what they're about anymore**.*
>
> — P007_PARIS

This participant highlighted the challenges they faced during the final stage of the project. They specifically mentioned that the final paper required the most amount of searching compared to the earlier stages (proposal, outline, and rough draft). This aligns with the quantitative findings that showed an increase in the number of query reformulations during the final paper stage for the low group. The participant's response also shed light on the reasons behind the increased searching during the final paper stage. They mentioned the need to find additional sources, as the requirement was to include 20 sources in total. Furthermore, the participant mentioned the importance of revisiting the old 10 sources used in the rough draft. This suggests that they recognized the need for reviewing previously accessed sources to refresh their memory and ensure accurate and relevant citations in the final paper. This aligns with the notion of low metacognition, as the participant demonstrates the lack of awareness of the requirements of the final paper for successful completion of the task.

On the other hand, a participant in the high group responded:

> *searching, probably in the **outline** stage, but the most **analyzation** of those sources came in the **rough draft** stage, and then the **final is just expanding** upon that.*
>
> — P021_JAVA

The response from the participant in the high group offers a contrasting perspective on the stage of the project that required the most searching. According to this participant, the outline stage involved the most searching, suggesting a different pattern of information seeking behaviors compared to the participant from the low group. Furthermore, the participant mentioned that the rough draft stage involved the most analysis of the sources they had found. This suggests that during this stage, the high group participants were actively engaging with and evaluating the information they had gathered, potentially indicating a higher level of metacognition and critical thinking skills. Lastly, the participant noted that the final stage was primarily focused on expanding upon the analysis conducted during the rough draft stage. This implies that the high group participants had already established a foundation of information and analysis, and the final stage involved building upon that groundwork. This suggests a strategic approach to information utilization, with a focus on analysis and synthesis of the gathered sources during the rough draft stage, which is reflected by higher counts of query reformulations earlier in the semester, and lower counts later in the semester.

From the above observations, we posit that the high group were more effective in their query reformulation strategies. Specifically, the high group were better able to identify new information needs as they worked on the rough draft, and then refine and specialise their queries as they worked on the final paper. This ability to adapt and refine their queries may have allowed them to find more relevant and useful information, which in turn may have contributed to their higher self-perceived learning and search outcomes.

6.5.3 Entropy of Query Reformulation Types

Entropy is a measure of the diversity or unpredictability of a sequence of events. In the context of search queries, entropy can be used to quantify the variability or randomness of the query reformulations issued by participants. Transition analysis and entropy helps to cover differences in disparate tasks and activities. Inspired by previous works in analysing eye-movement sequences (Krejtz et al., 2014, 2015) and search tactics sequences (He et al.,

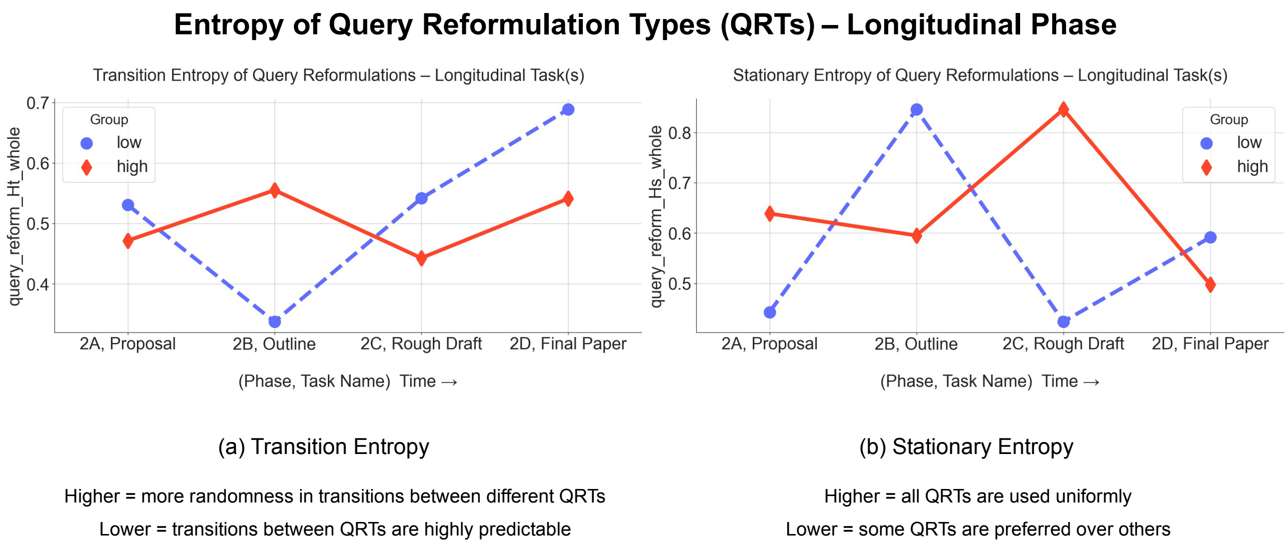


Figure 6.8: Stationary and transition entropies of query reformulation type (QRT) sequences.

2016), we employed a similar entropy analysis of query reformulation sequences, and search tactic patterns of the participants.

For query reformulations, the possible set of states were the five query reformulation types: Generalization, Specialization, Word Substitution, Repeat, and New. If we consider a sequence of query reformulations issued by a participant (e.g., *New -> New -> Specialization -> Specialization -> Word Substitution -> Generalization*) then this sequence can be considered as a first order Markov chain, wherein, the next step in the chain depends only on the current state. Entropy analysis on these Markov chains quantifies how predictable the states are, and yields two categories of uncertainty measures: transition entropy, H_t, and stationary entropy H_s. Similar stationary and transition entropy measures can be obtained for sequences of search tactics.

Guided by the above, we conducted entropy analysis of query reformulation sequences produced by the participants. In the context of query reformulations, the maximum **transition entropy**, $s \log s$, can be reached when there is an equal probability of switching between each of the $s = 5$ states, or QRTs (query reformulation types). The minimum transition entropy (0) is achieved in a fully deterministic Markov chain, where all transition probabilities are either 1 or 0. This means that with a higher transition entropy there is more randomness in the participant's transitions between different QRTs. This randomness is an indication that the participants do not have a clear progression from one QRT to another. On the other hand, a lower transition entropy indicates that the participant's transition between QRTs are highly predictable. **Stationary entropy** is calculated from the distribution of QRTs. A higher stationary entropy value indicates that the QRTs were used uniformly, while a lower stationary entropy indicates that some QRTs are preferred over others. Values of stationary entropy vary between 0 and $\log s$, where s is the number of possible states (QRTs)[4]. All the entropy values presented in this chapter were normalized by their theoretical maximums, for equivalent comparison across different tasks.

The transition entropy of query reformulations followed interesting patterns for the low and high groups (Figure 6.8(a)). The low group had a V-shaped pattern showing a decrease in transition entropy from proposal to outline, then an increase from outline to rough draft to final paper. On the other hand, the high group had a zig-zag pattern, with low transition entropy during the proposal, an increase during the outline, a decrease during the rough draft, and then another increase during the final paper. This indicates that the low group had the least randomness in query reformulation strategies during the outline, while the high group had the most randomness at this stage. Subsequently, the randomness in the high group decreased, whereas that in low group increased. This suggests that during the outline stage, the low group had a more structured approach to query reformulations, compared to the high group. However, as the semester progressed, the low group's approach became more random, while the high group's approach became structured. These pattern suggests that the low group may have struggled to adapt their query reformulation strategies as they moved through the different stages of writing the paper, while the high group was more able to adjust their strategies and maintain a predictable structure in their approach.

The stationary entropy of query reformulations of the low and high groups varied over the different phases of the research paper writing process as well (Figure 6.8(b)). The low group's stationary entropy reached its maximum value at the outline phase, whereas that for

[4]This explanation is adapted from He et al. (2016)

the high group became maximum at the rough draft phase. This indicates that these two groups had distinct information searching behaviours throughout the writing process. The low group tried out all possible types of query reformulations during the outline (as we saw from the query reformulation counts), and then settled on using repeat queries (or hub and spoke behaviour) more, during the rough draft phase. This lowered their stationary entropy at the rough draft phase, and may have limited their ability to find new and relevant information during the later stages of the writing process.

In contrast, the high group employed all the types query reformulations with equal probability during rough draft phase (Figure 6.7), resulting in a higher stationary entropy value. The increase in the high group's stationary entropy from outline to rough suggests that they were exploring a broader range of topics and concepts at this stage of the writing process, which may have allowed them to identify more relevant and useful information. The subsequent decrease in stationary entropy from rough draft to final paper suggests that they were able to narrow down their focus and consolidate their understanding of the subject-matter as they progressed, which may have contributed to their higher self-perceived learning and search outcomes.

6.6 URL Categorization for Analysing Interactions

In order to understand the relationship between users' information search behavior and the type of webpages they visit, we needed to categorize webpages into different types. To accomplish this, we developed a classification system based on URL patterns.

URL patterns were first extracted from the web browsing data collected in our study. These URL patterns contain information about the structure and content of each webpage visited by the users. Based on this information, we were able to classify each URL present in the log data into the following hierarchical taxonomy:

- `L`: Search Result Pages, i.e., a **L**ist of Information Objects
  - `L.PUB`: Publication Search Results, e.g., on university library websites, digital libraries, Google Scholar, etc.

  - `L.WEB`: Web Search Engine Result Pages (SERPs)

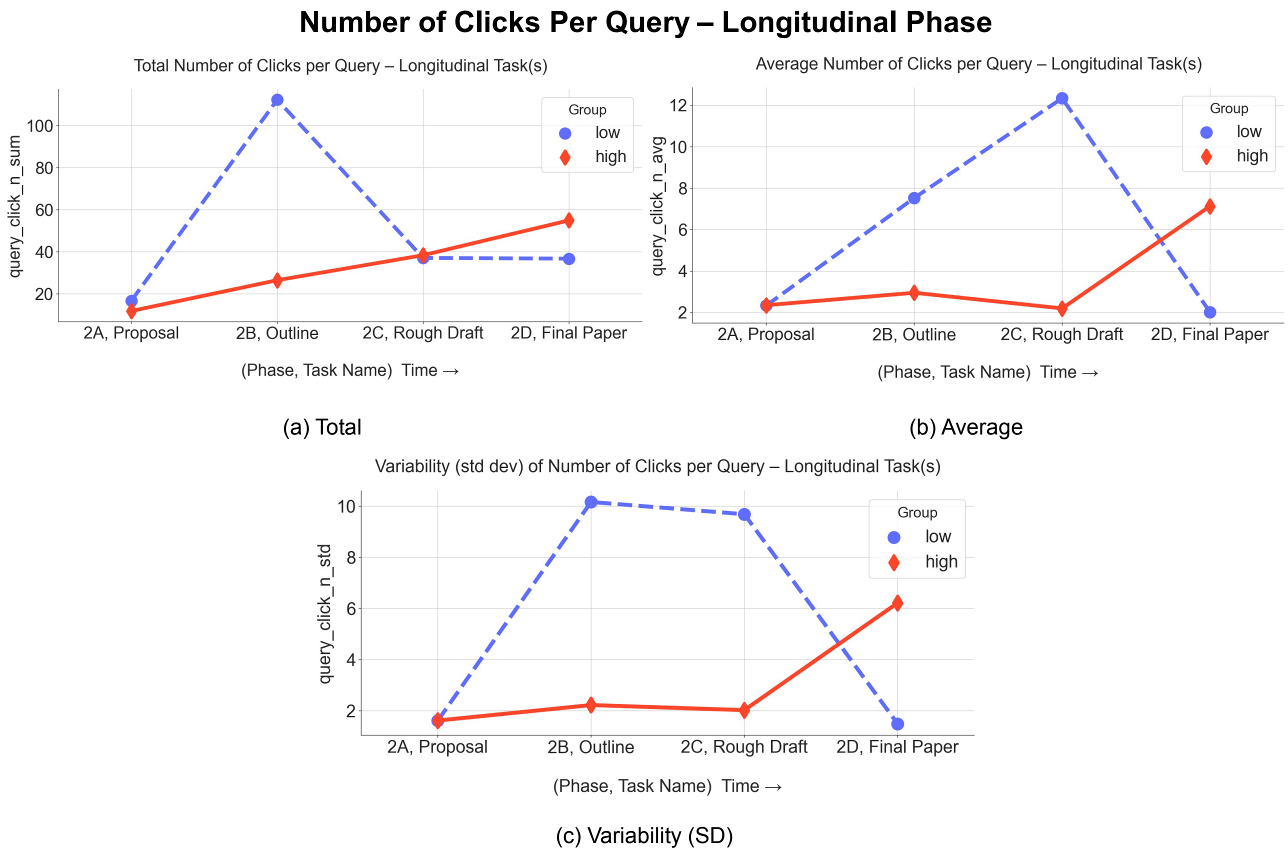
- `I`: Content pages, i.e., Individual **I**nformation Objects

  - `I.PUB`: Academic Publications
  - `I.WEB`: Webpages that have the potential to provide relevant (academic) information for the search task, but are not publication. E.g., Wikipedia articles, relevant blog posts, government and non-profit websites, etc. Some of them were classified automatically (e.g., Wikipedia), while others were classified after manual inspection.

- `MISC`: URLs for webpages that did not fit in any of the above category

To identify search engine result pages, we looked for URLs that contained URL query parameters such as `q` (Google, Bing), `search`, `query`, or `k` (Yahoo) along with specific strings associated with popular search engines such as Google or Bing. We also identified content pages by looking for URLs that contained strings such as "`article`", "`blog`", or "`news`". Scientific peer-reviewed publications were identified based on URLs that contained specific strings associated with academic publishers or databases (ACM DL, Elsevier, Scopus, Springer etc.), while Wikipedia articles were identified by their URLs containing the string "`wikipedia`" in the hostname. Library websites were identified by URLs that contained terms such as "library", "catalogue", or "database" as well as specific strings associated with major library systems (e.g., UT Austin uses Primo VE system from Ex Libris). Finally, we used the catch-all category `MISC` to identify other types of webpages that did not fit into any of the other categories.

The URL-based classification system provided a useful way to categorize webpages based on their type, allowing us to gain insights into how users' search behaviour varies across different types of webpages. By analysing the patterns of webpage types visited by users during their information search process, we were able to identify which types of webpages were most commonly visited and how they related to users' search behaviour.



(a) Total

(b) Average

(c) Variability (SD)

Figure 6.9: Number of clicks per query - longitudinal phase.

6.7 L: Interaction with Lists / Search Results – Source Selection

6.7.1 Number of Clicks per Query

Number of clicks per query refers to the number of times a participant clicked a link on a search result page after conducting a search query. This metric reflects the level of interaction and engagement of the participant with the search results, as well as their ability to assess the relevance and usefulness of each search result presented to them. A higher value of clicks per query may indicate that the participant is more engaged and willing to explore a wider range of information sources, while a lower value may suggest a more focused and targeted search approach. Figure 6.9 shows the trend in total, average, and variability of clicks per query for the low and high groups at different points in the semester.

The low group had much higher total (Figure 6.9(a)) and average (Figure 6.9(b)) count of clicks per query, than the high group, at all stages of the semester – proposal, outline, and rough draft – except the last stage: writing the final paper. The highest total clicks per query was during the outline phase (about 100 clicks total), while the highest average clicks per query was during the rough draft phase (about 12 clicks per query on average). The high group maintained a relatively stable clicks per query during the proposal, outline, and rough draft stages (less than four clicks per query), and had a peak value of 7 clicks per query during the final paper. Additionally, the high group had lower variability (standard deviation) in their number of clicks per query, compared to the low group (Figure 6.9(c)).

The low group's higher total, average, and standard deviation of clicks per query throughout most of the semester, except for the final paper stage, suggests that they may have been less efficient in their searching behaviours, requiring more clicks and potentially spending more time on each query. The may have struggled to refine their search strategies, resulting in more clicks per query throughout the semester. This could have contributed to their lower self-perceived learning and search outcomes.

In contrast, the high group's fewer clicks per query throughout most of the semester, except for the final paper stage, suggests that they may have been more efficient and effective in their searching behaviours, requiring fewer clicks and potentially finding more relevant information per query. They may have been able to refine their search strategies and be more efficient during the semester, resulting in fewer clicks per query. This indicates the high group's ability to better assess the relevance and usefulness of search results, and to use their knowledge and cognitive strategies more effectively during the search process. This could have contributed to their higher self-perceived learning and search outcomes. The peak value of clicks per query for the high group during the final paper stage suggests that they may have needed to invest more effort in finding the most relevant and useful information for their final paper. However, even at this stage, their average number of clicks per query was still lower than the low group's peak value during the rough draft stage.

It is also possible that the differences in average clicks per query between the two groups during different phases of the semester reflect differences in the complexity or specificity of the information needed for the different tasks. For example, the paper outline phase may have required more broad and exploratory searches, while the final paper phase may have required more targeted and specific searches.

6.7.2 Counts and Dwell Time on Search Results

The Ethical Dilemma research paper writing task involved searching for 20 references, and incorporating them into the narrative of the research paper. Therefore, we structure the discussion around visits to scholarly publication search results, and (non-scholarly) web SERPs. Examples of scholarly publication websites are Google Scholar, digital libraries such as ACM DL, Springer, Elsevier, PubMed and others. We examined how visits to these two categories of websites changed across the different stages of writing the research paper for each group. Figure 6.10 shows the counts of publication search results and web search results visited by the two groups, as well as total and average dwell time on such pages by both the groups.

For both publication search results and web search results, the high group visited more of those webpages than the low group (Figure 6.10(a) and (b)). The high group visited more publication search results during the outline phase, and more web SERPs during the rough draft phase. The low group on the other hand, had a dip in their visit count for both the search result categories during the rough draft phase. However, they had significantly longer average dwell time on academic publication search results, in all the four stages, compared to the high group ($U = 153.0, p = .01, ES = 0.77$) (Figure 6.10(e)). Total dwell time of the low group was also longer, except at the final paper stage, when the high group surpassed the low group in dwelling on publication search results. The difference was approaching significance ($U = 138.0, p = .08, ES = 0.70$) (Figure 6.10(c)). This suggests that the low group spent more time examining and considering scholarly publication search results compared to the high group. It is possible that the low group's lower levels of self-regulation and metacognition may have led them to spend more time on search results, as they may have found it harder to quickly

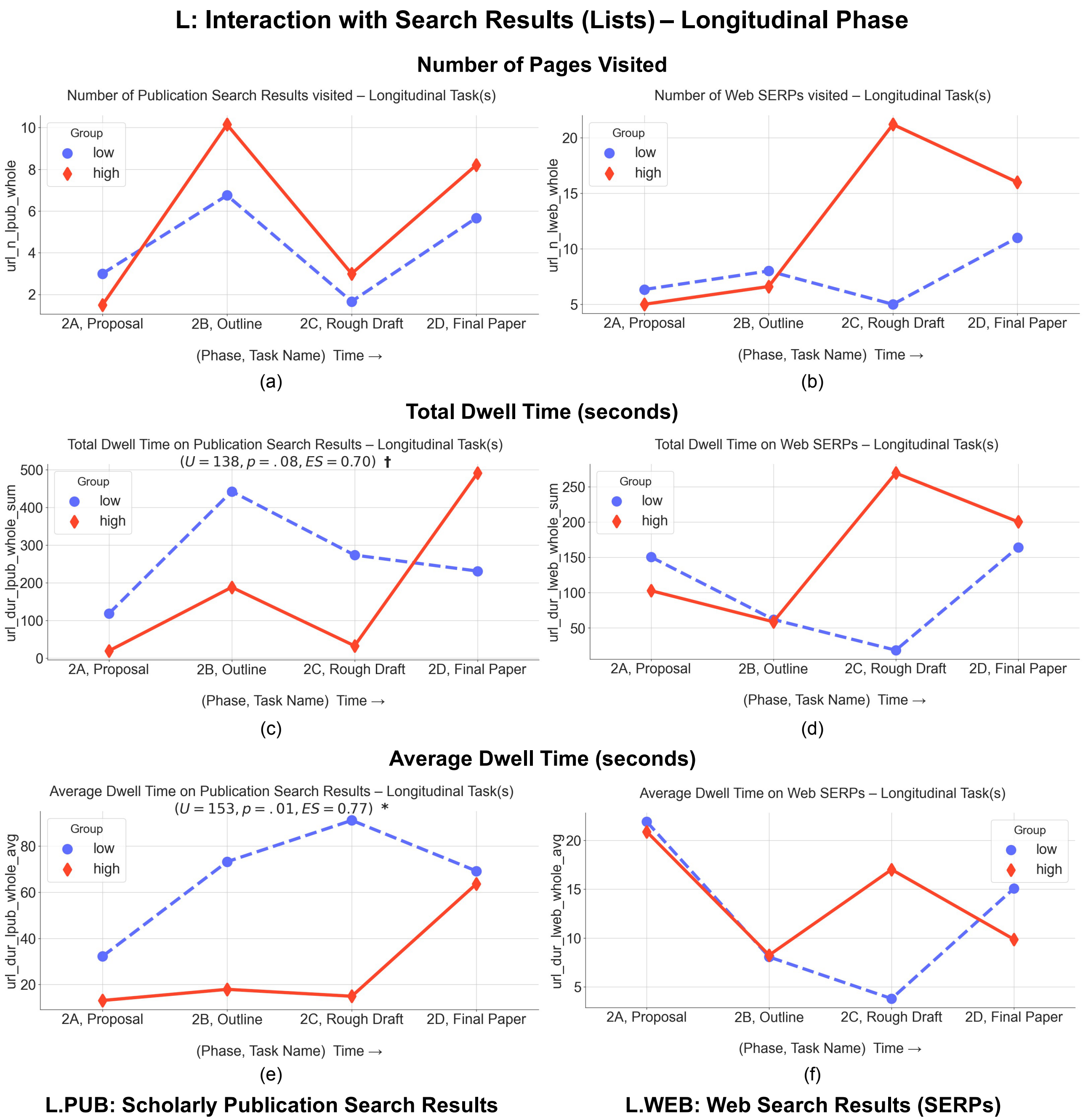


Figure 6.10: Interactions with search results - Longitudinal Phase.

evaluate and assess the relevance of search results to their task. On the other hand, the high group's higher levels those individual traits may have enabled them to quickly identify relevant search results and move on to the next stage of their task. However, at the final paper stage, the high group spent more time on search results as they may have needed to ensure that they had not missed any important information and had thoroughly covered their topic.

In general, the high group engaged more with web search results, and less with scholarly publication search results. The low group demonstrated the opposite pattern. This is an interesting finding. The high group may have relied more on web search engines and popular sources, such as news articles or blogs, to get a broader understanding of their research topic and its context. In contrast, the low group may have relied more on scholarly publications to find more in-depth and specialized information. They may have been more thorough in searching for and evaluating academic publications, which was arguably one of the main aspects of writing the research paper. This difference in strategy may have contributed to the difference in perceived learning outcomes between the two groups. The high group may have been able to find a broader range of information from a variety of sources, while the low group may have limited themselves to more specialized sources. It is also possible that the high group's use of web search engines may have resulted in them encountering more diverse perspectives and interpretations of the research topic, which could have enhanced their critical thinking and analytical skills.

6.8 I: Interaction with Information Objects – Sources / Content Pages

We analysed interactions with content page in the same manner as counts and dwell time on search results (Section 6.7.2): looking at visits to scholarly publications, vs visits to non-scholarly content pages. Figure 6.11 shows the counts of scholarly publications and non-scholarly content pages visited by the low and high groups, as well as total and average dwell time on such pages by both groups.

In a similar vein to publication vs web search results (Section 6.7.2), the high group engaged less with scholarly publications, and more with non-scholarly content pages, compared to the low

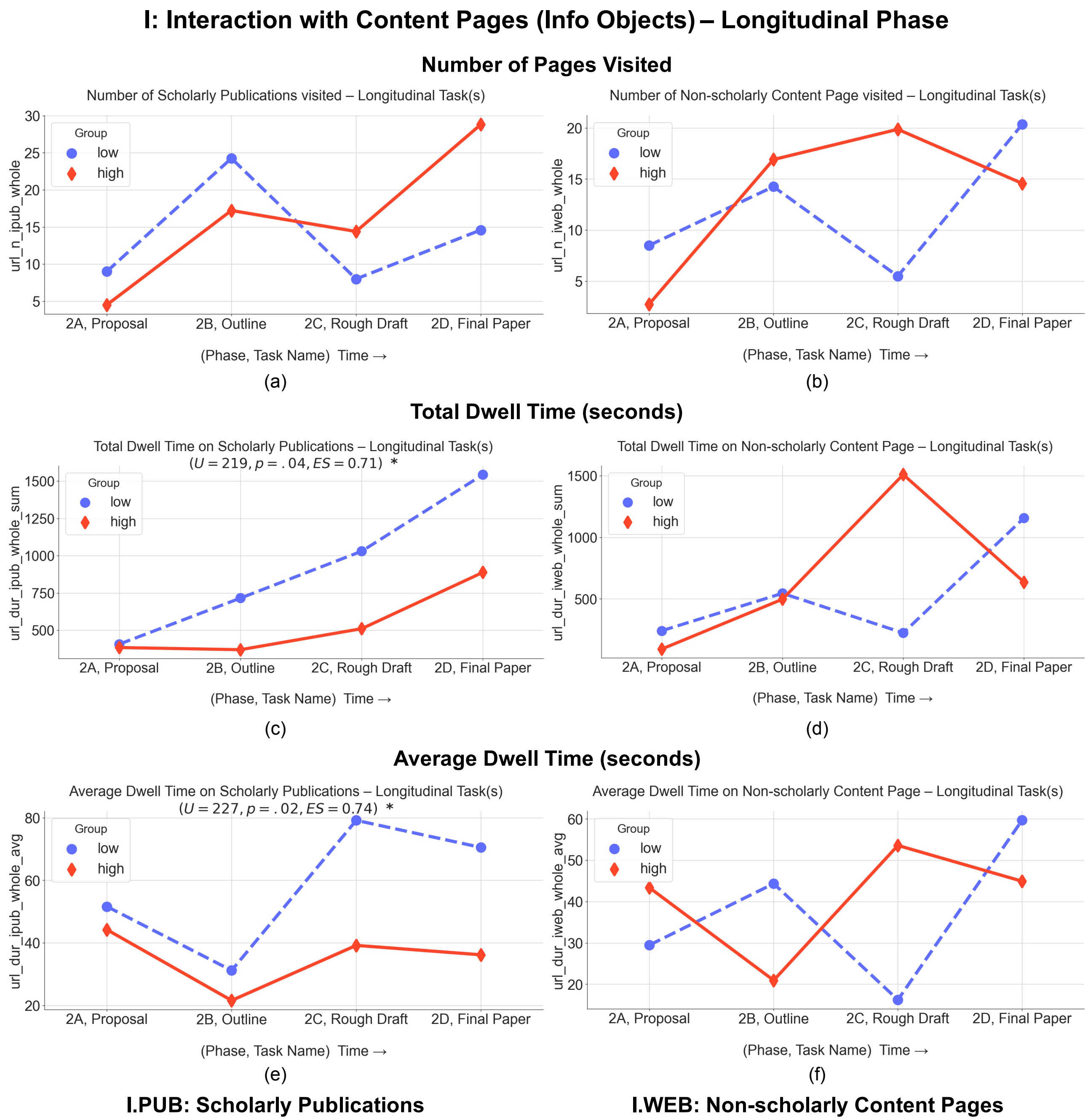


Figure 6.11: Interactions with content pages - Longitudinal Phase.

group. Earlier in the semester, while writing the outline, the low group visited more academic publications, while the high group visited more content pages. The trend reversed later in the semester while writing the final paper, when the low group viewed fewer publications and more content pages, while the high group did the opposite (Figures 6.11(a) and (b)).

Speaking of dwell times, the low group spent significantly more time viewing academic publications, in total ($U = 219.0, p = .04, ES = 0.71$) and on average ($U = 227.0, p = .02, ES = 0.74$), compared to the high group (Figures 6.11(c) and (e)). While writing the rough draft, the high group spent more time viewing non-scholarly content pages.

The high group's preference for non-academic content pages may reflect their use of web search engines to find relevant information, as such search engines may often prioritize non-academic content over scholarly publications. The high group seemed to be more focused on finding information that was relevant to their topic, regardless of its source. They also appeared to be more interested in exploring a wider range of topics and concepts, which is reflected in their higher stationary entropy of query reformulations during the rough draft phase.

On the other hand, the low group's preference for academic publications may reflect their reliance on scholarly publication search engines to find information, as they may have perceived that being the main ask of the research paper. The low group seemed to be more concerned with finding information from scholarly publications, perhaps as a way to demonstrate the rigour of their research. They also appeared to have a more limited scope of inquiry, as reflected in their lower stationary entropy of query reformulations during the rough draft phase.

Overall, these findings suggest that the high group may have been more creative and adaptable in their information searching behaviours, while the low group may have been more rigid and focused on adhering to traditional academic norms.

6.9 Search Result Pages vs Content Pages

Figure 6.12 describes differences in visits to all search results pages versus all content pages (scholarly and non-scholarly combined), for the high and low groups. The high group visited

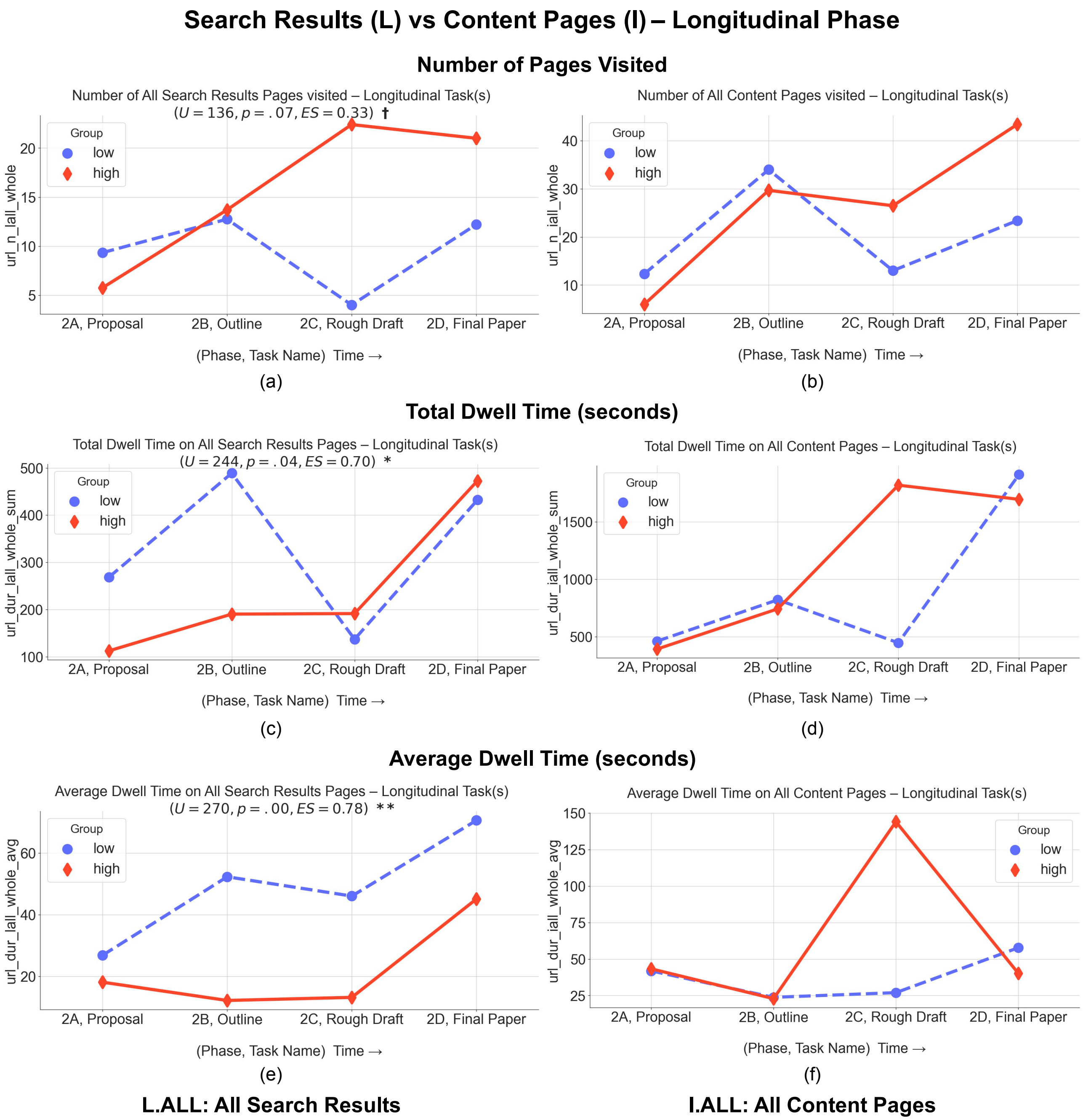


Figure 6.12: Differences in interactions with search results vs. content pages.

more search result pages and content pages as the semester progressed, while the low group had a drop in these visits after the outline phase (Figure 6.12 (a), (b)). The difference in the count of Search Results pages visited was almost significant ($U = 136, p = .07, ES = 0.33$). This suggests that the high group may have been more engaged and persistent in their information searching behaviours, while the low group may have experienced a decrease in motivation or self-regulation as the semester progressed, specifically before writing the rough draft. It is also noteworthy that the low group had a rebound in the count of pages visited while writing the final paper. This could indicate that they were able to re-engage with the task, and their information searching behaviours improved as the final-paper deadline approached.

However, although the high group visited more webpages in general, they dwelt less on search results, and more on content pages. The differences are significant for total and average dwell times on search results (Figure 6.12 (c) and (e)). This indicates that the high group was more efficient at evaluating search result pages and quickly identifying relevant content. On the other hand, the low group may have spent more time on search result pages, possibly indicating that they had a more challenging time evaluating and selecting relevant results. For instance, when asked when if the participant had an experience where initially they thought they had found a useful resource, but upon later examination, they found it almost useless, a participant in the high group said:

> *I don't think so. I feel like I used all the papers that I found in my outline in my final paper, like some sort of degree.*
>
> — P023_LONDON

Another participant said:

> *I did find some articles that weren't useful, but I think I kind of quickly ruled them out all I'm looking like, from the title, they looked okay. Or sometimes even from the title, I just, like, didn't even look at them. But if I like looked at them a little bit closer and just clicked into them. And I didn't really find what they were saying very useful. Like, even in the introduction, I would just click out of them.*
>
> — P012_MIAMI

The responses from participants in the high group suggest that they were more efficient at evaluating search result pages and quickly identifying relevant content. The first participant, `P023_LONDON`, mentioned using all the papers found during the outline stage in their final paper, indicating a careful selection process early on and a successful integration of relevant sources throughout the writing process. The second participant, `P012_MIAMI`, described their approach of quickly ruling out articles that appeared less useful based on title or a cursory examination. This suggests a discerning approach to source evaluation and a proactive effort to focus only on the most relevant materials.

In contrast, the response from a participant in the low group highlights the challenges they faced in identifying relevant sources:

> *Yes. Quite a lot, actually. A lot of them, like I saw Google highlights certain parts of the paper where it has the key words that I put in, and then I read about it. And it only briefly mentioned about that word or a couple of times. The distributed justice part, there's quite a lot. There's a lot of papers that has distributive justice in it. And then it's not really relevant. It just talks about distributive justice. Overall, it doesn't talk about distributive justice, as in terms of event, ensuring privacy. So it was pretty irrelevant.*
>
> — P007_PARIS

The participant mentioned encountering papers that initially appeared useful based on Google's highlighted keywords, but upon closer examination, found that they did not actually address the relevant topic of interest. This demonstrates the difficulties the low group participant experienced in assessing the relevance and content of potential sources. These qualitative responses provide valuable insights into the differences in information evaluation and selection processes between the high and low groups. The high group participants seemed to possess more efficient strategies for quickly identifying relevant sources and filtering out irrelevant ones. In contrast, the low group participants faced challenges in accurately assessing the relevance and content of potential sources, leading to more time spent on search result pages and potentially encountering less relevant materials. These differences in information behaviour could be related to the higher self-perceived learning outcomes and search outcomes seen in the high group, as they were able to find and engage with relevant content efficiently.

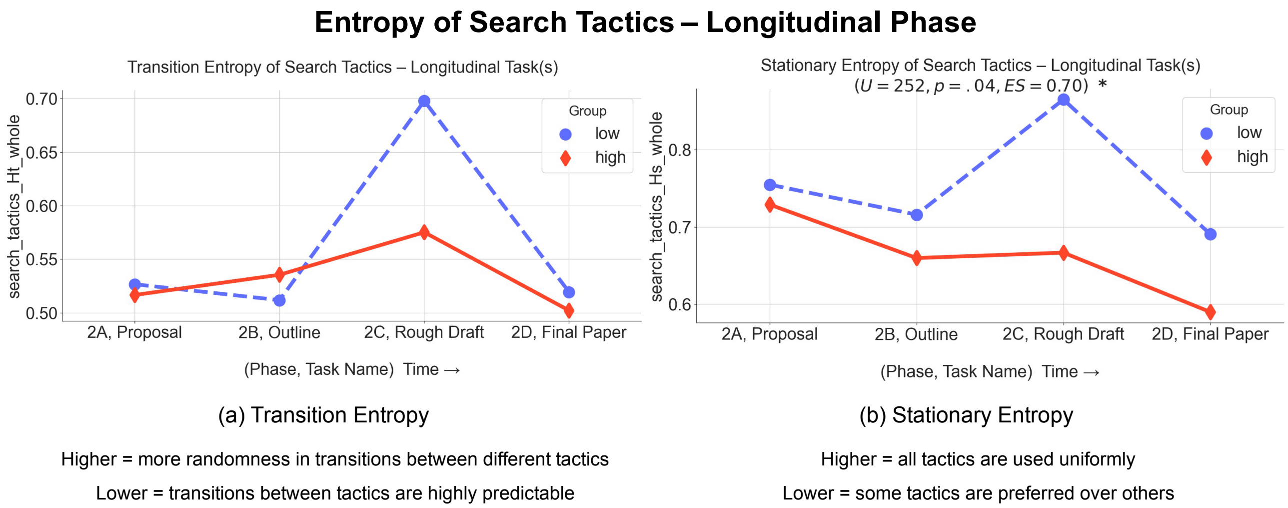


Figure 6.13: Entropy of search tactic sequences for longitudinal phase.

6.10 Entropy of Search Tactic Sequences

Similar to the entropy analysis of Query Reformulation types (Section 6.5.3), we performed entropy analysis of search tactic transitions. This analysis is directly inspired by He et al. (2016), who in turn were inspired by Krejtz et al. (2015). To characterise the entropy of students' search tactics, we used the following set of states, or tactics:

1. **QUERY**: issuing a search query
2. **CLICK**: mouse click
3. **IDLE**: participant stays idle for more than one minute (adapted from Taramigkou et al. (2018))
4. **SESSION_BREAK**: participant becomes idle for more than 30 minutes (Google Analytics defines a session break as 30 minutes of inactivity [5])
5. **L.PUB**: visiting a publication search result page
6. **L.WEB**: visiting a web SERP
7. **I.PUB**: visiting a scholarly publication
8. **I.WEB**: visiting a non-scholarly content page

[5] https://support.google.com/analytics/answer/2731565#zippy=%2Cin-this-article

9. **TASKPAGE**: visiting webpages related to the study, i.e. the Qualtrics questionnaires

In the context of search tactic transitions, a higher value of transition entropy (H_t) indicates more randomness and uncertainty in the participant's search behaviour (which is composed of different search tactics, and transitioning or switching between those tactics). A lower value of transition entropy indicates that the search behaviour (i.e. tactic switching behaviour) is highly predictable. For stationary entropy of search tactics (H_s), a higher value indicates that participants utilize all the search tactics with equal probability, while a lower value suggests that certain search tactics are favoured over others. Figure 6.13 describes the trends in this values over the duration of the semester.

The low group demonstrated a sharp increase in both transition entropy and stationary entropy of search tactics from the proposal stage to the outline stage. Both entropies subsequently decreased in the final paper stage. The high group had a relatively stable trend in their transition entropy of search tactics, while their stationary entropy decreased as the semester progressed. Also, the high group's stationary entropy was significantly lower than that of the low group ($U = 252.0, p = .04, ES = 0.70$).

The low group's sharp increase in transition and stationary entropy from the proposal to the outline stage suggests that they were exploring a wider range of search tactics, and were less certain of which tactics to use during the early stages of the writing process. This is consistent with their high counts of query reformulations, and tendency to click on many search results and content pages. The subsequent decrease in both entropies in the final paper stage suggests that the low group became more focused and efficient in their search tactics, possibly due to the feedback they received during the earlier stages of the writing process.

The high group's relatively stable trend in transition entropy suggests that they were consistent in their use of search tactics throughout the writing process. However, their decreasing stationary entropy suggests that they became more focused and efficient in their use of search tactics as the semester progressed, which is consistent with fewer query reformulations, and tendency to dwell more on content pages.

These quantitative findings align with the qualitative responses from the participants. When asked if they had a plan before starting the project, or starting to search, a participant in the low group responded:

> ***Not really.*** *My plan was just to find sources and see how they kind of fit in with my research question. And* ***if I didn't really find anything, I would just alter the research question****.*
>
> — P012_MIAMI

In contrast, a participant in the high group responded:

> *whenever I start searching,* ***I go in with the mindset of: this is what I'm searching for****... I always try to reference back to that main goal to help guide my searching process,... like, Okay, I'm searching for content articles, right? And so* ***I'm not gonna go ahead and get distracted by anything else****, that's going to be like my main goal. And as long as I'm able to go ahead and reference that back to my main goal, then I'm doing a good job.*
>
> *I feel this is something that I've gotten used to being a college student. I realized, this is probably the most efficient way to search for things (and)* ***not get overwhelmed****.* ***Breaking it down and having a very clear set goal makes things more manageable for me****.*
>
> — P015_LIMA

The participant from the low group expressed a lack of a specific plan before starting the project or the search process. They mentioned their approach of finding sources and altering their research question if they did not find anything relevant. This suggests a more exploratory and adaptive approach to the search process, aligning with the higher entropy observed in the quantitative analysis. In contrast, the participant from the high group described a clear plan and a goal-oriented mindset before starting the search process. They emphasized the importance of having a main goal and using it as a reference point to guide their search process efficiently. This aligns with the lower entropy observed in the high group and suggests a more focused and directed approach to information searching.

Overall, these quantitative results from the entropy analyses, combined with the qualitative responses from the participants, provide further support and insights into the differences in search tactics and planning approaches of the high and low groups.

6.11 Summary of Longitudinal Phase

We summarise the findings from this chapter, on the longitudinal searching-as-learning task of writing a research paper, as follows.

Participants were divided into high and low groups based on their self-reported values of motivation, metacognition, self-regulation, and memory span. Their search behaviour and perceived learning and search outcomes were studied over the course of a semester. During the longitudinal phase, both the high and low groups exhibited changes and differences in their search behaviour from the proposal to the outline stage to the rough draft, and finally to the final paper stage.

Investigating into specific interaction patters, we saw that the high group visited more search result pages, but spent less time dwelling on them. They also visited more content pages in the later parts of the semester, and spent more time dwelling on them. The low group visited fewer search result pages, but spent more time on evaluating search results.

Transition entropy refers to the uncertainty of the next search tactic that a user will apply during their search. In other words, it is a measure of how much the user explores different search tactics over the course of their search. Stationary entropy refers to the uncertainty of the search tactic distribution over time. It is a measure of how stable or consistent the user is in their use of search tactics throughout their search process. The low group showed sharp increases in both transition entropy and stationary entropy of search tactics from the proposal stage to the outline stage, followed by a decrease in both entropies in the final paper stage. This indicates that their search tactics became more diverse and unpredictable in the middle stages of the task, possibly due to uncertainty and lack of clarity on the topic. The high group had a relatively stable trend, or gentle increase in their transition entropy of search tactics, indicating that they had a consistent and well-defined search strategy. This group's stationary entropy decreased as the semester progressed, suggesting that they became more focused and efficient in their search tactics over time. Additionally, the high group's stationary entropy was significantly lower than that of the low group, indicating that they had a more structured and organized approach to their search tactics.

Regarding learning and search outcomes, the high group demonstrated significantly higher perceived learning and search outcomes compared to the low group. Although the high group received slightly better grades on their research paper assignments, though there was no significant difference between the two groups. Possibly, other factors beyond self-perceived searching and learning outcomes may have contributed to the overall grade.

7 Results and Discussion: Repeated vs Non-repeated Search Tasks

Apart from the longitudinal phase of the study discussed in the previous chapter, participants also completed two search tasks at the beginning of the semester (`PHASE1`), and two search tasks at the end of the semester (`PHASE3`). One set of tasks, on the topic of "personal finance for college students", was repeated at the end of the semester (repeated search tasks). The other set of tasks was not repeated (non-repeated search tasks), and the topics were "ubuntu ethics" in the beginning of the semester, and "algorithmic bias" at the end of the semester. These topics for the non-repeated search tasks were selected from the content of the I303 course that the participants were enrolled in.

The initial and final phases of the study aimed to compare the information search behaviours of students across repeated and non-repeated search tasks, at the beginning and end of the semester. This chapter presents the results of the analysis, which involved comparing the entropies of search tactics and query reformulation sequences, clicks per query, and interaction with different categories of webpages. Let us now discuss some of the findings for these repeated versus non-repeated tasks We use the same low-high groups from the LPA analysis discussed in Section 6.3.

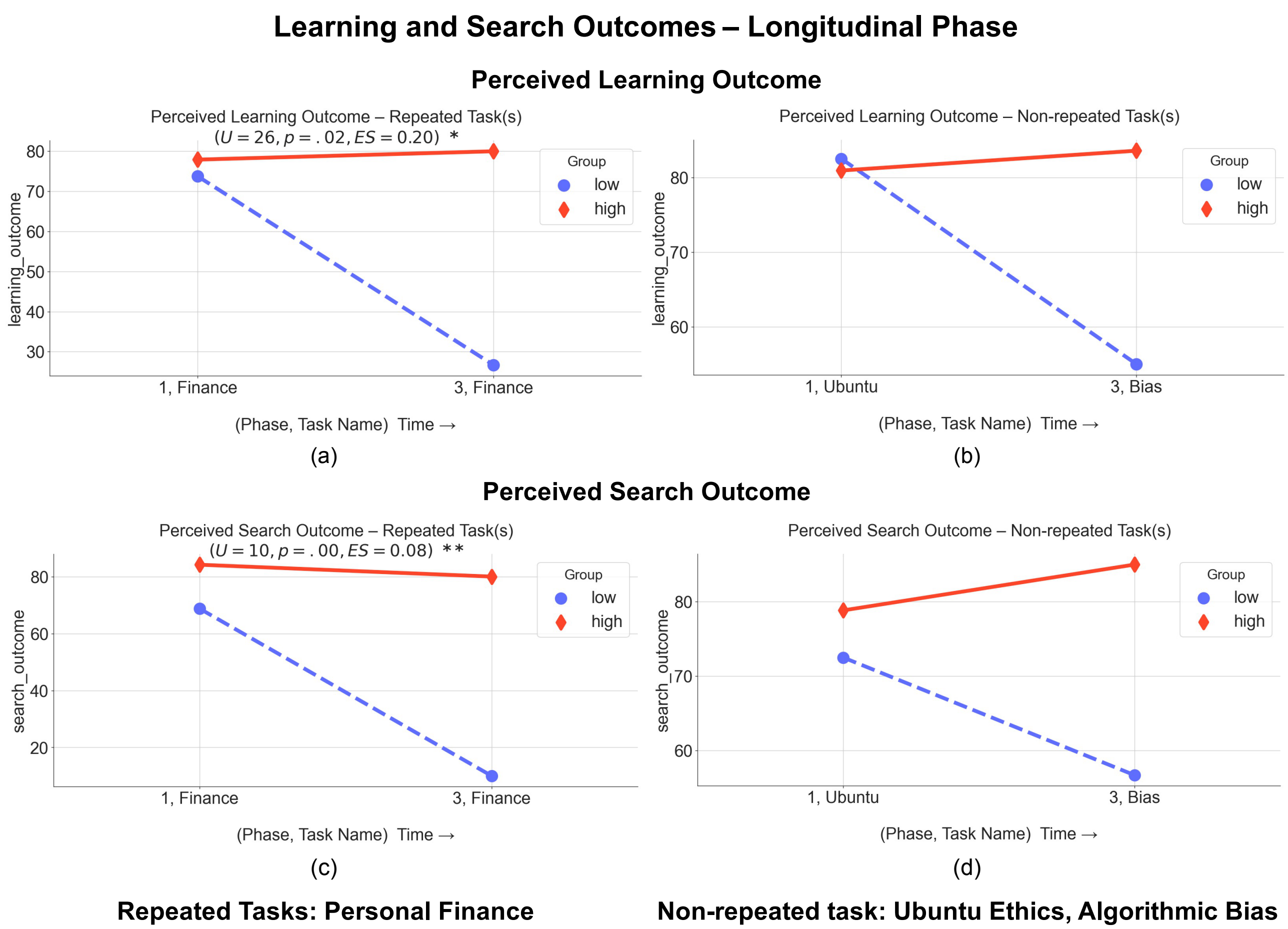


Figure 7.1: Learning and Search Outcomes – Longitudinal Phase.

7.1 Learning Outcomes

Figure 7.1 shows the differences in perceived learning outcomes and perceived search outcomes for the two sets of tasks for the low and high groups. The high group reported higher learning and search outcomes for both repeated and non-repeated tasks, at both the beginning and the end of the semester. For the low group, their perceived learning and search outcomes decreased for all the tasks at the end of the semester. The differences between the groups were statistically significant for the repeated task (on the topic of Personal Finance) – $(U = 26.5, p = .02, ES = 0.20)$ for perceived learning outcome, and $(U = 10.5, p = .001, ES = 0.08)$ for perceived search outcome.

There could be several factors contributing to the differences in perceived learning and search outcomes between the two groups. One possible explanation is that the high group had better information-seeking strategies and habits that allowed them to more effectively find and evaluate relevant information, leading to higher perceived learning outcomes. As discussed in the longitudinal phase findings, the high group engaged more with web search results and content pages, while also spending less time on search results and academic publications. This suggests that they were able to efficiently navigate through search results and find the most relevant information. Another possible explanation is that the high group had better prior knowledge and familiarity with the topics, which allowed them to more quickly and effectively identify relevant information. Additionally, it is possible that the high group had more motivation and interest in the topics, leading to more engagement and effort in the search process, and ultimately higher perceived learning outcomes.

For the low group, the decrease in perceived learning and search outcomes at the end of the semester could be due to a variety of factors, such as burnout or fatigue from the research paper writing process, or a lack of engagement or motivation. The decrease in their search tactics entropy and dwell time on academic publications and search results over the course of the semester suggests that they may have become more narrow in their search strategies and less exploratory, which could have limited their ability to find and evaluate relevant information.

7.2 Q: Query Formulations

7.2.1 "Need to Search Again" for `PHASE3` tasks

Of the two search tasks in `PHASE3`, the Personal Finance task was repeated from `PHASE1`, while the Algorithmic Bias task was on the topic of what the students had learnt in the I-303 course. So when presented with these search tasks again at `PHASE3`, we asked participants if they needed to search the web again for completing these tasks, and explain their choice.

Ten participants completed `PHASE3`, thereby leading two 20 user-task pairs. In 14/20 (60%) of these user-task pairs, participant responded "yes" to have felt the need to search again, while

5/20 (25%) responded "no", and one responded "other". Of these five "no" responses, three came from high group participants, while the remaining two came from low group participants.

For the **repeated** personal finance task, 4 participants (high: 2, low: 2) did not need to search again for updating their summary that they had written during PHASE1. Some of the explanations for not needing to search include:

- *"I felt like I knew enough information through my personal experiences through the semester"* – P023_LONDON
- *"I changed my way of thinking"* – P007_PARIS
- *"The advice from the start of the semester still applies to me. . . "* – P012_MIAMI
- *"I felt pretty confident in my past answer– I remember spending a good amount of time looking for resources and eventually they started to repeat themselves. . . However, I did add more to the writing section without looking anything up because I realized some other things could be added to the writing"* – P015_LIMA

For the **non-repeated** algorithmic bias task, which was based on course content, only one participant – P023_LONDON, high group – did not need to search again, stating: *"I felt like I had a good enough understanding of the topic".* All other participants needed to search again for this task. Selected explanations from the high group for needing to search again are quoted below.

- *"I needed more information on this topic"* – P001_MILAN
- *"I want to ensure I'm giving accurate information"* – P009_KIEV
- *"I was not sure what I know. . . However . . . when I saw the information on the wikipedia, I remembered what I know and just wrote it down"* – P002_CAIRO
- *"Although I remember reading and researching about this topic, this is not something that I talk or think about on a day to day basis. Therefore, I needed a little help to jog my memory and use outside sources"* – P015_LIMA
- *"One question I needed a refresher. . . and the other two I wanted to learn more to be able to write a summary I was confident with"* – P021_JAVA

In contrast, selected explanations from the low group for needing to search again are as follows.

- *"I do not feel confident enough about my memory on this topic"* – P007_PARIS
- *"Even though I remember the topic from my classes last semester, I wanted to double check and make sure that my understanding was correct* – P012_MIAMI
- *"I had to refresh my memory* – P016_AUSTIN

These qualitative responses hint at the perceptual differences that the high and low group had towards their knowledge of the topic. The responses from the high group indicates a higher level of confidence on their perceived understanding of the topic, which could be one of the factors contributing to their higher perceived learning and search outcomes; whereas, the responses from the low group suggest a greater degree of hesitance, which may be reflected in their lower perceived learning and search outcomes.

7.2.2 Length and Count of Queries per Search Task

Figure 7.2 shows the differences in total query length (a, b), average query length (c, d), and count of queries (e, f) for the two sets of tasks for the low and high groups. The high group had a decrease in query count, total query length, and average query length, for all the tasks, from the beginning of the semester to the end of the semester. The low group had a decrease in query count as well, but their average query length increased for both the repeated and the non-repeated tasks. For the non-repeated tasks, the Algorithmic Bias task at the end of the semester was based on course content that students learnt during the semester. So ideally they would not have needed to search for new information if they felt confident of their own knowledge.

The fact that the Algorithmic Bias task was based on course content could have influenced the search behaviour of the participants. As we saw in Section 7.2.1, it is possible that the high group felt more confident in their understanding of the topic. This was also indicated by their higher perceived learning outcome, which led them to issue fewer queries of shorter length. On the other hand, the low group may have felt less confident with their knowledge (and

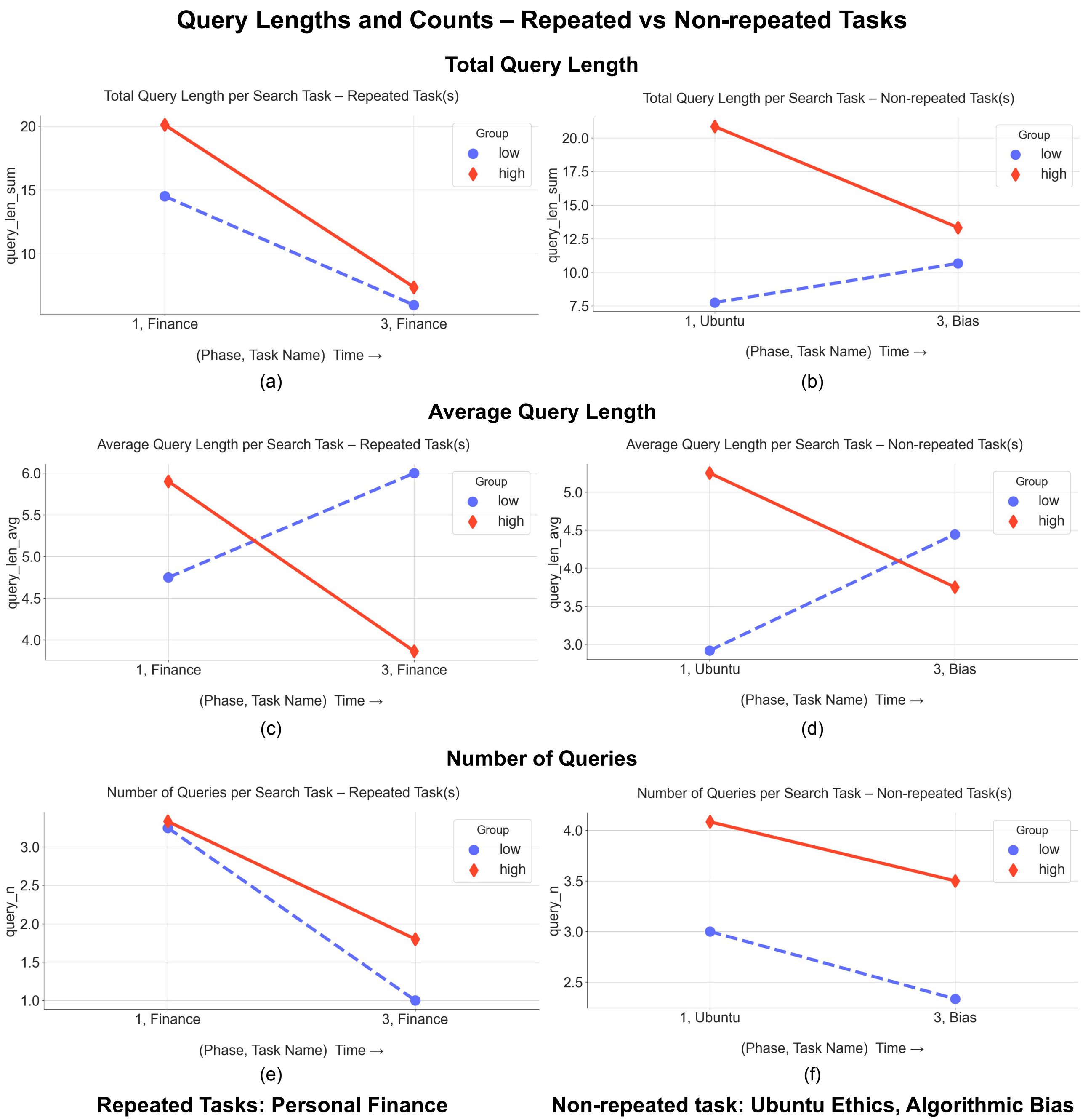


Figure 7.2: Query Lengths and Counts – Repeated vs Non-repeated Tasks.

presumably, search abilities), and still felt the need to explore and search for new information, leading them to issue longer queries on average at the end of the semester, in an effort to find the information they needed.

7.2.3 Query Reformulation Types (QRTs)

Figure 7.3 shows the differences in the five categories of query reformulations (QRTs) for the two sets of tasks, for the low and high groups. Both the groups showed a decrease in all query reformulation types from the start of the semester to the end of the semester, for both the task categories, except for certain specific cases. For the non-repeated task, the high group had an increase in query specializations (Figure 7.3 (f)), while the low group had an increase in query generalizations (Figure 7.3 (d)).

These findings suggest that both groups improved their search skills over the course of the semester, as they needed to perform fewer query reformulations to find relevant information. However, the high group demonstrated a more nuanced approach to query reformulation, as evidenced by their increase in query specializations for the algorithmic bias task. This may suggest that the high group was able to better hone in on specific information needs and tailor their queries accordingly. On the other hand, the low group's increase in query generalizations for the same task may suggest a more broad and less focused approach to information seeking.

For the repeated task on personal finance, the decrease in all types of query reformulations for all groups indicates that participants had already acquired a baseline knowledge on the topic from the first round of searching earlier in the semester, and were able to more efficiently retrieve relevant information with fewer queries and reformulations.

7.2.4 Entropy of Query Reformulation Types

Figure 7.4 shows the differences in the entropies of query reformulation sequences for the low and high groups, across the two sets of tasks. For the repeated tasks on personal finance, both the groups showed an increase in transition entropy of query reformulations from the beginning of the semester to the end. Regarding the stationary entropy of query reformulations,

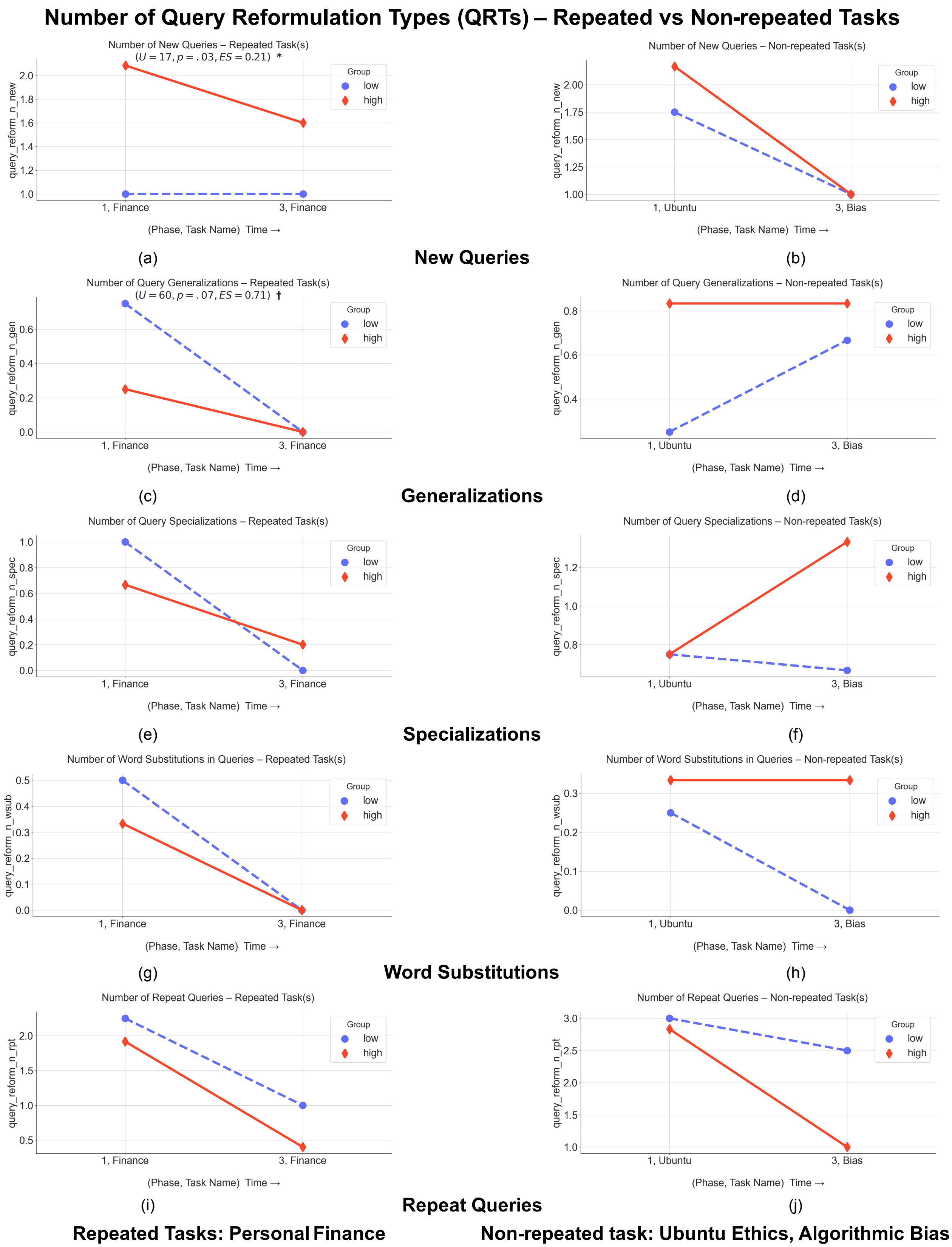


Figure 7.3: Number of Query Reformulation Types (QRTs) – Repeated vs Non-repeated Tasks.

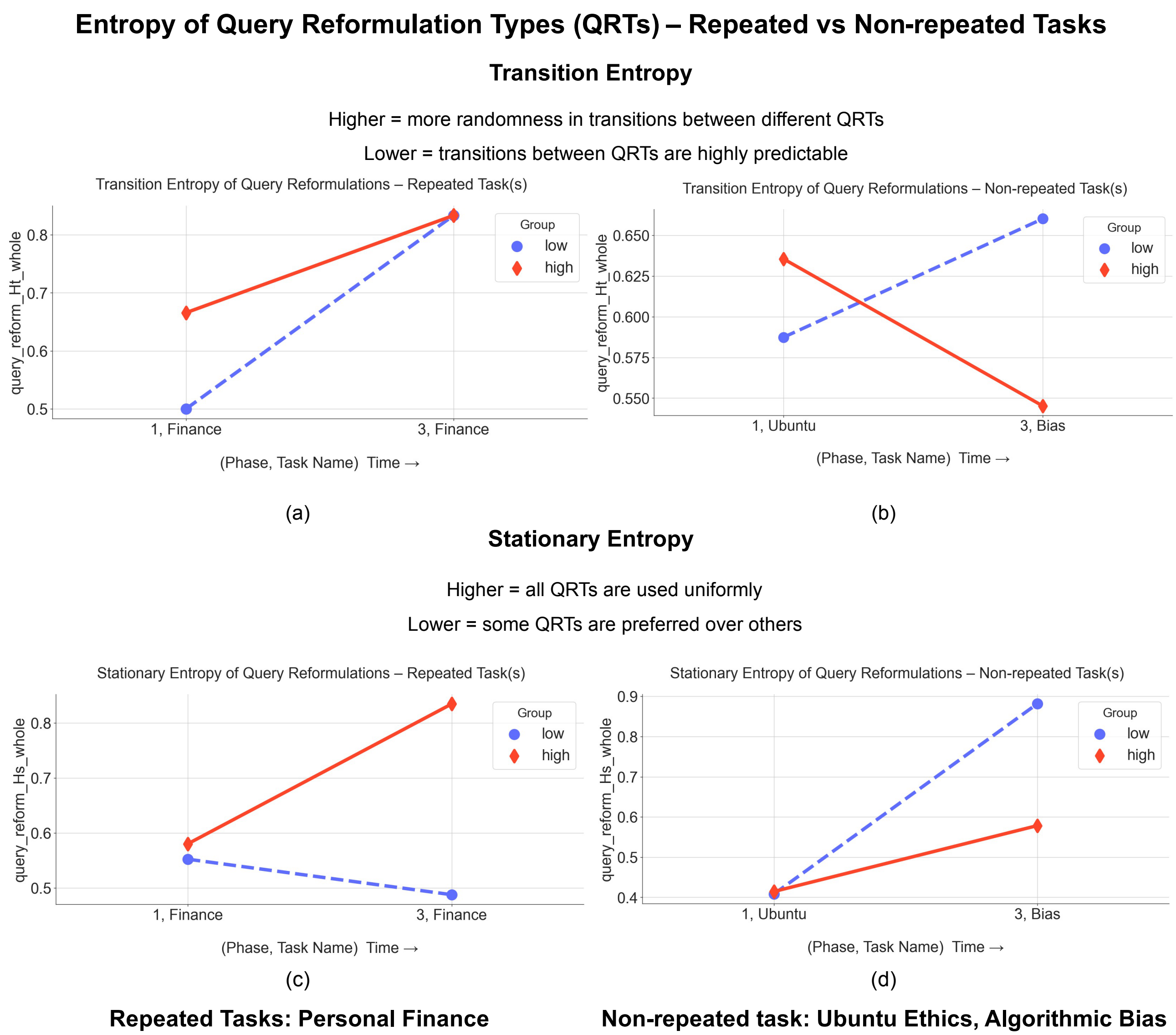


Figure 7.4: Entropy of Query Reformulation Types (QRTs) – Repeated vs Non-repeated Tasks.

it increased for the high group across the semester, and decreased for the low group. Coming to the non-repeated tasks of Ubuntu Ethics and Algorithmic bias, the high group had a decrease in transition entropy and increase in stationary entropy. The low group showed increase in both stationary and transition entropy.

The increase in transition entropy of query reformulations for both groups in the repeated task on personal finance suggests that participants were exploring different avenues and perspectives as they continued their search. This could be attributed to the fact that they were trying to find alternate information than what they had previously encountered in the beginning of the semester. The increase in stationary entropy of query reformulations for the high group across the semester indicates that their search queries became more diverse and exploratory as they gained a deeper understanding of the topic. On the other hand, the decrease in stationary entropy for the low group suggests that they became more focused and narrowed down their search queries as they progressed through the semester.

For the non-repeated tasks, the decrease in transition entropy and increase in stationary entropy for the high group on Ubuntu Ethics and Algorithmic bias indicate that they were able to refine their search queries and find more relevant information as they gained a deeper understanding of the topics. On the other hand, the increase in both stationary and transition entropy for the low group suggests that they struggled with finding relevant information and had to explore more avenues to refine their search queries.

7.3 Number of Clicks per Query

Figure 7.5 shows the differences in total, average, and variability of clicks per for the low and high groups, across the two sets of tasks. Across the board, all the groups had a decrease in the count of clicks per query for all the tasks, from the beginning to the end of the semester.

The decrease in clicks per query for both groups over time could be due to an increase in search experience and familiarity with the topics, as well as improved search strategies and tactics developed over the course of the semester. As participants became more familiar with the topics, they likely needed to click on fewer search results to find the information they were looking for. This is because they may have developed a better understanding of what search terms to use, what types of sources to look for, and how to evaluate the relevance and reliability of search results. This increased familiarity and experience likely contributed to the decrease in clicks per query observed in both groups over time. Additionally, as participants developed more effective search strategies and tactics over the course of the semester, they may

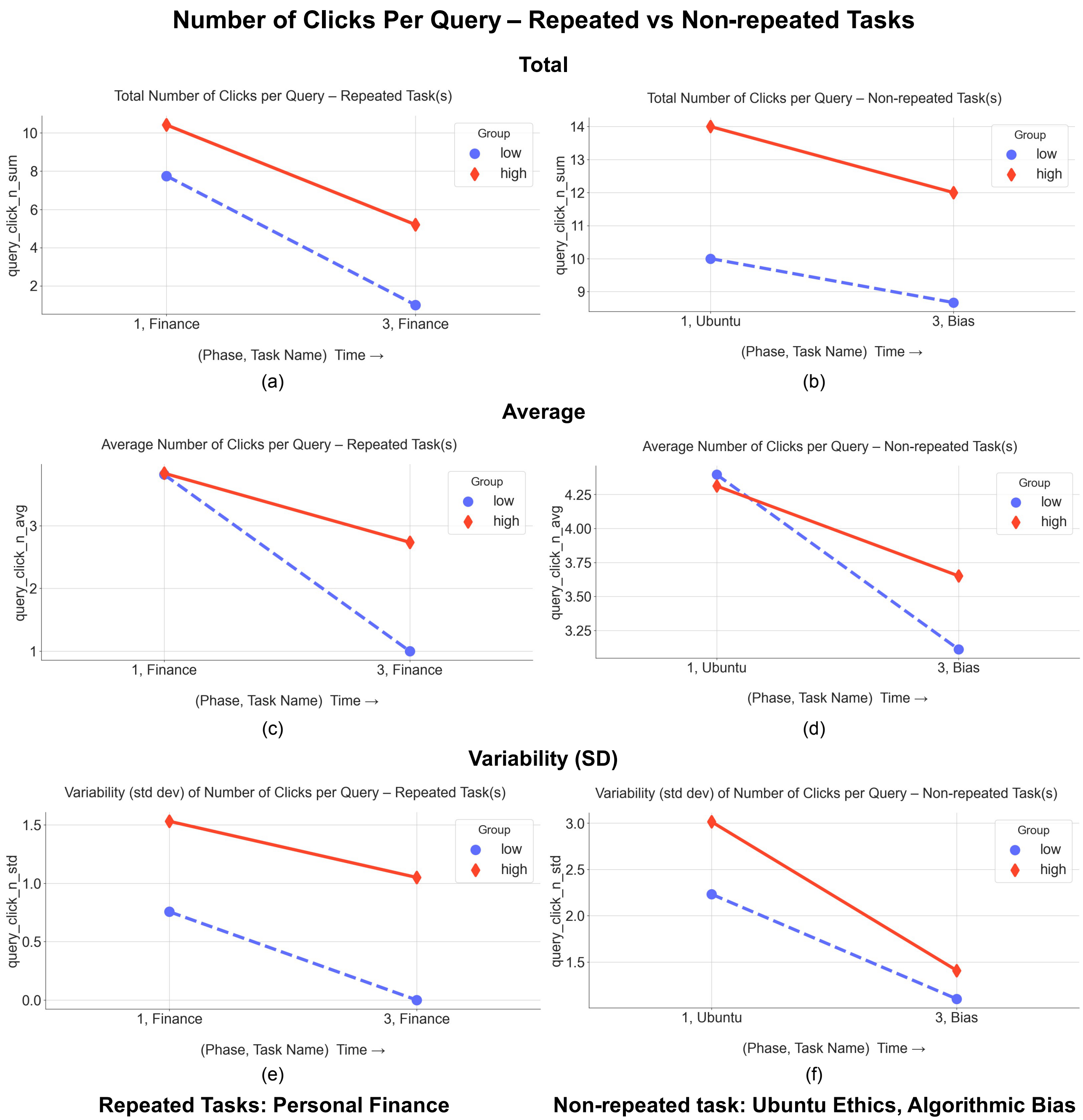


Figure 7.5: Number of Clicks Per Query – Repeated vs Non-repeated Tasks.

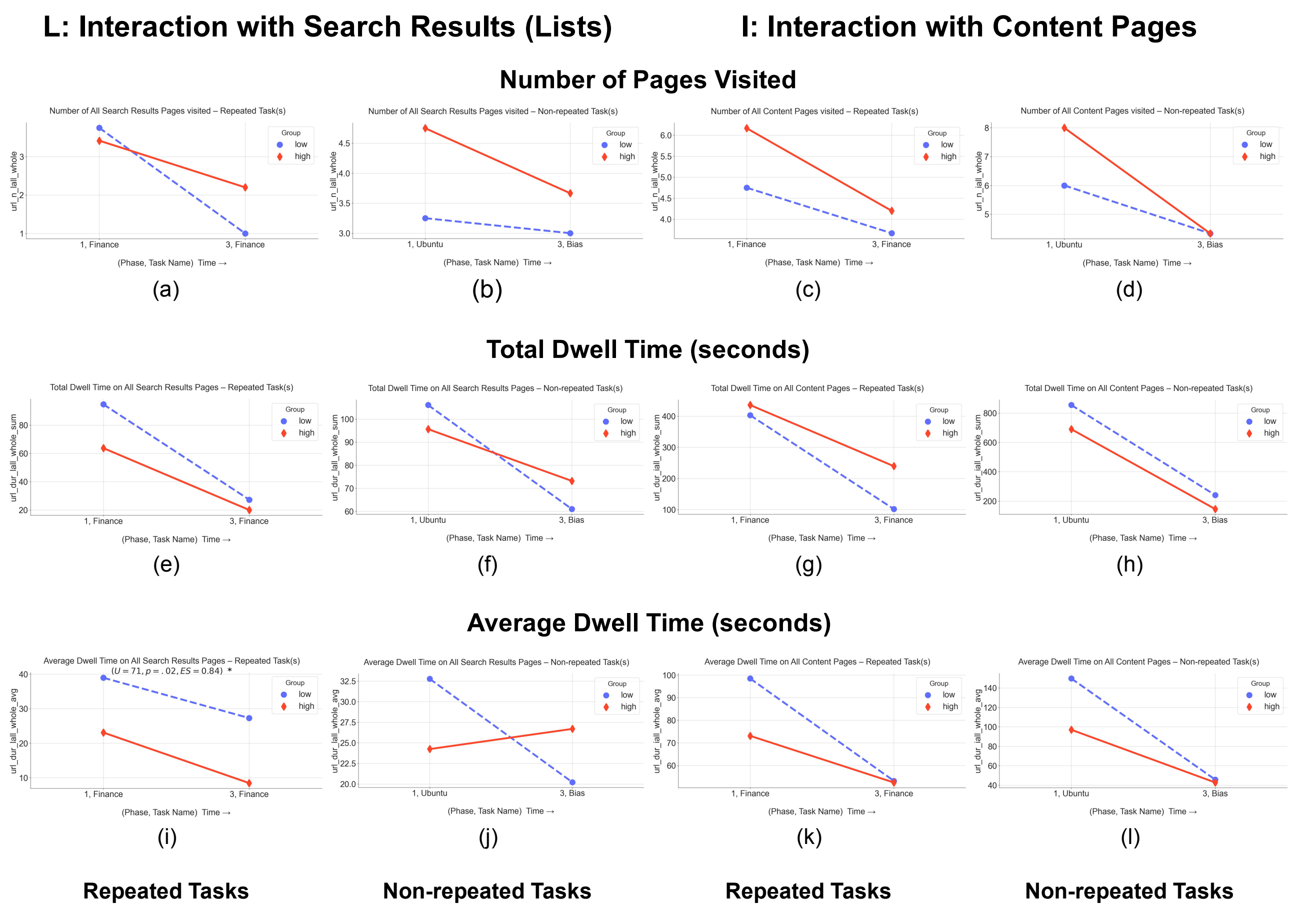


Figure 7.6: Differences in interactions with search results vs. content pages - repeated and non-repeated tasks.

have been able to find the information they needed more quickly, resulting in a decrease in the count of clicks per query.

7.4 L vs I: Interaction with Search Results vs Content Pages

Figure 7.6 shows the differences in interactions with search results and interaction with content pages for the low and high groups, across the two sets of tasks. Similar to the number of clicks per query, there was an overall decrease from semester beginning to semester end, for number of pages visited, total dwell time, and average dwell time, across all types of webpages – search results and content pages. This could be due to an increase in search experience and familiarity with the topics, as well as improved search strategies and tactics developed over the course of the semester. As students become more familiar with the topics and develop better strategies for searching, they may have been able to quickly identify and access the information they needed, leading to a decrease in dwell time, and the number of pages visited. These decreases may also be related to the fact that students may have become more efficient in their search process over time. They may have learned to quickly identify and assess the relevance of search results and content pages, leading to a more targeted approach in their search process.

7.5 Entropy of Search Tactic Sequences

Figure 7.7 shows the differences in the entropies of search tactics for the low and high groups, across the two sets of tasks. Across the semester, the high group had a decrease in both transition entropy and stationary entropy for the repeated task, while the low group had an increase in transition entropy, but decrease in stationary entropy. For the non-repeated task, both the groups had an increase in transition entropy, and decrease in stationary entropy.

The decrease in transition entropy and stationary entropy for the high group on the repeated tasks indicate that they were able to develop more focused and efficient search strategies over time, leading to more predictable patterns in their search tactic sequences. On the other hand, the increase in transition entropy for the low group on the repeated task suggests that they may have struggled to find effective search strategies, resulting in more varied and unpredictable sequences of search tactics. However, the decrease in stationary entropy for the low group suggests that they were still able to find and stick to effective search tactics over time. For the non-repeated tasks, the increase in transition entropy for both groups may indicate that they were exploring a wider range of search tactics and approaches to find relevant information. The decrease in stationary entropy suggests that they were still able to identify and use effective search tactics, but that they were more flexible in their approach overall.

Comparing between the entropies for query reformulation sequences (Figure 7.4) and entropies of search tactic sequences (Figure 7.7), it is interesting to note that the trends of change

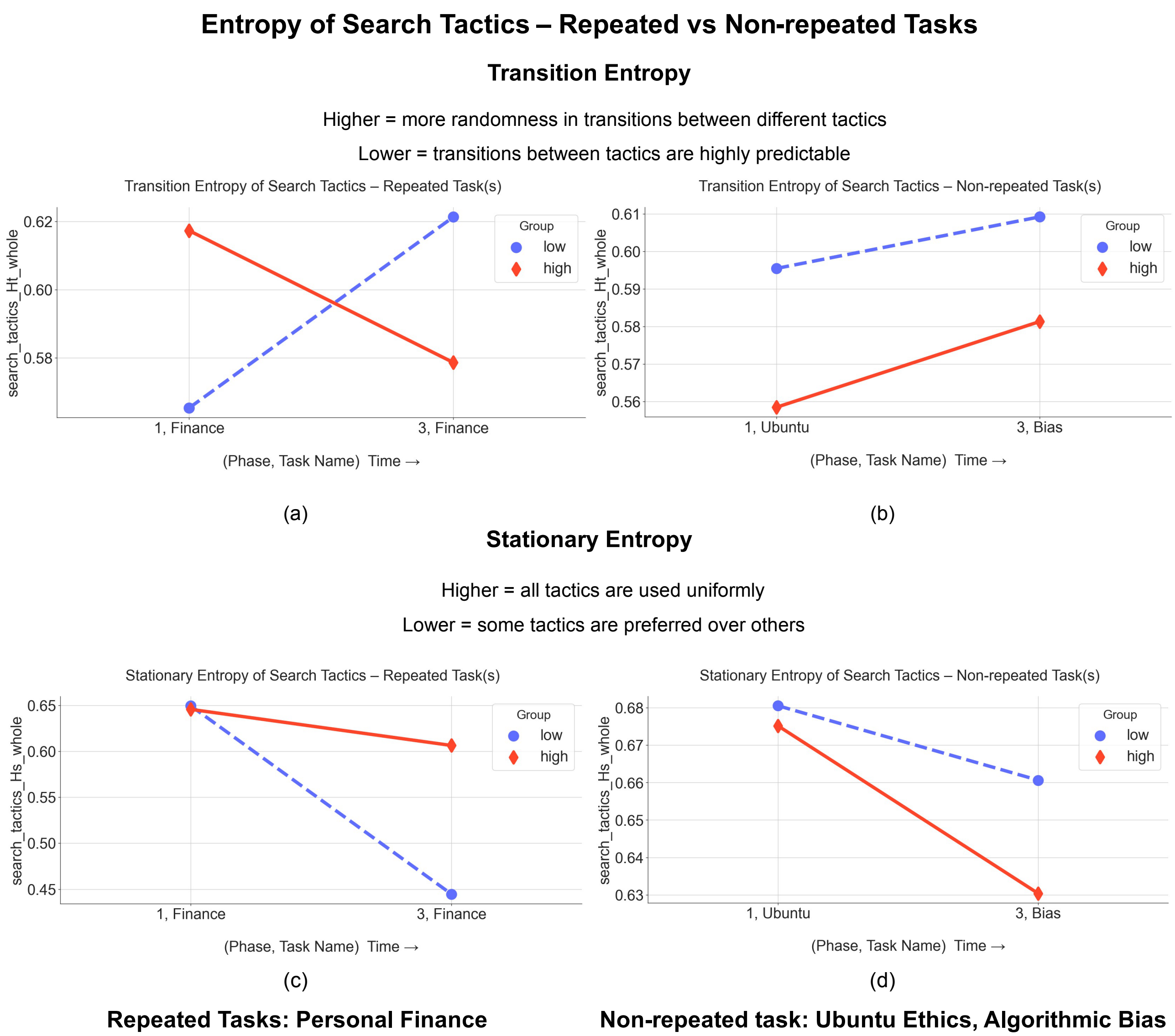


Figure 7.7: Entropy of Search Tactics – Repeated vs Non-repeated Tasks.

in these two classes of entropy values were opposite for the high group, but was similar for the low group. The high group had an increase in the transition entropy of query reformulations, but decrease in the transition entropy of search sequences, and so on. The high group showed an increase in transition entropy of query reformulations – meaning that they were exploring a wider range of query reformulation types over time – but they showed a decrease in transition entropy of search tactic sequences – indicating that they were relying on a smaller set of search tactics as they became more familiar with the topics. Conversely, the low group showed similar trends for both types of entropies. They had an increase in both transition entropy of query reformulations and transition entropy of search tactic sequences. This suggests that the low group was still exploring different types of search strategies and query reformulation types over time, perhaps due to a lack of confidence in their own knowledge or search skills.

7.6 Summary

We summarize the findings from this chapter, on repeated vs. non-repeated search tasks across the semester as follows.

Both the low and high groups demonstrated a general decrease in query behaviour from the start to the end of the semester (The high group showed an increase in query specializations for the non-repeated task, and the low group showing an increase in query generalizations for the same task). Search tactics became more random for the high group on the repeated task, and less random on the non-repeated task. For the low group, their tactics became more random regardless of the task type.

Regarding learning and search outcomes, the high group reported higher learning and search outcomes for both repeated and non-repeated tasks at both the beginning and end of the semester. For the low group, their perceived learning and search outcomes decreased for all tasks at the end of the semester. The qualitative responses from participants for needing to search again at the end of the semester indicated that the high group had a stronger sense of confidence and perceived understanding of the subject-matter, compared to the low group.

The findings from the initial and final phase of the study suggest that there are differences in information search behaviours for repeated and non-repeated search tasks. Overall, the high group demonstrated more effective and efficient search behaviour, with better search outcomes and lower entropy values, while the low group struggled with search behaviour and outcomes, showing increases in entropy values and decreased confidence in their knowledge. This indicates that repeated engagements with search task topics may have improved the information search behaviours for the group with higher values of motivation, metacognition, self-regulation, and memory span.

8

Revisiting Research Questions

After discussing the findings from the LongSAL study in detail in the previous chapters, we now revisit the research questions introduced in Chapter 4. The chapter presents a discussion of the implications of the findings of the study, in light of the research questions proposed.

8.1 RQ1: Individual Differences and Longitudinal Search Behaviour

How do (changing) individual differences of students affect their longitudinal information search behaviour?

The study found that there were (often significant) differences in information search behaviour between student groups who rated high versus low on individual traits such as motivation, metacognition, self-regulation, and memory-span.

Metacognition and self-regulation are closely related concepts that involve thinking about and controlling one's own cognitive processes and learning strategies (Ambrose et al., 2010; Garca et al., 2023). They can help students plan, monitor and evaluate their information searching and learning goals, and increase motivation and engagement (Williamson, 2015).

Metacognition and self-regulation can improve students' ability to learn independently and overcome barriers to learning (Winne & Azevedo, 2022).

In the context of search as learning, metacognition can affect information searching behaviour in several ways. Metacognition help students develop effective search queries, compare and evaluate the information obtained, identify relevant websites and sources, and reformulate queries as needed. Students with higher levels of metacognition monitor and regulate their own search process, such as setting goals, planning strategies, checking progress and reflecting on outcomes. Metacognition also help students improve their search performance and learning outcomes by enhancing their self-awareness, confidence and motivation (Reisolu et al., 2020; Zhou & Lam, 2019).

A. Cole & O'Brien (2023) found that metacognitive strategies shift students' thinking away from search as a routine task towards reflections on their learning, as well as how they might apply their learning to future tasks. One participant in their study commented that metacognitive nudges made the participant think more about what they were doing, instead of just aimlessly searching and reading a sentence or two. Metacognition helped to give purpose to their activities, in the form of asking questions like why they were searching for a certain piece of information, and whether they would be able to talk about what they found later in group discussion settings (A. Cole & O'Brien, 2023).

In our study, we found that students in the high group, with higher values of metacognition, self-regulation, and motivation, demonstrated more efficient search behaviours with time. The high group were able to better refine their search strategies and become more efficient as the semester progressed, resulting in fewer clicks per query when writing the final paper. They had higher counts of word substitutions and lower counts of repeat queries, which are both indicative of more focused and targeted search strategies. The randomness of their search behaviour decreased, indicating they became more efficient and strategic in their search processes. They engaged more with content pages than search results, and reported overall better levels of learning and search outcomes. In contrast, the low group, with lower levels of motivation, metacognition, self-regulation, and memory-span, showed less efficient search behaviours. They showed signs of struggling, when moving across different stages of the research paper, and more clicks per query when writing the final paper. They had more randomness and higher entropies of search tactics, more engagement with search results than content pages at later stages of the semester (which was done in earlier stages by the high group), and a general lower level of learning and search outcome.

As the high group progressed through the semester, their search behaviour gradually changed as described by established models of information seeking behaviour, such as Vakkari's searching-as-learning model (Vakkari, 2016) and Kuhlthau's Information Seeking Model (Kuhlthau, 1991). Vakkari outlines three stages in the search process: (1) assimilation, (2) restructuring, and (3) tuning. According to the model's predictions, in the initial stages, students acquire knowledge through assimilation. Bogers & Kaya (2021) reports that searchers in this stage perform some basic 'quick-and-dirty' searching in the beginning to get to know the space of available resources. As students progressed in their search task, they increasingly demonstrate more deliberate and strategic querying behaviour. This implies students progressively enhanced their search efficiency across the session, which has also been reported by other studies (Bogers & Kaya, 2021; Kaya & Bogers, 2023) This transition from divergent to convergent behaviour is also in line with Kuhlthau's information seeking model(Kuhlthau, 1991).

These findings also complement prior work on identifying struggling search behaviour. For instance, Hassan et al. (2014) investigates search behaviours of users to identify signs of struggling versus exploring. Their findings indicated that certain predictors, such as minimal similarity between consecutive queries, increased clicks per query, as well as differences in the nature of query reformulation patterns (i.e., less query term substitution and more addition/removal with exploring), were indicative of struggling search sessions.

It is important to note that the use of scholarly publications may not necessarily guarantee better quality information or higher self-perceived learning outcomes. The relevance and credibility of the sources used, as well as the ability to critically evaluate and synthesize the information, are important factors that can impact the effectiveness of the search and learning outcomes.

The quality of information is not solely determined by the type of source, but rather by the relevance, credibility, and reliability of the information found. While scholarly publications may provide more specialized and in-depth information, they may not always be the most relevant or up-to-date sources for a given research topic. In these situations, web search results may provide a broader range of sources, including news articles, blogs, and websites, that can offer alternative perspectives and insights on the research topic. However, the quality and reliability of the information found in these sources may vary, and it is important to critically evaluate and verify the information before using it in a research paper.

In addition, sensemaking – the ability to synthesize and integrate information from different sources, regardless of their type – is a key skill in conducting research and writing a research paper. This involves the ability to critically evaluate the relevance and credibility of the sources, as well as to identify and articulate the relationships between different pieces of information.

Overall, the choice of sources and the search strategies used should be based on the research question, the scope of the project, and the specific information needs of the researcher. Both scholarly publications and web search results can provide valuable information, and the key is to use them effectively and efficiently in order to achieve the desired learning outcomes.

8.2 RQ2: Repeated vs Non-repeated Search Tasks

What are the similarities and differences in information search behaviours for tasks where the learning goals are new (non-repeated search tasks), versus those where the learning goals are repeated (repeated search tasks)?

Non-repeated search tasks are those where the learning goals are new and require exploration and discovery of new information. Repeated search tasks are those where the learning goals are repeated and require reinforcement and retrieval of existing information. The findings from this study suggest that there are similarities and differences in information search behaviours for tasks where the learning goals are new versus those where the learning goals are repeated.

Regarding **similarities**, both the high and low groups showed a decrease in query reformulation types, and count of clicks per query across the semester, regardless of whether the tasks were repeated or non-repeated. However, there were some **differences** as well. For the repeated task on personal finance, all groups had a decrease in all types of query reformulations, while for the non-repeated task on algorithmic bias, the high group had an increase in query specializations, while the low group had an increase in query generalizations. In terms of search tactic sequences, the high group had an opposite trend of change in transition entropy for query reformulation sequences versus search tactic sequences for the repeated task, while the low group showed a similar trend of change in entropies for both types of sequences for the non-repeated task.

These findings complement and extend prior work that has linked topic familiarity expertise with search strategies and tactics, in influencing search behaviour. Task familiarity and intention impacts the types of query reformulations and search tactics used (Rha et al., 2016), as well as the entropy of search sequences (He et al., 2016). For instance, Qu et al. (2010) found that task type and familiarity influenced search behaviours, such as completion time and query count, but not habitual behaviours, such as the search entrance. Li (2008) reported that users' topic familiarity and task experience affected their task performance, which could lead to higher searching efficiency and effectiveness. Finally, Karimi et al. (2011) reported that topic familiarity affected query formulation strategies, such as query length, query count, use of Boolean operators and use of quotation marks.

8.3 RQ3: Searching Behaviour and Learning Outcomes

> *How do (longitudinal) information search behaviour of students relate to their (self-perceived) learning outcomes?*

The study found that the participant group with higher levels of metacognition, motivation, and self-regulation demonstrated significantly higher perceived learning outcomes and search outcomes compared to the participant group which were low on these individual traits. This also affected their longitudinal information search behaviour.

These findings are also in line with prior research, that has linked search behaviour with learning outcomes. For instance, Weber et al. (2019) examined a large sample of German students from all academic fields in a two-phase longitudinal study, and found that advanced levels of search behaviour and search tactics predicted better grades (Zlatkin-Troitschanskaia et al., 2021).

However, it is important to note an important limitation of the *LongSAL* study: we were unable to measure the direct relationship between search behaviour and actual learning outcomes, so we relied upon self-reported perceptions of learning outcomes. Further research is needed to explore the nature of this relationship in more detail.

9 Conclusion

9.1 Summary

> *"Social science exploration is a broad-ranging, purposive, systematic, prearranged undertaking designed to maximize the discovery of generalizations leading to description and understanding of an area of . . . life"*
>
> — Stebbins (2001)

In this dissertation, an exploratory longitudinal study was conducted to investigate how students' longitudinal information search behaviours change with time, what role individual differences play in this process, and how it affects their learning and search outcomes. The study consisted of three phases, with the main longitudinal tracking phase observing students search behaviour as they worked on a research paper final project for a class.

The findings from the study suggest that metacognition, motivation, and self-regulation are important factors that determine, direct, and sustain what students do to search and learn. Students with high levels of these traits demonstrated higher perceived-learning and search outcomes, compared to those with low levels of these traits. Additionally, the high group demonstrated more stable information searching behaviour over time compared to the low group.

As depicted in the opening quote from Stebbins (2001), our exploratory research was inductive, aiming to illuminate new concepts through observation. We purposefully did not follow a deductive approach, which usually proves or tests an existing theory or hypothesis. This resulted in very few statistically significant results in our findings. However, we were more interested in discovering interesting patterns, and leave the task of confirmatory, deductive investigation to follow-up studies.

9.2 Contributions

Apart from the findings discussed at length in previous chapters, the LongSAL study also advances the field of Interactive IR in several aspects.

First, while the initial sample size may appear small with only 16 participants, it is important to consider the extensive amount of search log data collected from each participant over the course of the semester. This accumulation of data translates to a substantial amount of time spent on information searching by study participants, providing a robust foundation for drawing meaningful conclusions. Considering that we collected and analysed more than 1500 minutes, equivalent to over 26 hours of search log data, it becomes evident that our study has amassed a substantial quantity of information. This large amount of data allows for a comprehensive examination of participants' information-searching behaviours, their evolution over time, and their relationship with individual differences in motivation, metacognition, and self-regulation. By collecting such a significant volume of data, the LongSAL study possesses a strong empirical basis for reasonable and reliable findings. It provides a rich and detailed understanding of how undergraduate students engage in information searching while writing a research paper. This extensive breadth and depth of data collected bolsters the credibility and robustness of the findings, within the context of our study population.

Second, the fact that the student participants in the study were from one class is another important contribution. Previous works often examined search tasks from different classes or disciplines, which may introduce variability and make it difficult to isolate the specific effects of motivation, metacognition, and self-regulation on information-searching behaviours and learning outcomes. By focusing on a single class and a specific research paper writing task, the LongSAL study provides a more controlled and focused approach to understanding the relationship between these factors. This allows for a deeper exploration of how individual differences in motivation, metacognition, and self-regulation influence information-searching behaviours and learning outcomes within a consistent context. Additionally, studying participants from one class offers the advantage of a shared learning environment and potentially similar prior knowledge and skill levels. This helps to minimize confounding variables and enhance the internal validity of our findings. This emphasizes the unique aspect of our study and provides valuable insights into the specific dynamics of information-searching behaviours and learning outcomes within a particular educational context.

This dissertation also has some methodological contributions. The first is to relate individual differences in motivation, metacognition, and self-regulation differences in a combined, holistic format with information search behaviour. This was achieved through the person-centred approach of Latent Profile Analysis. To the best of our knowledge, this is the first study in information science and IIR literature to have employed Latent Profile Analysis in such a manner.

Our second methodological contribution is the development of the YASBIL browsing logger (Bhattacharya & Gwizdka, 2021), which was developed primarily as a response to the COVID-19 pandemic. As human subjects research in labs came to a halt, we had to find an alternative approach to carry out IIR research. The YASBIL logger was developed to enable us to collect data on students' online browsing behaviour as they searched for information. This tool allowed us to track students' search behaviour and analyse it in detail, providing insights into how they engage with information sources, evaluate information, and how their information search behaviour evolves over time.

Third, the URL-based classification system (Section 6.6) provided a useful way to categorize webpages based on their type, allowing us to gain insights into how users' search behaviour varies across different types of webpages. By analysing the patterns of webpage types visited by users during their information search process, we were able to identify which types of webpages were most commonly visited and how they related to users' search behaviour. This information can be used to improve the design of information systems and search engines, as well as to inform the development of tailored interventions that support users' information search needs.

Together, these methodological contributions offer new ways of understanding the complex relationships between individual differences in motivation, metacognition, and self-regulation, and how they impact information search behaviour and learning outcomes. Additionally, the YASBIL browsing logger provides a powerful tool for researchers to gather detailed information about students' online browsing behaviour, making it possible to track their search behaviour and analyse it in detail. These contributions provide valuable resources for future researchers in the field of Information Science and Information Retrieval, and offer insights into how we can design more effective searching as learning environments.

9.3 Limitations

Like any other scientific endeavour, the LongSAL study came with its limitations.

The most prominent **theoretical limitation** of the study was the choice of learning outcomes. Although we discuss at length about the inefficacy of traditional learning outcome measures in Chapter 2, we were involuntarily forced to use two of them in this study – self-perceived learning outcomes, and instructor assigned grades. Our initial plan was to use Concept Maps for assessing qualitative and quantitative changes in students' learning and knowledge of concepts. But we were limited by technology, and had to settle for self-ratings. Education Scientists are repeatedly calling for better assessment strategies for learning (Cope & Kalantzis, 2017; Urgo & Arguello, 2022). Future researchers in search-as-learning must work hand in hand with educators and education researchers to investigate and apply more sophisticated forms of learning assessments, that are more equitable in the face of learner diversity.

In terms of **technical limitations**, there were a handful. First, due to the nature of current web-technologies, we could not determine when participants were reading a PDF file on their browser. Browser level JavaScript works only on webpages, and that is what YASBIL used to log user behaviour. If a participant downloaded a bunch of PDFs at a given time, and read them later offline, even when turning YASBIL on, YASBIL would be blind to such readings. Second, we could not analyze clicks on content pages. This is due to an abundance of advertisements and cookie preference popups that any user first has to encounter, before even beginning to settle on the content. This is often quite an annoyance, and also taints the dwell time measure on webpages. Last but not the least, the low sample size is always a limitation. We had initial hopes of recruiting about 30-40 participants for the study. However, despite our best efforts, only 18 signed up, 16 remained till the middle of the semester, and 10 completed the entire study. Previous literature also shows that past longitudinal studies had similar low sample sizes. For instance, Kuhlthau (2004) had 20 participants, Vakkari (2001a) had 11 and Kelly (2006a) had 7 participants.

9.4 Future Work

This dissertation study was monumental effort in planning, organization, and execution. Even after an almost 200-page dissertation, we have barely managed to scratch the surface of the amount of data that was collected in the study.

Some of the most promising directions of future work from this project include: understanding what factors are responsible if/when students change their latent profiles at different points in the semester; understanding parallel and cross session browsing behaviour, and how it affects learning; deeper dive into struggling versus exploring search behaviours; in-depth and qualitative analysis of search queries issued by participants; understanding of long term information use; visits and revisits to webpages, and its effects on relevance judgement; and others.

In conclusion, this dissertation has explored the role of motivation, metacognition and self-regulation in shaping the information search behaviours and learning outcomes of students. The findings demonstrate that differences in these individual traits are crucial components of successful searching as learning behaviour. As Winne & Azevedo (2022) argues, metacognition is the engine of self-regulated learning. To help learners develop and apply productive self-regulated learning, search as learning environments should be designed to foster effective use of metacognitive strategies. Learning technologies should be used to induce, track, model, and support learners' metacognition across tasks, domains, and contexts. As motivation and metacognition are closely intertwined in complex ways, understanding their relationships is the key to designing the next paradigm of searching as learning systems.

> *"It was great to be able to participate in the research this semester. Using the (YASBIL) extension somehow brings me positive feedback and that helps me to study I303. So I wanna say thank you"*
>
> — Participant P022_PISA

Appendices

A
Pilot Study

A pilot study was conducted in the Summer 2021 semester at the School of Information, University of Texas at Austin (Texas iSchool). This was mainly a feasibility study to determine the technical logistics and participant retention rates. It included `PHASE1`, `PHASE2`, and `PHASE3` from the final study procedure (Figure 5.1). There was no recording of individual differences questionnaires. Eight students from two courses at the Texas iSchool – *Academic Success in the Digital University* (ACS), and *Information in Cyberspace* (CYB) – participated in the pilot study. The study ran from start of June 2021 to mid-August 2021. There was no participant drop-off. Synchronous sessions (SES1 and SES3) were conducted over the Zoom video conferencing platform. Log data was captured using the YASBIL browser extension (Bhattacharya & Gwizdka, 2021). All setup and technical logistics worked out properly, without any major technological issues. Details of the search task descriptions are presented below. Participants were compensated with USD 15 for SES1, 15 points of extra course credit for longitudinal tracking in SES2, and USD 15 for SES3.

A.1 Pilot Study Phase 1: Initial Phase

Participants performed a training task to familiarize themselves with the YASBIL browser extension. Then they performed two search tasks as described below. Each search task was followed by measurement of mental workload using NASA-TLX.

Prompt for Task 1: Financial Literacy (Repeated in PHASE3)

Money management and financial literacy are essential life skills, and what better time to learn about them than in college? Write a note to your future self, about essential money-related advice and skills that college students should know and practice.

What to do:

- Find at least 3 unique, good quality online resources that are relevant to this topic
- Look for resources that help establish connections and develop a narrative

What to deliver:

- Write a summary of the lessons, advice, and/or tips you found across the different resources. This is a note to your future self, so the narrative can be in a format that is most useful and interesting to YOU
- Paste the links of ALL the resources that you finally selected to develop your narrative, in the second text box, one link per line

Prompt Task 2: Social Media during COVID-19 (Topic was part of course content in ACS and CYB)

"What was the role of Social Media during the COVID-19 pandemic? How did it affect people's lives during quarantine and social distancing?" Suppose a family member (say your aunt) or a friend asked you these question over a phone call, and you want to talk to them on this topic for a couple of minutes.

What to do:

- Find at least 3 unique, good quality online resources that are relevant to this topic
- Look for resources that help establish connections and develop a narrative

What to deliver:

- Write a short summary of the content that you found across the different resources. The length and writing style can be such that you can read it out to your family member/friend over a phone call, without them losing interest.
- In the summary, briefly mention your thoughts about each resource - do you agree or disagree with the content in the resource? Anything else?
- Paste the links of ALL the resources that you finally selected to develop your narrative, in the second text box, one link per line

A.2 Pilot Study Phase 2: Longitudinal Tracking

The longitudinal tracking phase Phase 2 involved student participants submitting log data for two final-project assignments for the ACS course, and four final project assignments for the CYB course. Participants received reminder emails to log and sync their data a few days before each assignment was due. Seven (out of 8) participants logged their data and synced it with our data server in a timely fashion, without major technical issues. One participant CYB course forgot to log their data for the first two assignments, despite the email reminder. However, upon following up with them, they remembered to log their data for the third and fourth sessions.

A.3 Pilot Study Phase 3: Final Phase

All eight participants from Phase 1 completed Phase 3 (no drop off). Participants performed two search tasks.

Prompt for Task 1: Financial Literacy (Repeated from SES1)

At the start of the semester, you wrote a note to your future self, about essential money-related advice and skills that college students should know and practice.

Here is what you wrote:

{dynamic content showing participants' previous responses}

Here are the resources you took help from:

{dynamic content showing participants' previous responses}

Now you have a chance to **update or revise the note with more information**. You can either choose to write afresh, or copy-paste the note from above into the first textbox below and add to it /edit it. Feel free to search the web if you need to, after turning YASBIL on. You can choose **NOT to search**, as well.

If you do choose to search, please paste the links of ALL the resources that you finally selected for updating your note, one link per line, in the second textbox. The links can be the same ones you visited earlier, or different.

Did you need to search the web for updating the note? Why?

Prompt for Task 2: HTML CSS (Topic was part of course content in ACS and CYB)

In your course, you studied about websites, HTML, and CSS. Therefore, for answering the questions below, **you may choose NOT to search the web**, if you feel you can answer the questions reasonably well. If you do need to search the web, feel free to do so, after turning on YASBIL.

As you understand these concepts, please explain (with examples if necessary)

1. what is the purpose of HTML?

2. what is the purpose of CSS?

3. how do HTML and CSS come together when someone visits a website?

List as many HTML tags as you can, one per line

List as many CSS properties as you can, one per line.

Did you need to search the web for this task? Why?

B

QSNR: Questionnaires

B.1 QSNR0: Recruitment Questionnaire

Thank you SO much for your willingness to participate in the LongSAL research study. The aim of this study is to identify how search engines can better support the needs of university students' learning and education. To be eligible for this study, you must be enrolled in the I 303 Ethical Foundations for Informatics course for the Spring 2022 semester. Please fill out the information requested below. We will get back to you if you are selected to participate in the study. The principal investigator, Nilavra Bhattacharya, can be reached at `<email-address>` for any questions or concerns.

1. Please select which section of the I-303 Ethical Foundations for Informatics course you are enrolled in.

    - TUE: FLEISCHMANN, VERMA
    - WED: FLEISCHMANN, GURSOY
    - THU: FLEISCHMANN, BAUTISTA
    - FRI: FLEISCHMANN, DAY

2. Please select the degree level/name of the program you are in.

   - Bachelor's
   - Master's
   - Integrated Bachelor's and Master's
   - PhD
   - Other .....

3. Please state which year of the program you are in.

   - Freshman
   - Sophomore
   - Junior
   - Senior
   - Graduate Year 1
   - Graduate Year 2
   - Other .....

4. Please state your major(s) .....

5. Do you have native-level familiarity with English language?

   - Yes
   - No
   - Other: .....

6. Please state your age (in years) .....

7. Please state your gender .....

8. With which ethnicities do you identify? Please select all that apply:

   - African

- African American / Black
- Asian - East
- Asian - South East
- Asian - South
- Asian - Middle East
- Caucasian / White
- Hispanic / Latinx
- Native American
- Pacific Islander
- Mixed
- Other .....

9. Are you an international student? If "yes", where are you originally from?

   - Yes .....
   - No

10. We need your contact information to communicate with you over the semester (if you are selected). Your contact information will not be used in any other way, and will be kept private. Please enter an email address that you check regularly. We will use this email address to send communications and Amazon Gift Cards as payment. .....

11. Your name as you would like us to address you (solely for communication). .....

B.2 QSNR1 - QSNR3: Entry, Mid-term and Exit Questionnaires

B.2.1 Consent Form

Consent to Participate in Research

Basic Study Information:

- UT Austin IRB Approved
- **Submission ID:** STUDY00002136
- **Date Approved:** December 8, 2021
- **Title:** LongSAL: A Longitudinal study on Searching as Learning
- **Principal Investigator:** Nilavra Bhattacharya, PhD Student, School of Information, UT Austin
- **Faculty Advisor:** Jacek Gwizdka, Associate Professor, School of Information, UT Austin

Invitation to be Part of a Research Study Things you should know:

- The purpose of the study is to identify how search engines can be improved to better support university students' learning and education.
- In order to participate, you must be enrolled in the I303 Ethical Foundations for Informatics course in the Spring 2022 semester.
- If you choose to participate, you will be asked, over the course of the semester, to take three surveys (10-15 mins each), attend two Zoom sessions (60-90 mins each), and record browsing activity while working on Final Project Paper. All parts of the study will be conducted online.
- Risks or discomforts involved in this research study are not greater than everyday life.
- There is no direct benefit for participating in this study.
- Taking part in this research study is voluntary. You do not have to participate, and you can stop at any time.

More detailed information may be described later in this form.

Please take time to read this entire form and ask questions before deciding whether to take part in this research study.

What is the study about, and why are we doing it? The aim of this longitudinal study is to identify how university students search the web for educational research activities.

Findings from this study will help to understand how search engines can be improved to better support university students' learning and education, and therefore help to build more human-centred and learning-centric search systems.

What will happen if you take part in this study? If you agree to take part in this study, you will be asked to perform the following activities over the duration of the Spring 2022 semester.

How long will this study take and how many people will be in the study? Participation in this study will take approx. 10-15 minutes each for the three surveys, and 60-90 minutes each for the two synchronous Zoom sessions. There will be about 30-40 participants in total in this study.

What risks and discomforts might you experience from being in this study? There are no major foreseeable risks to participating in this study. There may be a very minimal potential risk of confidentiality, or possibly frustrations with some tasks. To address the risk of confidentiality, once data collection is completed, all personally identifying data will be destroyed by erasing all digital files and shredding all the physical records. To address the risk of frustration, you can move at your own pace, or stop whenever you wish.

How could you benefit from this study? You will receive no direct benefit from participating in this study; however, this study will help to improve our current understanding of how students search the web for education and learning-related goals over time. This will the development of better learning-centric search systems.

What data will we collect from you? As part of this study, we will collect your:

- audio, screen recordings, and browsing logs when you are participating in the Zoom sessions. You can turn off your face video during these sessions.
- browsing log data, when you are performing research for the course final project. You can start and stop the logging when you choose.
- anonymized submissions for the final project at various points in the Semester
- self-reported grades for the final project assignments that you received

The holistic data about your research-assignment related internet search activity, the material that you produce for your assignments, and the scores you receive for those assignments, will help us understand where students perform well, where things can be improved, and how search engines can be improved to better support university students' learning and education.

How will we protect your information? We will protect the privacy and the confidentiality of your data by:

- Assigning you a coded username at the beginning of the study to protect confidentiality, and all your submitted data will be linked to this coded username.
- All digital data generated in the study will be stored via a university-approved secure cloud-based storage service and password-protected computers. All computers used in the project are password protected.
- Audio recordings will be listened to only for research purposes. Audio recordings will be transcribed and coded. No information that can be used to uniquely identify an individual will be present

We may share your data with other researchers for future research studies that may be similar to this study or maybe very different. In these cases, the data shared with other researchers will NOT include any information that can directly identify you.

We plan to publish the results of this study. To protect your privacy, we will NOT include any information that could directly identify you.

What will happen to the information we collect about you after the study is over? We will keep your research data to use for future analyses and publications. Any information that can directly identify you will be deleted from the research data collected as part of the project.

How will we compensate you for being part of the study? You will receive up to USD 150 in Amazon Gift cards if you complete all the components of the study, as described above. If you choose to withdraw early from the study, you will receive compensation for the parts you have completed. You will be responsible for any taxes assessed on the compensation.

Your Participation in this Study is Voluntary It is totally up to you to decide to be in this research study. Participating in this study is voluntary. Your decision to participate will not affect your relationship with The University of Texas at Austin. You will not lose any benefits or rights you already had if you decide not to participate. Even if you decide to be part of the study now, you may change your mind and stop at any time. You do not have to answer any questions you do not want to answer.

This Study is NOT a part of the I 303 Ethical Foundations of Informatics course:

- The study researchers intend to only recruit participants from the student pool enrolled in the course.
- The course instructors will not share any student data with the researchers.
- The course instructors will not be aware of which students did or did not participate in this study.
- Participation in this study is completely voluntary, and in no way affects the outcome of this course for you, or your academic relations with the course instructors.

Even after consenting to participate, you can choose to withdraw consent anytime during the semester. We will delete all the data collected from you up to that point. You will receive compensation for the parts you have completed, as outlined above.

Contact Information for the Study Team and Questions about the Research Prior to, during, or after your participation, you may contact the researchers below if you have any questions about this research, or feel you may have been harmed due to participation:

Nilavra Bhattacharya

Phone: `<phone-number>`

Email: `<email-address>`

Or

Jacek Gwizdka

Email: `<email-address>`

Contact Information for Questions about Your Rights as a Research Participant If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact the following:

The University of Texas at Austin

Institutional Review Board

Phone: `<phone-number>`

Email: `<email-address>`

Please reference the study protocol number (STUDY00002136) in your communications.

Your Consent By clicking the button below, you are agreeing to participate in this study. Make sure you understand what the study is about before you consent. If you have any questions about the study after you consent, you can contact the study team using the information provided above.

- By clicking this button I understand what the study is about and my questions so far have been answered. I agree to participate in this study.

Please enter the coded username assigned to you (shared via email) .....

B.3 Motivation

Adapted from Intrinsic Motivation Inventory (IMI) (Ryan, 1982). Items will be randomly ordered.

Scoring directions: Score each response from 1 (not at all true) to 5 (very true). Then reverse score the items marked with **(R)**. To do that, subtract the item response from 6, and use the resulting number as the item score. Then, calculate subscale scores by averaging across all the items on that subscale. The subscale scores are then used in the analyses of relevant research questions.

For each of the following statements, please indicate how true it is for you, using the following scale:
(1) not at all true — somewhat true — very true (5)

B.3.1 Interest/Enjoyment

1. I will enjoy taking this course very much.
2. This course will be fun to do.
3. I think this will be a boring course. **(R)**
4. This course will not hold my attention at all. **(R)**
5. I would describe this course as very interesting.
6. I think this course will be quite enjoyable.

B.3.2 Perceived Competence

1. I think I will be pretty good at this course.
2. I think I will be doing pretty well at this course, compared to other students.
3. After working at this course for awhile, I will feel pretty competent.
4. I think I will be satisfied with my performance in this course.
5. I think I am pretty skilled at this course.
6. This is a course that I think would not be able to do very well. **(R)**

B.3.3 Effort/Importance

1. I plan to put a lot of effort into this course.
2. I don't think I will try very hard to do well at this course. **(R)**
3. I will try very hard on this course.
4. It is important to me to do well in this course.
5. I do not plan to put much energy into this course. **(R)**

B.3.4 Value/Usefulness

1. I believe the course and the final project activities could be of some value to me.
2. I think that doing the final project activities is useful for me.
3. I think the final project is important activity to do because it can equip me with skills that are necessary for making ethical decisions in my adult and professional life.
4. I would be willing to do research on the final project topic again because it has some value to me.
5. I think doing the final project activities will help me in my adult and professional life
6. I believe doing the final project activities will be beneficial to me.
7. I think this is an important course.

B.3.5 Pressure / Tension (not in QSNR1)

1. I do not feel nervous while doing the final project activities. **(R)**
2. I feel very tensed while doing the final project activities.
3. I am very relaxed while doing the final project activities. **(R)**
4. I feel anxious while working on the final project parts.
5. I feel pressured while doing the final project activities.

B.3.6 Perceived Choice (not in QSNR1)

1. I believe I have some choice about doing the final project activities.
2. I feel like it is not my own choice to do the final project parts. **(R)**
3. I don't really have a choice about doing the final project tasks. **(R)**
4. I feel like I have to do the final project tasks. **(R)**
5. I do the final project activities because I have no choice. **(R)**
6. I do the final project activities because I want to.
7. I do the final project activities because I have to. **(R)**

B.4 Self-regulation

Self-Regulation Questionnaire (SRQ) by J. M. Brown et al. (1999).

Please answer the following questions by selecting the option that best describes how you are. There are no right or wrong answers. Work quickly and don't think too long about your answers.

(1) Strongly Disagree – Disagree – Neutral – Agree – Strongly Agree (5)

1. I usually keep track of my progress toward my goals.
2. My behavior is not that different from other people's. **(R)**
3. Others tell me that I keep on with things too long. **(R)**
4. I doubt I could change even if I wanted to. **(R)**
5. I have trouble making up my mind about things. **(R)**
6. I get easily distracted from my plans. **(R)**
7. I reward myself for progress toward my goals.
8. I don't notice the effects of my actions until it's too late. **(R)**
9. My behavior is similar to that of my friends. Evaluating
10. It's hard for me to see anything helpful about changing my ways. **(R)**
11. I am able to accomplish goals I set for myself.
12. I put off making decisions. **(R)**
13. I have so many plans that it's hard for me to focus on any one of them. **(R)**
14. I change the way I do things when I see a problem with how things are going.
15. It's hard for me to notice when I've "had enough" (alcohol, food, sweets, internet, social media) **(R)**
16. I think a lot about what other people think of me.
17. I am willing to consider other ways of doing things.
18. If I wanted to change, I am confident that I could do it.
19. When it comes to deciding about a change, I feel overwhelmed by the choices. **(R)**

20. I have trouble following through with things once I've made up my mind to do something. **(R)**
21. I don't seem to learn from my mistakes. **(R)**
22. I'm usually careful not to overdo it when working, eating, drinking, or being on social media.
23. I tend to compare myself with other people.
24. I enjoy a routine, and like things to stay the same. **(R)**
25. I have sought out advice or information about changing.
26. I can come up with lots of ways to change, but it's hard for me to decide which one to use. **(R)**
27. I can stick to a plan that's working well.
28. I usually only have to make a mistake one time in order to learn from it.
29. I don't learn well from punishment. **(R)**
30. I have personal standards, and try to live up to them.
31. I am set in my ways. **(R)**
32. As soon as I see a problem or challenge, I start looking for possible solutions.
33. I have a hard time setting goals for myself. **(R)**
34. I have a lot of willpower.
35. When I'm trying to change something, I pay a lot of attention to how I'm doing.
36. I usually judge what I'm doing by the consequences of my actions.
37. I don't care if I'm different from most people. **(R)**
38. As soon as I see things aren't going right I want to do something about it.
39. There is usually more than one way to accomplish something.
40. I have trouble making plans to help me reach my goals. **(R)**
41. I am able to resist temptation.
42. I set goals for myself and keep track of my progress.
43. Most of the time I don't pay attention to what I'm doing. **(R)**
44. I try to be like people around me.

45. I tend to keep doing the same thing, even when it doesn't work. **(R)**
46. I can usually find several different possibilities when I want to change something.
47. Once I have a goal, I can usually plan how to reach it.
48. I have rules that I stick by no matter what.
49. If I make a resolution to change something, I pay a lot of attention to how I'm doing.
50. Often I don't notice what I'm doing until someone calls it to my attention. **(R)**
51. I think a lot about how I'm doing.
52. Usually I see the need to change before others do.
53. I'm good at finding different ways to get what I want.
54. I usually think before I act.
55. Little problems or distractions throw me off course. **(R)**
56. I feel bad when I don't meet my goals.
57. I learn from my mistakes.
58. I know how I want to be.
59. It bothers me when things aren't the way I want them.
60. I call in others for help when I need it.
61. Before making a decision, I consider what is likely to happen if I do one thing or another.
62. I give up quickly. **(R)**
63. I usually decide to change and hope for the best. **(R)**

Scoring Directions: Score each response from 1 (strongly disagree) to 5 (strongly agree), and calculate the following seven subscale scores by summing the items on that subscale. Items marked **(R)** are reverse-coded (i.e. 1 = strongly agree and 5 = strongly disagree). To do that, subtract the item response from 6, and use the resulting number as the item score.

1. *Receiving relevant information:* 1, 8, 15, 22, 29, 36, 43, 50, 57
2. *Evaluating the information and comparing it to norms:* 2, 9, 16, 23, 30, 37, 44, 51, 58
3. *Triggering change:* 3, 10, 17, 24, 31, 38, 45, 52, 59
4. *Searching for options:* 4, 11, 18, 25, 32, 39, 46, 53, 60

5. *Formulating a plan:* 5, 12, 19, 26, 33, 40, 47, 54, 61
6. *Implementing the plan:* 6, 13, 20, 27, 34, 41, 48, 55, 62
7. *Assessing the plan's effectiveness:* 7, 14, 21, 28, 35, 42, 49, 56, 63

Based on our clinical and college samples, we tentatively recommend the following ranges for interpreting SRQ total scores with the 63-item scale:

- **>= 239**: High (intact) self-regulation capacity (top quartile)
- **214 - 238**: Intermediate (moderate) self-regulation capacity (middle quartiles)
- **<= 213**: Low (impaired) self-regulation capacity (bottom quartile)

B.5 Metacognition

Metacognitive Awareness Inventory (MAI) proposed by Schraw & Dennison (1994) and revised by Terlecki & McMahon (2018).

*Think of yourself as a **learner**. Read each statement carefully, and rate it as it generally applies to you when you are in the role of a learner (student, attending classes, university etc.) Please indicate how true each reason is for you using the following scale:*

Score	Response
1	I **NEVER** do this
2	I do this **infrequently**
3	I do this **inconsistently**
4	I do this **frequently**
5	I **ALWAYS** do this

1. I ask myself periodically if I am meeting my goals.
2. I consider several alternatives to a problem before I answer.
3. I try to use strategies that have worked in the past.
4. I pace myself while learning in order to have enough time.
5. I understand my intellectual strengths and weaknesses.
6. I think about what I really need to learn before I begin a task.

7. I know how well I did once I finish a test.
8. I set specific goals before I begin a task.
9. I slow down when I encounter important information.
10. I know what kind of information is most important to learn.
11. I ask myself if I have considered all options when solving a problem.
12. I am good at organizing information.
13. I consciously focus my attention on important information.
14. I have a specific purpose for each strategy I use.
15. I learn best when I know something about the topic.
16. I know what the teacher expects me to learn.
17. I am good at remembering information.
18. I use different learning strategies depending on the situation.
19. I ask myself if there was an easier way to do things after I finish a task.
20. I have control over how well I learn.
21. I periodically review to help me understand important relationships.
22. I ask myself questions about the material before I begin.
23. I think of several ways to solve a problem and choose the best one.
24. I summarize what I've learned after I finish.
25. I ask others for help when I don't understand something.
26. I can motivate myself to learn when I need to.
27. I am aware of what strategies I use when I study.
28. I find myself analyzing the usefulness of strategies while I study.
29. I use my intellectual strengths to compensate for my weaknesses.
30. I focus on the meaning and significance of new information.
31. I create my own examples to make information more meaningful.
32. I am a good judge of how well I understand something.
33. I find myself using helpful learning strategies automatically.
34. I find myself pausing regularly to check my comprehension.

35. I know when each strategy I use will be most effective.
36. I ask myself how well I accomplish my goals once I'm finished.
37. I draw pictures or diagrams to help me understand while learning.
38. I ask myself if I have considered all options after I solve a problem.
39. I try to translate new information into my own words.
40. I change strategies when I fail to understand.
41. I use the organizational structure of the text to help me learn.
42. I read instructions carefully before I begin a task.
43. I ask myself if what I'm reading is related to what I already know.
44. I reevaluate my assumptions when I get confused.
45. I organize my time to best accomplish my goals.
46. I learn more when I am interested in the topic.
47. I try to break studying down into smaller steps.
48. I focus on overall meaning rather than specifics.
49. I ask myself questions about how well I am doing while I am learning something new.
50. I ask myself if I learned as much as I could have once I finish a task.
51. I stop and go back over new information that is not clear.
52. I stop and reread when I get confused.

Scoring Directions: Score each response from 1 (never) to 5 (always), and calculate the following subscale scores by summing the items on that subscale.

Knowledge about Cognition:

1. *Declarative Knowledge:* 5, 10, 12, 16, 17, 20, 32, 46 (score out of $8 \times 5 = 40$)
2. *Procedural Knowledge:* 3, 14, 27, 33 (score out of $4 \times 5 = 20$)
3. *Conditional Knowledge:* 15, 18, 26, 29, 35 (score out of $5 \times 5 = 25$)

Regulation of Cognition:

1. *Planning:* 4, 6, 8, 22, 23, 42, 45 (score out of $7 \times 5 = 35$)

2. *Information Management Strategies:* 9, 13, 30, 31, 37, 39, 41, 43, 47, 48 (score out of $10 \times 5 = 50$)
3. *Comprehension Monitoring:* 1, 2, 11, 21, 28, 34, 49 (score out of $7 \times 5 = 35$)
4. *Debugging Strategies:* 25, 40, 44, 51, 52 (score out of $5 \times 5 = 25$)
5. *Evaluation:* 7, 19, 24, 36, 38, 50 (score out of $6 \times 5 = 30$)

C
Task Materials of Initial `PHASE1` and Final `PHASE3` Phases

Phase 1 was conducted at the beginning of the semester, and Phase 3 was conducted at the end of the semester.

C.1 Pre-Task Questionnaire (for `PHASE1` and `PHASE3`)

(The following items are adapted from Collins-Thompson et al. (2016).)

1. How much do you know about this topic?
   (1) nothing / I know a lot (5)
2. How interested are you to learn more about this topic?
   (1) not at all / very much (5)
3. How difficult do you think it will be to search for information about this topic?
   (1) very easy / very difficult (5)

(The following items are adapted from Crescenzi (2020).)

Indicate your agreement with the following statements.

(1) Strongly Disagree / Neutral / Strongly Agree (5)

4. I am interested to learn more about the topic of this task.
5. I know a lot about this topic.
6. I can write a good summary now without needing to look for information.
7. It will be difficult to determine when I have enough information to write my summary.
8. I think this will be a difficult task.
9. I am confident I know (or can find) adequate information to write a good summary.

C.2 Post-Task Questionnaire (for SES1 and SES3)

(The following items are adapted from Collins-Thompson et al. (2016).)

Indicate your agreement with the following statements.

(1) Not at all / Unlikely / Somewhat / Likely / Very Likely (5)

Search for information exploration:

1. I was cognitively engaged in search task.
2. I made an effort at performing the search task.
3. The time for search was spent productively on meaningful tasks.
4. I was able to explore relationships among multiple concepts.
5. I was able to expand the scope of my knowledge about the topic.
6. I feel that I was able to put together pieces of information into one big concept.

Learner interest and motivation:

7. I feel that I have full understanding of the topic of this task
8. I became more interested in this topic.

9. I would like to find more information about this topic
10. I would like to share what I learned with my people I know.
11. I feel that I learned useful information as a result of this search.
12. I was able to develop new ideas or perspectives.

Perceived learning and search success:

On a scale of 0 - 100

13. How would you grade your learning outcome?
14. How would you grade your search outcome?

(The following items are adapted from Crescenzi (2020).)

Indicate your agreement with the following statements.

(1) Strongly Disagree / Neutral / Strongly Agree (5)

15. Overall, it was difficult to search for information to make the summary.
16. It was difficult to determine search terms to use to find relevant information.
17. It was difficult to decide whether to continue inspecting the search results or to search again.
18. It was difficult to choose which search results to view.
19. It was difficult to determine when to stop looking for information.
20. I would have preferred to think longer about my summary.
21. If I had more time, I would have considered more information.
22. I felt anxious while completing this task.

23. I did not have enough time.
24. It was difficult to decide which sources to select.
25. I felt hurried or rushed during this task.
26. I had adequate information to make a good summary.
27. I felt I had enough information.
28. My understanding of the topic was no longer changing.
29. I collected enough information to make a summary.
30. I was no longer learning about the topic.
31. I felt I had adequate information to make a summary.
32. I was focused on getting information about one thing.
33. I felt continuing the search was a waste of time, as the same information was showing up.
34. I had a list of certain things I was interested in.
35. I stopped searching because I was not finding new information.
36. I stopped searching when I had an option that satisfied the things that were important to me.
37. I only considered looking for the piece of information most important to me.
38. I kept finding the same information in every search.
39. My view of the topic was no longer changing.
40. I was most concerned about finding information on one specific aspect.

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