The Effects of Learning Objectives on Searchers' Perceptions and Behaviors

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ABSTRACT

In recent years, the "search as learning" community has argued that search systems should be designed to support learning. We report on a lab study in which we manipulated the learning objectives associated with search tasks assigned to participants. We manipulated learning objectives by leveraging Anderson and Krathwohl's taxonomy of learning (A&K's taxonomy) [2], which situates learning objectives at the intersection of two orthogonal dimensions: the *cognitive process* and the *knowledge type* dimension. Participants in our study completed tasks with learning objectives that varied across three cognitive processes (apply, evaluate, and create) and three knowledge types (factual, conceptual, and procedural knowledge). We focus on the effects of the task's cognitive process and knowledge type on participants' pre-/post-task perceptions and search behaviors. Our results found that the three knowledge types considered in our study had a *greater* effect than the three cognitive processes. Specifically, conceptual knowledge tasks were perceived to be more difficult and required more search activity. We discuss implications for designing search systems that support learning.

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1 INTRODUCTION

In recent years, the "search as learning" movement has argued that search systems should be designed to support learning [19]. Several IR summits have taken place to develop research agendas at the intersection of searching and learning. Participants at the 2012 SWIRL workshop proposed that future research should aim to: (1) understand the cognitive biases fostered by existing systems; (2) help people become more critical consumers of information; and (3) help searchers achieve higher levels of learning [1]. Similarly, participants at the 2017 Dagstuhl Seminar on Search as Learning identified three areas for future work: (1) understanding the contexts in which people use search systems to learn; (2) understanding the relations between searching and learning activities; and (3) developing search interfaces and tools to support learning [7]. Prior research in the area of "search as learning" has focused on a wide range of questions. Some studies have investigated whether search behaviors can predict learning outcomes [7]. Other studies have focused on understanding how learning outcomes are impacted by characteristics of the searcher [11], the search system [10, 12, 14], and the search task [16]. In this paper, we investigate how a searcher's type of *learning objective* may influence perceptions and search behaviors.

We report on a lab study (N=36) in which participants completed three search tasks with a specific type of learning objective. That is, our tasks asked participants to gather information in order to achieve a specific learning-oriented goal. To manipulate learning objectives, we used Anderson and Krathwohl's two-dimensional taxonomy [2]. In the field of education, A&K's taxonomy was designed to help educators more precisely define learning objectives for students. The taxonomy situates learning objectives at the intersection of two orthogonal dimensions. First, the *cognitive process* dimension defines the central cognitive process associated with the learning objective. Cognitive processes range from simple to complex: remember, understand, apply, analyze, evaluate, and create. A simple objective may involve rote memorization, while a complex objective may involve weighing the trade-offs between different alternatives. Second, the *knowledge type* dimension defines the type of knowledge related to the learning objective. A&K's taxonomy defines four types of knowledge: (1) factual knowledge (i.e. knowledge about declarative bits of information); (2) conceptual knowledge (i.e., knowledge about concepts, principles, models, and schemas); (3) procedural knowledge (i.e., knowledge about how to do something); and (4) metacognitive knowledge (i.e., knowledge about one's own cognition).

Prior research has also used A&K's taxonomy to manipulate and study learning-oriented search tasks [6, 13, 15, 21]. However, prior studies have *only* considered the cognitive process dimension—the knowledge type dimension has neither been systematically manipulated nor controlled. Ignoring the knowledge type dimension raises important questions. For example, is it more challenging to meet learning objectives associated with one knowledge type than another (irrespective of cognitive process)? And, are the effects of the cognitive process dimension *different* across knowledge types?

During our study, participants completed three learning-oriented search tasks. During each task, participants were asked to search for information and make notes in an external document. After this, participants were asked to video record a response to the task's main question (e.g., "using a graphic, explain how Bernoulli's principle enables a plane to fly."). In other words, during the video assessment phase, participants were asked to *demonstrate that they accomplished the task's learning objective.* The learning objective of each task was designed to fit into one cell in A&K's taxonomy

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(e.g., evaluate/conceptual). Learning objectives were manipulated by considering all combinations of three cognitive processes (apply, evaluate, create) and three knowledge types (factual, conceptual, procedural). Our study investigated three main research questions: How does a task's learning objective (i.e., main cognitive process and knowledge type) influence participants' (RQ1) pre-task perceptions, (RQ2) post-task perceptions, and (RQ3) search behaviors?

2 RELATED WORK

The "search as learning" movement has gained momentum partly because people *already* use search systems to support their learning-oriented goals. Bailey et al. [4] analyzed search logs gathered over a 3-month period and developed a taxonomy of common search task types, which included learning-oriented search tasks—fact-finding, exploratory, comparison, and procedural knowledge tasks. Similarly, Eickhoff et al. [9] inferred that 3% of web search sessions had a *knowledge acquisition* intent involving either declarative (i.e., factual or conceptual) or procedural knowledge.

Prior work in the area of "search as learning" has focused on a wide range of questions. Several studies have investigated whether certain search behaviors can be used to predict learning outcomes. A commonly observed trend is that the time spent reading pages (vs. searching) is associated with deeper levels of learning [7, 11]. Additionally, studies have investigated how learning outcomes are influenced by characteristics of the individual searcher [11], the system [10, 12, 14], and the search task [16].

In terms of individual differences, Gadiraju et al. [11] found that participants who reported lower levels of (pre-task) prior knowledge achieved greater improvements on quizzes completed before and after the task. In terms of system differences, Hersh et al. [12] evaluated two systems (a keyword search versus a Boolean search system) based on their ability to help medical students improve their performance on a 10-question test. Both systems performed equally well, suggesting that searchers can achieve comparable learning outcomes with systems that afford different search strategies. Kammerer et al. [14] evaluated an experimental system that allowed users to filter search results using social tags. To measure learning, participants completed two post-task exercises—one asked them to enumerate "factors" (e.g., arguments for/against human-caused global warming) and another asked them to the recall concepts/keywords. Participants performed higher on both tests after using the experimental system versus a baseline system without the social tags. Freund et al. [10] investigated the impact of two factors on participants' reading comprehension of pre-selected articles. One factor considered whether articles were displayed in plain text versus HTML, which included potentially distracting elements (e.g., advertisements, images, navigation widgets, etc.). A second factor considered whether participants had access to a note-taking tool that allowed them to highlight text and make "sticky notes". Results found an interesting interaction effect—reading comprehension was higher in the text versus HTML condition, but this effect was eliminated when participants had access to the note-taking tool.

In terms of task characteristics, Liu et al. [16] studied learning in the context of multi-session search. Study participants completed three related sub-tasks. In the *dependent* condition, sub-tasks built on each other. In the *parallel* condition, they were independent. To assess learning, participants rated their familiarity with the sub-task *and* general domain before/after each sub-task. In general, participants' sub-task and domain familiarity increased with each sub-task. However, their familiarity with the general domain *plateaued* faster in the parallel sub-task condition. More closely related to our work, studies have also investigated how learning objectives influence perceptions and behaviors. To this end, studies have also leveraged A&K's taxonomy [6, 13, 15, 21]. However, these studies have *only* considered A&K's cognitive process dimension. Studies have found that tasks involving more complex cognitive processes are perceived to be more difficult [6, 13, 15, 21], require more search activity [6, 13, 15, 21], and are associated with more divergent search strategies across participants [15].

3 A&K'S 2D TAXONOMY

A&K's 2D taxonomy [2] was developed to more precisely define learning objectives for students. A&K's 2D taxonomy situates learning objectives at the intersection of two orthogonal dimensions: (1) the cognitive process dimension and (2) the knowledge type dimension. A&K view learning objectives as a verb/noun combination (e.g., recall factual knowledge). The cognitive process defines the "verb" and the knowledge type defines the "noun".

The cognitive process dimension defines the types of mental activities related to the learning objective. A&K's taxonomy defines six cognitive processes (from simple to complex). A *remember* objective involves memorization. An *understand* objective involves more deeply engaging with information in order to summarize, explain, or exemplify. An *apply* objective involves using knowledge to perform a task. An *analyze* objective involves understanding the similarities, differences, or relations between elements. An *evaluate* objective involves critiquing, judging, or evaluating alternatives. A *create* objective involves inventing a new solution to a problem.

The knowledge dimension of A&K's taxonomy relates to the types of knowledge associated with the learning objective. The taxonomy considers four knowledge types. *Factual* knowledge is defined as declarative knowledge about discrete, isolated elements. *Conceptual* knowledge relates to concepts, principles, models, or theories. A&K argue that factual knowledge relates to bits of information, while conceptual knowledge relates to concepts, mental models, schemas, and theories that people can use to organize bodies of knowledge in a systematic and interconnected manner [2, p.42]. *Procedural* knowledge relates to step-by-step (or "how to") knowledge about performing a specific task. Finally, *metacognitive* knowledge relates to knowledge about one's own cognition.

Much prior work has adopted the cognitive process dimension of A&K's taxonomy to design search tasks involving different cognitive processes [5, 6, 13, 15, 20, 21]. However, the knowledge type dimension has neither been manipulated nor controlled. In this paper, we investigate tasks with learning objectives involving a specific cognitive process (apply, evaluate, create) and knowledge type (factual, conceptual, and procedural). Next, we discuss how different knowledge types may influence the complexity of learning-oriented search tasks. Factual, conceptual, and procedural knowledge differ in several ways. To illustrate these differences, we consider them in terms of the cognitive process of *understand* (i.e., understanding factual, conceptual, and procedural knowledge).

Interconnectedness: Compared to factual knowledge, conceptual and procedural knowledge is more interconnected. As noted by A&K, "factual knowledge can be isolated as elements or bits of information that are believed to have value in and of themselves." [2, p.42]. Conversely, understanding a concept (e.g., a specific form of government or artistic style) may require understanding related concepts (e.g., other, similar forms of government or artistic styles). Similarly, understanding a procedure may require understanding other procedures nested within. For example, understanding how to cook lasagna requires understanding how to boil pasta.

Subjectivity: By definition, facts are objective bits of information. In other words, facts are presumed to be true regardless of one's own perspective. Conversely, understanding concepts and procedures may involve more subjectivity. For example, determining whether a work of art *exemplifies* an artistic style or determining whether a specific procedure is appropriate in a given scenario may require activities that involve subjectivity—weighing other people's opinions and/or making a judgement call.

Abstractness: Facts are often about tangible things that can be perceived by the senses. As noted by A&K, "for the most part, factual knowledge exists at a relatively low level of abstraction." [2, p.42]. Conversely, some concepts (e.g., automatism, totalitarianism) and some procedures (e.g., computing a derivative, decomposing the structure of an argument) may deal with higher levels of abstraction.

Measuring success: Satisfying a learning objective requires an individual to decide when the objective has been met. In this respect, it may be easier for searchers to decide when they have successfully acquired factual knowledge versus conceptual or procedural knowledge. For example, how does one decide that they sufficiently understand (i.e., are able to summarize or explain) a concept such as Bernoulli's principle or a procedure such as a specific algorithm? Compared to factual knowledge, conceptual and procedural knowledge may be associated with *broader* levels of understanding.

4 METHODS

To investigate RQ1-RQ3, we conducted a laboratory study with 36 participants (25 female). Participants were recruited using an opt-in mailing list of employees from our university. Their ages ranged from 19 to 61 ($M = 32.61$, $S.D. = 12.82$).

Study Protocol: Participants completed three learning-oriented search tasks. The study used a *think-aloud* protocol [8]. That is, participants were instructed to narrate their thoughts as they searched. Think-aloud comments and screen activities were recorded but not analyzed as part of this paper. Think-aloud comments will be analyzed in future work as described in Section 7.

The study session proceeded as follows. First, after providing informed consent, participants completed a demographics questionnaire and an example task to practice thinking aloud. Second, participants completed three learning-oriented search tasks, which followed the same sequence of steps. After reading the task description, participants completed a pre-task questionnaire. Then participants completed the *search phase* of the task. Participants were given 15 minutes to search for information using a custom-built search system and took notes on an electronic document. After the search phase, participants were given two minutes to review their notes. Then participants completed the *video assessment phase* of the task (described below). After the video assessment, participants completed a post-task questionnaire. The study session lasted about 1.5 hours and participants were compensated US $40.

Video Assessment: As mentioned above, each of the three tasks completed by participants included a video assessment phase. The goal of the video assessment was for participants to demonstrate that they accomplished the task's learning objective. For example, one of our evaluate/factual tasks asked participants to: "Determine why the most expensive painting ever sold was so expensive?" This is an evaluate/factual task because it involves comparing different facts and choosing the most influential. In this case, during the video assessment, participants were asked to: "Explain and justify the primary reason for why the painting was so expensive." Participants were given two minutes to provide a response. Participants' responses were video recorded by the study moderator. We decided to use a video assessment to encourage participants to take the task seriously and avoid satisficing.

Tasks: Twenty-seven tasks were constructed across three topical domains: art, finance, and science. For each domain, we constructed nine tasks that varied along three cognitive processes (apply, evaluate, create) and three knowledge types (factual, conceptual, procedural) from A&K's taxonomy. We limited ourselves to three cognitive processes and three knowledge types to keep the study design and data analysis manageable. In terms of cognitive processes, we omitted A&K's cognitive processes of remember, understand, and analyze. We omitted remember and understand because they are the least complex, and analyze because it is considered a prelude to evaluate [2, p.79]. In terms of knowledge types, we omitted metacognitive knowledge because it is very different than the other three—it relates to self-knowledge about one's own cognition. Next, we provide three example tasks from the science domain: (1) apply/factual, (2) evaluate/conceptual, and (3) create/procedural. Each task included a background scenario (to contextualize the task) and a description of the task's main objective.

(1) Apply/Factual—**Scenario:** You recently watched a TV documentary about the deepest part of the ocean. The documentary mentioned the depth of the deepest part of the ocean in meters. However, this number (in meters) did not quite give you clear "perspective" on just how deep this is. You want to get a more "tangible" appreciation for the depth of the deepest part of the ocean. **Task:** Use the height of the world's tallest building as a unit to measure the deepest part of the ocean.

(2) Evaluate/Conceptual—**Scenario:** During a recent trip to the National Air and Space Museum with your extended family, your younger cousin, who is in high school, said she is interested in better understanding how planes are able to fly. You are not very familiar with the principles behind the notion of lift, so when you get home you decide to do some investigating. After some initial research you notice that there are two predominant explanations of lift, Bernoulli's principle and Newton's laws of motion. **Task:** Determine which best explains the notion of lift and why: Bernoulli's principle or Newton's laws of motion? Provide a well-reasoned, logical argument to support your explanation.

(3) Create/Procedural—**Scenario:** You are building a firepit in your backyard. You have constructed a large circle so that chairs can fit around the firepit. You have not yet dug the firepit because you want to be sure that it is positioned precisely in the center of the circle. **Task:** Explore different methods for finding the mathematical center of a circle, then create a novel method for finding the mathematical center of your firepit circle. The method can be completely different from those you find, a combination of methods, or a method you find with slight variations.

Task #1 is 'apply/factual' because the verb "use" corresponds to the 'apply' cognitive process and "the deepest part of the ocean" is an example of factual knowledge. Task #2 is 'evaluate/conceptual' because the verb "determine" corresponds to the 'evaluate' cognitive process and because Bernoulli's principle and Newton's laws of motion are examples of conceptual knowledge. Finally, Task #3 is 'create/procedural' because it requires the learner to "create" a new method and because "methods for finding the center of a circle" are examples of procedural knowledge. All 27 tasks were developed iteratively using A&K's definitions and examples as a guide [2]. We iterated on our tasks until all authors agreed that every task's learning objective matched the intended A&K cell (i.e., involved the intended cognitive process and knowledge type). Our 27 tasks and pre-/post-task questionnaires (described below) are available at: http://www.kelseyurgo.com/ictir-2020/.

Task Assignment: As previously mentioned, our 27 tasks covered 9 cells from A&K's taxonomy (i.e., 3 cognitive processes × 3 knowledge types). Each participant completed *three* tasks from the same domain (art, finance, or science), and tasks were assigned such that each participant experienced all three cognitive processes and all three knowledge types considered in our study. The ordering of tasks was rotated such that every participant experienced our three cognitive processes and knowledge types in a different order (i.e., 6 CP orders × 6 KT orders = 36 participants).

Questionnaires: Participants completed pre-/post-task questionnaires before/after each task (search + video assessment phase). In both questionnaires, participants responded to agreement statements using a seven-point scale from strongly disagree (1) to strongly agree (7). The pre-task questionnaire included 21 items that measured prior knowledge (1 item), interest (1 item), *a priori* determinability (6 items), expected difficulty in searching for information (3 items), expected difficulty in completing the video assessment (1 item), and participants' expectations about the task involving 6 specific cognitive processes and 3 knowledge types (9 items). Based on Cronbach's alpha, the items for expected difficulty and determinability had high internal consistency (diff_search = 0.92, determinability = 0.89). Thus, we averaged participants' responses to these items to form two measures.

The post-task questionnaire included 20 items that measured knowledge increase (1 item), interest increase (1 item), difficulty in searching for information (3 items), difficulty in completing the video assessment (1 item), satisfaction with the search experience (3 items), satisfaction with the video assessment (2 item), and participants' perceptions about the task involving 6 specific cognitive processes and 3 knowledge types (9 items). Again, using Cronbach's alpha, the items associated with difficulty searching, satisfaction with the search process, and satisfaction with the video assessment had high internal consistency (diff_search = 0.79, sat_search =0.92, sat_video =0.92). Thus, we averaged participants' responses to these items to form three measures.

In our pre-/post-task questionnaires, we included 9 items about participants' perceptions of the task involving specific cognitive processes (i.e, remember, understand, apply, analyze, evaluate, create) and knowledge types (i.e., facts, concepts, procedures). These types of perceptions have not been measured in prior work. Thus, we list these items below. The pre-/post-task agreement statements were identical except for their tense ("will require" vs. "required"). The pre-task items were as follows:

(1) The task will require me to memorize information.
(2) The task will require me to go beyond memorization and more deeply understand the information I find.
(3) The task will require me to apply information I learn to solve problems.
(4) The task will require me to differentiate between related ideas.
(5) The task will require me to evaluate different alternatives to make informed decisions.
(6) The task will require me to create new solutions to a problem.
(7) The task will require me to learn about facts.
(8) The task will require me to learn about concepts and their definitions.
(9) The task will require me to learn about step-by-step procedures.

Items 1-6 measured participants' perceptions of the task involving cognitive processes of remember, understand, apply, analyze, evaluate, and create. Items 7-9 measured participants' perceptions of the task involving factual, conceptual, and procedural knowledge.

Search System: During each task, participants used a custom-built system to find information. The system used the Bing API to return search results from four verticals: web, images, news, and video (displayed on different tabs). The system logged all SERP-level interactions. To address RQ3 (i.e., effects on behavioral measures), we computed the following 8 measures: (1) # of queries, (2) # of clicks, (3) # abandoned queries, (4) avg. click rank, (5) avg. time (in secs.) between subsequent events (i.e., queries, clicks), (6) completion time (in secs.), and (7-8) # of queries/clicks not issued/clicked by another participant. Prior work has found that searchers adopt more *divergent* search strategies during complex (vs. simple) tasks [15]. Measures 7-8 were computed to capture this type of behavior.

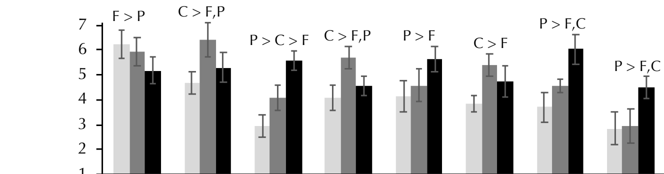
5 RESULTS

To address RQ1-RQ3, we performed two-way ANOVAs to investigate the effects of the task's cognitive process and knowledge type on: (RQ1) participants' pre-task perceptions, (RQ2) post-task perceptions, and (RQ3) search behaviors. In all cases, we considered the main effects of the task's cognitive process and knowledge type as well as their interaction effects. Post-hoc pairwise comparisons were performed using Bonferroni correction. For interaction effects, we were interested in comparing between knowledge types conditioned on the same cognitive process. For example, were there differences between knowledge types for create tasks (the most complex), but not for apply tasks (the least complex)? Thus, we focused on pairwise comparisons between knowledge types within each cognitive process category (i.e., 9 pairwise comparisons). Our RQ1-RQ3 results are shown in Figures 1-5, which display means and 95% confidence intervals. To conserve space, we visualize only those outcome measures with significant main and interaction effects.

5.1 Effects on Pre-task Perceptions (RQ1)

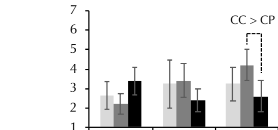
In RQ1, we investigate the effects of the task's cognitive process and knowledge type on participants' pre-task perceptions of (1) prior knowledge, (2) interest, (3) expected difficulty searching, (4) expected difficulty in completing the video assessment, and (5) determinability. Additionally, we considered participants' expectations about the task requiring (6) facts, (7) concepts, (8) procedures, as well as involving the cognitive processes of (9) remember, (10) understand, (11) apply, (12) analyze, (13) evaluate, and (14) create.

Main Effects: The task's cognitive process did not have a significant main effect for any pre-task measure. Conversely, the task's



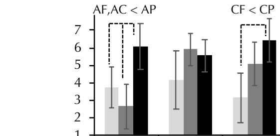
	facts	concepts	proc.	under.	apply	analyze	evaluate	create
factual	6.22	4.67	2.94	4.08	4.14	3.86	3.69	2.83
conceptual	5.94	6.42	4.08	5.69	4.58	5.39	4.56	2.92
procedural	5.17	5.28	5.58	4.56	5.61	4.75	6.03	4.50

Figure 1: Sig. main effects of knowledge type on pre-task expectations of knowledge types (leftmost columns) and cognitive processes (rightmost columns).



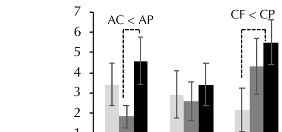
	apply	evaluate	create
factual	2.67	3.25	3.25
conceptual	2.21	3.42	4.21
procedural	3.42	2.42	2.63

(a) Diff. Search



	apply	evaluate	create
factual	3.75	4.17	3.17
conceptual	2.67	5.92	5.08
procedural	6.08	5.58	6.42

(b) 'Evaluate' Expectations



	apply	evaluate	create
factual	3.42	2.92	2.17
conceptual	1.83	2.58	4.33
procedural	4.58	3.42	5.50

(c) 'Create' Expectations

Figure 2: Sig. interaction effects on pre-task measures.

knowledge type had a significant main effect on *eight* pre-task measures. Figure 1 shows these measures and indicates all significant pairwise comparisons. Knowledge type had a significant effect on participants' perceptions about the task requiring them to engage with facts ($F(2, 99) = 5.27$, $p = .007$), concepts ($F(2, 99) = 13.9$, $p = .000$), and procedures ($F(2, 99) = 20.15$, $p = .000$). As expected, participants expected factual knowledge tasks to require facts, conceptual knowledge tasks to require concepts, and procedural knowledge tasks to require procedures.

The task's knowledge type also had a significant effect on participants' perceptions about the task involving the cognitive processes of understand ($F(2, 99) = 8.09$, $p = .001$), apply ($F(2, 99) = 6.02$, $p = .003$), analyze ($F(2, 99) = 6.08$, $p = .003$), evaluate ($F(2, 99) = 15.66$, $p = .000$), and create ($F(2, 99) = 11.09$, $p = .000$). In other words, the knowledge type associated with the task's learning objective influenced participants' perceptions of the cognitive processes involved in achieving that objective. These results suggest three main trends (Figure 1). First, factual knowledge tasks were perceived to require less cognitive activity across *all* cognitive processes. Second, conceptual knowledge tasks were perceived to require more 'understanding' and 'analyzing'. Third, procedural knowledge tasks were perceived to require more 'applying', 'evaluating', and 'creating'. We elaborate on these differences in Section 6.

Interaction Effects: The task's cognitive process and knowledge type had a significant interaction effect on *three* pre-task measures. First, as shown in Figure 2a, cognitive process and knowledge type had a significant interaction effect on participants' expectations of difficulty in finding information ($F(4, 99) = 3.63$, $p = .008$). For the most complex cognitive process (create), conceptual knowledge tasks were expected to be more difficult than procedural knowledge tasks. Conversely, for the less complex cognitive processes (apply and evaluate), the differences were not significant.

Secondly, as shown in Figure 2b, cognitive process and knowledge type had a significant interaction effect on participants' expectations about the task requiring them to 'evaluate' ($F(4, 99) = 4.51$, $p = .002$). For evaluate tasks, all three knowledge types had similar levels (i.e., not sig.). Conversely, during apply tasks, participants expected to do more 'evaluating' for procedural versus factual or conceptual knowledge tasks. Similarly, during create tasks, participants expected to do more 'evaluating' for procedural versus factual knowledge tasks.

Finally, as shown in Figure 2c, cognitive process and knowledge type had a significant interaction effect on participants' expectations of the task requiring them to 'create' ($F(4, 99) = 4.81$, $p = .001$). For evaluate tasks, all three knowledge types had similar levels (not sig.). Conversely, during apply tasks, participants expected to do more 'creating' for procedural versus conceptual knowledge tasks. Similarly, during create tasks, participants expected to do more 'creating' for procedural versus factual knowledge tasks.

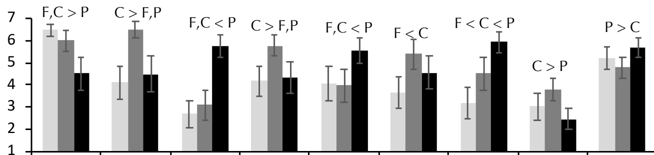
5.2 Effects on Post-task Perceptions (RQ2)

In RQ2, we investigate the effects of the task's cognitive process and knowledge type on participants' post-task perceptions of (1) knowledge increase, (2) interest increase, (3) difficulty in searching for information, (4) difficulty in completing the video assessment, (5) satisfaction with the search experience, and (6) satisfaction with the video assessment. Additionally, we considered participants' perceptions about the task requiring (7) facts, (8) concepts, (9) procedures, as well as involving the cognitive processes of (10) remember, (11) understand, (12) apply, (13) analyze, (14) evaluate, and (15) create.

Main Effects: The task's cognitive process did not have a significant main effect for any post-task measure. Conversely, the task's knowledge type had a significant main effect on *nine* post-task measures. Figure 3 shows these measures and indicates all significant pairwise comparisons. Consistent with our RQ1 results, participants reported engaging with facts for factual knowledge tasks ($F(2, 99) = 13.92$, $p = .000$), concepts for conceptual knowledge tasks ($F(2, 99) = 15.70$, $p = .000$), and procedures for procedural knowledge tasks ($F(2, 99) = 31.14$, $p = .000$).

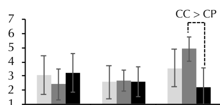
The task's knowledge type also had a significant effect on participants' perceptions about the task involving the cognitive processes of understand ($F(2, 99) = 7.34$, $p = .001$), apply ($F(2, 99) = 7.01$, $p = .001$), analyze ($F(2, 99) = 6.17$, $p = .003$), and evaluate ($F(2, 99) = 19.29$, $p = .000$). The observed trends are also consistent with our RQ1 results. First, factual knowledge tasks required less cognitive activity across the board. Secondly, conceptual knowledge tasks required more 'understanding' and 'analyzing'. Thirdly, procedural knowledge tasks required more 'applying' and 'evaluating'.

Finally, the task's knowledge type had a significant main effect on participants' perceptions of difficulty in searching for information ($F(2, 99) = 6.15$, $p = .003$) and satisfaction with their search experience ($F(2, 99) = 3.87$, $p = 0.024$). Specifically, participants



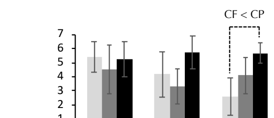
	facts	concepts	proc.	under.	apply	analyze	evaluate	diff. search	sat. search
factual	6.47	4.11	2.69	4.17	4.06	3.64	3.19	3.02	5.19
conceptual	6.00	6.50	3.08	5.78	3.97	5.39	4.53	3.79	4.78
procedural	4.53	4.50	5.78	4.33	5.56	4.56	5.94	2.46	5.70

Figure 3: Sig. main effects of knowledge type on post-task perceptions of knowledge types (leftmost columns), cognitive processes (middle columns), and diff. & satisfaction (rightmost columns).



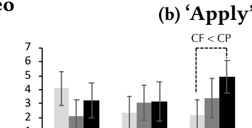
	apply	evaluate	create
factual	3.08	2.58	3.58
conceptual	2.42	2.67	4.92
procedural	3.25	2.58	2.25

(a) Diff. Video



	apply	evaluate	create
factual	5.42	4.17	2.58
conceptual	4.50	3.33	4.08
procedural	5.25	5.75	5.67

(b) 'Apply' Perceptions



	apply	evaluate	create
factual	4.08	2.33	2.17
conceptual	2.08	3.08	3.42
procedural	3.25	3.17	4.92

(c) 'Create' Perceptions

Figure 4: Sig. interaction effects on post-task measures.

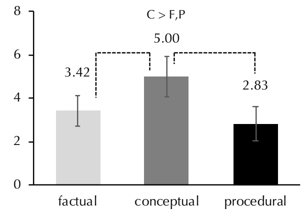
reported greater levels of difficulty and lower levels of satisfaction for conceptual knowledge tasks than procedural knowledge tasks.

Interaction Effects: The task's cognitive process and knowledge type had a significant interaction effect on *three* post-task measures. First, as shown in Figure 4a, cognitive process and knowledge type had a significant interaction effect on participants' perceptions of difficulty completing the video assessment ($F(4, 99) = 2.95$, $p = .024$). For the most complex cognitive process (create), conceptual knowledge tasks were perceived to be more difficult than procedural knowledge tasks. Conversely, for the less complex cognitive processes (apply and evaluate), the differences were not significant.

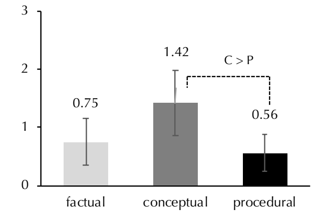
Additionally, as shown in Figure 4b and 4c, cognitive process and knowledge type had a significant interaction effect on participants' perceptions about the task requiring them to 'apply' ($F(4, 99) = 2.56$, $p = .043$) and 'create' ($F(4, 99) = 3.59$, $p = .009$). For the most complex cognitive process (create), procedural knowledge tasks were perceived to require more 'applying' (Figure 4b) and 'creating' (Figure 4c) than factual knowledge tasks. Conversely, for the less complex cognitive processes (apply and evaluate), the differences were not significant.

5.3 Effects on Search Behaviors (RQ3)

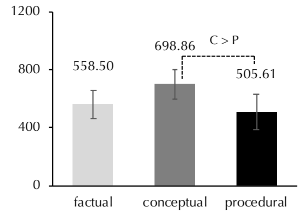
In RQ3, we investigate the effects of the task's cognitive process and knowledge type on participants' search behaviors. The task's cognitive process did not have a significant main effect on any behavioral measure. Conversely, the task's knowledge type had a significant main effect on *four* behavioral measures. As shown in



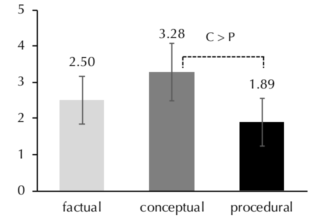
(a) Queries



(b) Abandoned Queries



(c) Duration (secs.)



(d) Unique Queries

Figure 5: Main effects of knowledge type on search behaviors.

Figures 5a-5d, knowledge type had a significant effect on the number of queries ($F(2, 99) = 7.66$, $p = .001$), number abandoned queries ($F(2, 99) = 4.20$, $p = .020$), the task completion time ($F(2, 99) = 3.74$, $p = .030$) and the number of queries not issued by another participant. Figures 5a-5d show a consistent trend—conceptual knowledge tasks required more search activity than procedural knowledge tasks and (to a lesser extent) than factual knowledge tasks.

6 DISCUSSION

Next, we summarize the main trends observed in our results, compare them to results from prior work, and discuss their implications.

Effects of Cognitive Process: Participants in our study completed tasks with learning objectives that varied along three cognitive processes (apply, evaluate, create). We found *no significant effects* from our manipulation of the cognitive process dimension. One possible explanation stems from our choice to focus on the cognitive processes of apply, evaluate, and create, which are associated with mid-to-high complexity levels. A&K's taxonomy considers *six* cognitive processes (from simplest to most complex): remember, understand, apply, analyze, evaluate, and create. Prior studies have indeed found that tasks involving more complex cognitive processes are perceived to be more difficult and require more search activity [5, 6, 13, 15, 20, 21]. However, most of the significant differences have been observed between tasks at the *extreme ends* of A&K's cognitive process dimension (e.g., between remember/understand and create tasks). Thus, we might have observed greater differences had we considered a wider range of cognitive processes.

Effects of Knowledge Type on Required Information Types: As shown in Figures 1 and 3, participants perceived the need for different types of information depending on the learning objective's knowledge type. In general, participants perceived a greater need for facts during factual knowledge tasks, concepts during conceptual knowledge tasks, and procedures during procedural knowledge tasks. This result is somewhat expected and can serve as a manipulation check. However, it is noteworthy that participants anticipated needing different information types *before* working on the task (i.e., pre-task perceptions). This suggests that search systems could help users by distinguishing between sources that focus on factual, conceptual, and procedural knowledge.

Effects of Knowledge Type on Perceptions of Cognitive Activities: The task's *knowledge type* had significant effects on participants' pre-task (RQ1) and post-task (RQ2) perceptions about the types of *cognitive activities* required by the task. At first, these results may seem paradoxical, considering that both dimensions of A&K's taxonomy were designed to be *orthogonal*.

While both dimensions are orthogonal, achieving a specific *type* of learning objective may involve *sub-goals* that fall under some A&K cells more often than other cells. In other words, some A&K cells may be more commonly traversed along the *pathways* (i.e., sub-goal sequences) learners tend to follow towards a type of objective. Our results suggest three main trends that were mostly consistent between pre- and post-task perceptions (Figures 1 & 3).

First, compared to conceptual and procedural knowledge tasks, factual knowledge tasks were perceived to involve lower levels of cognitive activity across all cognitive process categories. As argued in Section 3, one possible explanation is that factual knowledge tasks tend to involve bits of information that are more isolated (vs. interconnected), objective (vs. subjective), and concrete (vs. abstract). Additionally, factual knowledge tasks may involve success criteria that are more well-defined and measurable (vs. amorphous).

Secondly, conceptual knowledge tasks were perceived to involve more 'understanding' and 'analyzing'. Again, as argued in Section 3, this may be due to conceptual knowledge being highly interconnected. In other words, dealing with conceptual knowledge (at the level of apply, evaluate, and create) may require 'understanding' definitions (i.e., beyond rote memorization) and 'analyzing' how concepts relate to other concepts (i.e., analyzing similarities/differences and relations). A&K argue that understanding and analyzing are natural stepping stones in the learning process, with analysis serving as "an extension of understanding" [2, p. 79]. That is, *understanding* a concept leads to *analyzing* how it relates to other concepts.

Thirdly, procedural knowledge tasks were perceived to involve more 'applying', 'evaluating' and 'creating'. The connection between procedural knowledge tasks and 'applying' and 'creating' is quite natural—procedural knowledge tasks involve "how to" knowledge that can be *applied* in a given scenario to *create* something. The connection between procedural knowledge tasks and 'evaluating' deserves more consideration. One possible explanation is that procedural knowledge tasks tend to involve evaluating the importance of specific sub-steps (e.g., considering shortcuts) in a given scenario. A second explanation is that procedural knowledge tasks tend to involve evaluating the trade-offs between alternative procedures (or variants) towards similar goals. Indeed, our procedural knowledge tasks focused on "families" of procedures (e.g., methods for finding the mathematical center of a circle) but did not specify the exact variant to use. The choice of variant was left open for the participant, which may have resulted in more cognitive activities related to evaluation (e.g., judging, critiquing, prioritizing).

Effects on Perceptions of Difficulty and Satisfaction: The task's knowledge type influenced participants' perceptions of difficulty and satisfaction. In general, participants reported greater difficulty and lower satisfaction during conceptual versus procedural knowledge tasks (Figure 3). Interestingly, in some cases, this trend was *conditioned* on the learning objective's cognitive process (i.e., an *interaction* effect). In these cases, the effect was only present during tasks at the level of 'create' (most complex) and not during tasks at the level of 'apply' and 'evaluate' (less complex). Specifically, before the task, participants expected greater difficulty searching during conceptual versus procedural knowledge tasks, but only at the level of 'create' (Figure 2a). The same trend was observed for participants' post-task perceptions of difficulty completing the video assessment (Figure 4a). Below, we discuss explanations for why conceptual knowledge tasks may have been more difficult than procedural knowledge tasks.

Effects on Search Behaviors: The task's knowledge type had a significant main effect on four behavioral measures (Figure 5). Conceptual knowledge tasks had more evidence of query abandonment, longer completion times, and more *divergent* search strategies between participants (e.g., more queries not issued by another participant). These results resonate with our RQ1-RQ2 results—conceptual knowledge tasks were perceived as more difficult, had lower satisfaction levels, and required more search activity.

Conceptual vs. Procedural Knowledge Tasks: Our RQ1-RQ3 results suggest that conceptual knowledge tasks were more difficult than procedural knowledge tasks. A natural question is: Why? We see four possible explanations. We believe that the first *two* explanations are likely to generalize beyond our tasks. Conversely, the last *two* explanations may be due to characteristics of our tasks that we noticed in hindsight.

First, in general, concepts may be more interconnected than procedures. Procedures can be viewed as alternative methods (i.e., parallel paths) for performing a task. As such, it may be easier to consider a procedure in isolation. Conversely, concepts are inherently defined by their relations to other concepts [2]. For example, it is difficult to understand "automatism" without understanding how it relates to other artistic styles. Thus, working with conceptual knowledge requires learning about the interrelations between basic elements within a larger structure.

Secondly, achieving a learning objective requires an individual to decide when the objective has been met. In this respect, objectives involving procedural knowledge (regardless of cognitive process) may have more measurable (i.e., less amorphous) criteria for success: Can I envision myself successfully applying the procedure(s)? Conversely, conceptual knowledge may be associated with *broader* levels of understanding, making learning objectives involving conceptual knowledge more amorphous. Prior IIR research has found that search tasks with more amorphous goals (e.g., intellectual vs. factual goals) are more complex [18].

Third, our conceptual knowledge tasks focused on specific concepts (e.g., Bernoulli's principle, Newton's laws of motion). Conversely, our procedural knowledge tasks focused on "families" of procedures (e.g., methods for making a paper airplane or finding the center of a circle). In other words, our procedural knowledge tasks asked participants to consider procedures with the same purpose, rather than a precise procedure. Thus, it is possible that this *flexibility* in our procedural knowledge tasks allowed participants to satisfice (e.g., focus on the first procedure encountered).

Finally, our conceptual knowledge tasks focused on abstract concepts (e.g., laws of physics). Conversely, our procedural knowledge tasks focused on concrete procedures (e.g., finding the center of a circle). This was done for practical reasons. We designed procedural knowledge tasks that would allow participants to demonstrate their solution during the *two-minute* video assessment.

Implications: Our results have three important implications. First, to our knowledge, we are the first to systematically manipulate learning-oriented search tasks across *both* dimensions of A&K's taxonomy. The task's knowledge type significantly influenced measures related to participants' pre-/post-task perceptions and behaviors. Prior work has studied search task complexity through the lens of *cognitive* complexity (leveraging A&K's cognitive process dimension) [5, 6, 13, 15, 20, 21]. Our results suggest that future studies should *also* consider either systematically manipulating or controlling for the task's main knowledge type.

Second, our results contribute insights about factors that influence the complexity of learning-oriented search tasks. Conceptual knowledge tasks had higher perceptions of difficulty, lower satisfaction, and required more search activity.

We believe that our conceptual knowledge tasks were more complex because conceptual knowledge is highly interconnected, abstract (e.g., physical laws), and subjective (e.g., artistic styles). Additionally, learning objectives involving conceptual knowledge tasks have success criteria that are more amorphous (i.e., less measurable). Prior research has aimed at automatically predicting search task difficulty using behavioral measures [3, 17]. Our results suggest that future approaches may benefit from features that capture whether the searcher is engaging with conceptual knowledge.

Finally, our results have implications for designing systems to support searchers based on their learning objectives. Based on the task's knowledge type, participants were able to anticipate the need for factual, conceptual, and procedural information. Thus, these may be important categories along which to organize search results or sources. Additionally, depending on the objective's knowledge type, searchers may benefit from different types of support. For example, for conceptual knowledge tasks, searchers may need support with 'understanding' (e.g., seeing definitions, summaries, and examples) and 'analyzing' (e.g., seeing comparisons with related concepts). For procedural knowledge tasks, searchers may need support with 'applying/creating' (e.g., seeing procedures being implemented) and 'evaluating' (e.g., seeing critiques of specific sub-steps or comparisons between procedures).

7 CONCLUSION

In this study, we investigated how a searcher's type of *learning objective* may influence perceptions and behaviors. To manipulate learning objectives, we leveraged A&K's taxonomy of learning [2], which defines learning objectives as a combination of a main *cognitive process* and *knowledge type*. While prior IIR studies have varied tasks along A&K's cognitive process dimension, we systematically manipulated learning objectives along *both* dimensions.

Our results found several important trends. First, we found no significant effects from the cognitive process dimension, possibly because we limited our study to cognitive processes with mid-to-high levels of complexity. Second, the knowledge type dimension had many significant effects on participants' pre-/post-task perceptions (e.g., difficulty, satisfaction) and search behaviors. We have discussed possible explanations for these trends and implications.

Additionally, the type of learning objective influenced participants' perceptions about the task involving specific types of information and cognitive activities. For example, conceptual knowledge tasks were perceived to involve more 'understanding' and 'analyzing', while procedural knowledge tasks involve more 'applying', 'evaluating' and 'creating'. This suggests that searchers traverse common *pathways* (i.e., sequences of cells in A&K's taxonomy) towards a specific *type* of objective. As previously noted, for this paper, we did not analyze participants' think-aloud comments gathered as they searched. In future work, we plan to perform a qualitative analysis of these think-aloud comments to gain insights into the *pathways* people tend to follow toward a particular learning objective.

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