Adaptation in Information Search and Decision-Making under Time Constraints

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ABSTRACT

Prior work in IR has found that searchers under time constraints may adapt their search processes and perceive their task or their performance differently. In many of these prior studies, the task descriptions implicitly or explicitly conveyed an expectation of the amount of information needed to satisfy the task requirements in terms of number of pages (e.g., find N webpages on topic X) or the time to spend on the task (e.g., search until time is up) rather than allowing the participant to determine how much information was needed. In this lab-based study, we investigated the effects of time constraints on information search and decision-making. Participants completed a series of decision-making tasks with half of the participants receiving a 5-minute time constraint and half given no time guidance. They were asked to make good, specific recommendations for a friend, and they had considerable latitude in deciding how much information they needed. Results showed that participants in the time constraint condition made their decisions faster but there were few significant differences in measures of search behaviors between the time constraint conditions (RQ1). Qualitative analysis indicated that participants adapted their decision task by varying their recommendations in their specificity, justification strength, and contents *in both time conditions* (RQ2). Finally, we found evidence that the impact of the time constraint on time- and task-related perceptions was moderated by the extent to which participants adapted their decision task (RQ3).

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1 INTRODUCTION

A recognized challenge in information retrieval (IR) is that search systems need to better support users with open-ended, exploratory, and complex tasks [14]. These types of tasks are often not well-defined, require high levels of cognitive processing, and may trigger people to engage in *adaptation* to deal with the complexity of the task or the task process. For example, people can adjust their rate of information processing (i.e. acceleration), may choose to filter incoming information (filtration), or may queue information for later processing [40]. In addition, in some situations, a person may choose to adapt a task to meet their information processing capabilities. Adaptation has been studied in the field of decision-making [43], but has received relatively less attention in IR. In order to develop better IR systems, it is important to understand the types of adaptation that people make when searching.

Time constraints and perceived time pressure are situational factors that can trigger adaptation in search behavior. For example, Crescenzi et al. [12] found that searchers may adapt to time constraints by accelerating the pace of their search interactions and may explore search results options more shallowly under time constraints. Previous studies to investigate the effects of time pressure on search behaviors have typically done so in conjunction with setting an *effort expectation* – indicating explicitly or implicitly the amount of work the participant must do to complete a task (e.g., find 8-12 articles [12], assess the relevance of each document [35]).

However, in many real-world tasks, the amount of effort (or amount of output) is not specified *a priori*. In this way, prior research has only examined a subset of the scenarios in which search adaptation may occur under time pressure. The current study addresses this deficiency and builds on previous results by examining a different type of underlying task: decision tasks in which a participant is asked to make a recommendation (e.g., recommend a mesh wifi router) for someone else. These tasks do not contain an *a priori* effort expectation; the participant has flexibility in how much information they gather prior to making the recommendation. Investigating the effects of time pressure on recommendation decision tasks allows us to explore a broader set of possible adaptive behaviors, including adaptations to the search process, the decision-making process, and the content of the recommendation.

We conducted a laboratory study with 48 participants to investigate the effects of time constraints on search behaviors, outcomes, and users' perceptions about recommendation decision tasks. Participants completed up to six tasks in which they made a recommendation decision for a friend. They were not required to search for information, but a search system was provided if they wished to search as part of their decision-making. Half of the participants were given a 5-minute time limit for each task and half were given no time limit. Participants clicked a 'Make Recommendation' button when they were ready to make their recommendation. Participants were then asked to recommend an option and to identify other options considered, information important to their decision-making, and other information considered. Additional questions were asked about their time-, search-, and decision-related perceptions.

The current study extends prior work on adaptation in information search in several important ways. First, it addresses *decision*

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recommendation tasks – an important category of tasks for which the field of IR has not extensively examined adaptation. Second, the study uses a protocol that allowed participants to decide how much (if any) searching they needed to do to satisfy the task. This design allowed us to study not just how participants may adapt search processes, but also how they may adapt outcomes and the task itself. Finally, the study employed a novel method for reducing the "session level" implied time constraint that is common in laboratory studies that are scheduled for a fixed amount of time (e.g., a 1.5 hour study session).

Specifically, we address the following research questions:

RQ1: Are there effects of time limits on decision time and search behaviors? We examined logged interaction measures including decision time, number of queries, number of pages viewed from the search results page (SERP), and maximum click depth.

RQ2: Do searchers adapt the scope of their recommendations under time limits? We examined the specificity, accuracy, quality, justification strength, and clarity of their written recommendations.

RQ3: Are there combined effects of time limits and recommendation adaptation on post-task perceptions? We looked at the effects of time limits and recommendation adaptation on participants' time-, search-, and decision-related perceptions.

2 RELATED WORK

2.1 Time and Time Pressure

Time is an important factor of information behavior, information-seeking and interactive search [46]. For example, time is included as a factor in models of information behavior and information-seeking [e.g., 5, 50] and is often considered as a measure in user studies. Prior research provides evidence that time pressure can lead to differences in a searchers' information-seeking process [e.g., 1, 6, 24]. However, until recently, few experimental IIR studies have examined the impact of time constraints, and even fewer have included time constraints as an experimentally manipulated variable [e.g., 12, 13, 30, 33, 49, 51].

There is an important conceptual difference between time pressure and a time constraint or limit. A time limit is an objective time constraint whereas time pressure is a subjective experience of limited time [41]. The time pressure felt by an individual in a given situation is a function of their assessment of amount of time and the volume of work required to complete the given task. Time pressure can be caused by time constraints but also by other situational factors (e.g., task, urgency, interruptions, task complexity, prior knowledge). Time has been conceptualized similarly in research on information behavior and decision-making [2, 46].

Time pressure, information overload, and choice overload are related concepts. They are subjective perceptions (with affective components) that result from too little time, too much information, or too many choices. Information overload can result when an individual perceives that the flow of information is more and/or faster than can be processed effectively [21], and choice overload can result when the number of choice options is perceived as greater than can be processed effectively [7].

2.2 Adaptation

2.2.1 Adaptation in Decision-Making.

2.2.1 Adaptation in Decision-Making. In time-pressured decision-making, researchers have found several types of adaptation, including: acceleration, selective filtration, and the use of less information [15]. *Acceleration* can take the form of a participant working faster to complete the task [3, 25, 39], spending less time on each stage of the decision-making process [25], processing more information at the same time [16], or reducing the amount of time spent on each piece of information [19, 39]. *Selectivity* or *filtration* can take the form of participants making a decision based on what they already know [29, 47], seeking more general information [39], or focusing on the most reliable information [20], or the most salient attributes [42, 45]. Time-pressured decision-makers are also found to be more likely to *use less information* (e.g. a non-compensatory strategy, or simplifying heuristics) rather than to consider all of the information available to them [15, 42, 48]. Satisficing is an example of a non-compensatory strategy observed in studies of both decision-making and information-seeking [1, 36, 44, 52].

2.2.2 Adaptation in Search. Similar adaptations have been found in studies of time pressure in information search. Time-pressured searchers have been found to *accelerate* the pace of their work by working more quickly or spending less time on each piece of information [e.g., 12, 17, 31–33, 49]. Information-seekers have also been found to be *more selective* in the information they use to make a decision by filtering information to focus on a subset of the information [7, 12, 17], or by selecting different information sources [11, 49, 55, 56]. They also may shift their *search strategy* by more shallowly inspecting search results [7, 12, 31], more superficially processing found information [11], or by satisficing [1, 44, 52].

Time constraints or time pressure can have negative effects on actual and perceived performance leaving searchers feeling less confident and less satisfied with their outcome [10, 12, 13, 32, 49, 51], or feeling that a task was more difficult [10, 13, 49, 51]. Time pressure is also associated with greater time overestimates [34] and greater negative affect [17, 28, 32, 49].

2.3 Search in Support of Decision-Making

This study examines information search conducted as part of a decision-making process for a preferential choice decision. As a result, how people search for information and how they use the information to make a decision are equally important. Findings from decision-making studies can offer insights into the potential impact of time limits and time pressure on the series of decisions which take place during information search and information seeking (e.g., Where do I start? Which source? Which queries? Am I done?).

Freund [18] identified decision-making as one type of information task that may trigger information search and may be triggered by a broader work task. Jameson et al. [22] describe four elements of a good decision from the perspective of the decision-maker: (1) a good outcome with (2) time and effort expenditure in proportion to the benefits and (3) no or minimal distressing thoughts required, and (4) one that can be justified to oneself or others. In a preferential choice decision, there is no correct answer and a good choice is one in which the decision is in line with the decision-maker's preferences. In some cases, however, the quality of recommendations or answers to an information can be evaluated. For instance, Jeon et al. [23] used answer length and Kim and Oh [27] used qualitative criteria related to the contents (e.g., understandability) to assess the quality of written answers to online questions.

Task characteristics are known to have an important role in search behaviors, perceptions, and outcomes in interactive information retrieval. Marchionini [37] describes task goals on three dimensions. The first dimension, *goal specificity*, indicates that an information-seeker might require specific information (e.g., a fact) or more general information (such as in an exploratory task in which the searcher must learn and investigate ideas [38]) to meet task requirements. The *volume of information needed* to complete the task in units of information or time needed to process the information, and an individual's *expected task completion time* are also important dimensions of task goals. [37, p. 37].

3 METHOD

To investigate RQ1-RQ3, we conducted a laboratory study with 48 participants. Participants were recruited from a University staff, faculty, and student population using a campus-wide opt-in mailing list. Their ages ranged from 19 to 71 (M=32.8, SD=14.0). Screening criteria included age (18+), English language fluency, and enrollment or employment at the University. Participants were scheduled for 1.5 hour "decision study" sessions and were not informed of the focus on time constraints until the study debriefing. The study protocol, including deception by omission, was approved by the UNC non-biomedical institutional review board.[1]

Study protocol. During the study, participants completed up to six recommendation tasks to help a friend make a decision. The tasks were embedded in a simulated everyday life scenario. Participants were asked to make a recommendation for a friend on six different topics (e.g., recommend a mesh wifi system). Participants were not required to search for information to support their recommendation, but a search system was provided if they wished to search. Half of the participants were given a 5-minute time limit for the task, and half were given no time limit.

The study session proceeded as follows. First, participants were seated at a desktop computer and provided informed consent. Next, participants completed up to six decision recommendation tasks using an experimental system that guided them through the study. Each task followed the same sequence of steps. After reading the task description, participants completed a pre-task questionnaire. Then participants were shown a screen that displayed the task description, a button that allowed them to display the Web search system, and a button to press when they were ready to make their recommendation. Participants were free to work at their own pace and could choose to make a recommendation without searching. After clicking the 'Make a recommendation' button, participants were asked to complete a post-task questionnaire which started with open-ended questions about their recommendation.

Participants were only presented with the next task (of their six) if they had spent less than 55 minutes on the study. Participants were not informed in advance about how many tasks they would be asked to complete. This experimental method was used to minimize time pressure induced by the 1.5 hours scheduled for each study session and to prevent participants from allocating time across multiple tasks (e.g., if a participant knew there were six tasks to complete in 1.5 hours, they might allocate 15 minutes per task). As a result of this approach, participants completed between one and 6 tasks during the 1.5 hour sessions (M=5.15, SD=1.37; no time limit: M=4.58, SD=1.71; time limit: 5.71, SD=.46). After the last task, participants completed a post-experiment questionnaire and a post-experiment interview. At the end of the study, a debriefing was held: participants were informed of the true purpose of the study (i.e., study adaptation under time pressure). Participants were also offered an incentive of $30 USD for their participation.

Tasks. In each task, participants were asked to recommend (i.e., decide) the best option among the options they knew about or identified through searching. The instructions for each task included three elements: 1) an overarching scenario for the study, 2) a topic description which provided (a) background information about the situation and (b) the topic of recommendation, and 3) a decision description which described what they should produce (i.e., what their recommendation should address). The scenario and recommendation type were the same for all tasks but the topic changed.

The four topics of primary interest about which participants were asked to make recommendations were: 1) what to buy to set up a mesh wifi network (*mesh*), 2) where to board dogs when their friend travels for work (*board*), 3) how to move dogs when their friend has to fly to Austin (*move*), and 4) finding a short-term apartment for 3 months (*housing*). Participants were also asked to recommend 5) a local organization to consider if donating car (*donate*), and 6) how to transport car since their friend will fly to Austin (*transport*). The topic for the practice task was to recommend how to move plants. The task description for the mesh wifi topic is included as an example.

> Your friend has just accepted a new job in Austin, Texas. Because they will be moving from Austin as soon as possible, they have asked you for your help with some of the big decisions they will need to make. Your friend's new place will have a high-speed internet connection. They have asked you to recommend what they should buy to set up a mesh wifi network. They would like for you to identify their options, recommend the best option, and briefly describe why you recommended this option.

The researcher emphasized verbally that the friend wanted a recommendation of a specific option on which they could take action given their imminent move. Participants were instructed that they could search if they need additional information to make a recommendation, but they were not explicitly instructed to search.[2]

Time constraint. Participants were randomly assigned to complete tasks in one of two time constraint conditions: a 5-minute task time limit or no task time limit. Time constraint was a between-subjects factor as prior work [41] found carry-over effects of task time constraints. In addition, the experimental system used in this study was customized to remove all cues about the number of tasks to complete. These cues were removed to prevent participants from

[1]The full study protocol including the full text of the tasks and questionnaire items is available at https://bit.ly/crescenzi-chiir2021.

[2]Whether participants thought they expended adequate effort and made a good recommendation was explored in the interview.

feeling time pressure as a result of an experimental session time limits and a known number of tasks to complete as in [8].

In the task time constraint condition, participants were given a 5-minute time limit to complete each task. The time limit instructions appeared beneath the scenario and topic description on the first non-practice task: "You have **up to 5 minutes** to complete this task." After five minutes, the system displayed a time-out message ("Your time for this task is up. Please make your recommendation now.") and disabled interactions with the search results. The 5-minute time limit was selected based on the mean task completion time for the four primary topics in a preliminary study (M=4.79 min., SD=3.32, n=58) rounded to the nearest whole number (see [9]). Similar methods have been used to induce time pressure in studies of information search [12, 31] and decision-making [19, 51, 53].

For tasks in the no time limit condition, participants were given no time limit and no time-related guidance were given for the tasks. In both conditions, the only indication of time was the current time (HH:MM:SS) shown in the Windows 10 taskbar.

Task assignments. A 4x4 counterbalanced Latin Square was used to determine the order of the first four topics (mesh wifi, board dogs, move dogs, short-term housing), and a 2x2 Latin Square was used for the last two tasks (donate car, transport car). This 4x4 + 2x2 design was used to minimize the unbalancedness of the data for topics assigned for the first four tasks since previous studies have found that participants without a time constraint complete fewer tasks [13]. Half of the topic + time replications were paired with the task time limit condition, and half were paired with the no task time limit condition. Participants were randomly assigned to topic-order-time combinations.

Search system. A custom search system was available to participants during the tasks. The system used the Bing Web Search API and the interface was designed to look like a standard search engine (e.g., 10 results per page; title, url, snippet). The search system logged participants' interactions with the system.

3.1 Data collection.

Quantitative data were collected from pre-task, post-task, and exit questionnaires, and from logged interaction data. Qualitative data were collected from open-ended questions on the post-task and exit questionnaires, and an interview about decision criteria and perceived recommendation quality. Questionnaires contained agreement statements to which participants responded using a seven-point scale from strongly disagree (1) to strongly agree (7) and open-ended questions to which participants typed free responses.[3]

3.1.1 Questionnaires. The pre-task questionnaire included agreement statements about participants' interest, prior knowledge, perceived ability to make a recommendation without searching, expected task difficulty, expected difficulty deciding when to stop, confidence in finding information, confidence in finding options, and confidence in finding information about different options.

The post-task questionnaire contained open-ended questions that asked participants about their recommendation: 1) "Which option did you recommend and why?" 2) "Did you consider any other options? Which ones?" 3) "What information was most important to you to decide which option to recommend?" 4) "Did any other information help you decide which option to recommend? What information?" Additional items asked participants to indicate their agreement with a series of statements about time perceptions (time pressure and affect, time inadequacy, task pace), their recommendation decision (confidence, difficulty), the information they found (adequacy), and their search (difficulty). Each construct was measured using 3-5 questions and combined into a composite variable if indicated by factor analysis. The search difficulty questions only appeared for participants if they searched for information.

Demographic questions including age, role (e.g., student, staff), and search self-efficacy [4, 26] were asked in an exit questionnaire.

3.1.2 Logged interaction data. The experimental system logged start and end times for each task, when participants clicked the 'Make recommendation' button, and all interactions with the search system (e.g., queries, clicks, scrolls, hovers). We used this data to calculate a set of *search and decision behavior* measures.

Specifically, we analyzed: 1) *decision time* – the amount of time from the start of the task to the point at which the participant clicked the 'Make recommendation' button, 2) *# queries* – the number of queries the participant issued to the search system, 3) *query rate* – the number of queries issued per minute of decision time, 4) *# result hovers* – total number of hover events over SERP results, 5) *hover max rank* – rank of the deepest SERP result hovered over, 6) *click max rank* – rank of the deepest SERP result clicked, 7) *time spent per SERP*. We also analyzed 8) *# nonSERP pages viewed from SERP* – number of web pages viewed directly from the SERP, and 9) *rate of nonSERP pages viewed from SERP* – number of pages viewed directly from the SERP per minute of decision time; the nonSERP from SERP measures exclude web pages viewed from other web pages (e.g., if the user followed links from within a web page).

The median task time in both time conditions and the mean task time in the time limit condition was 2.93 minutes. This was used to construct a *decision speed* variable based on a median-split: participants who made decisions in less than 2.93 minutes were considered to make "fast" decisions versus "slow" decisions which made in more than 2.93 minutes.

3.2 Data analysis

3.2.1 Qualitative Analysis. Qualitative content analysis was used to analyze participant's responses to the open-ended post-task questionnaire items about their recommendations, the items they considered, and the attributes on which they considered items. We used an inductive, iterative coding approach to identify important themes and develop a coding guide, and we used closed coding using the developed coding guide. To identify the option(s) recommended and considered, the sampling unit of analysis was at the conceptual/option level. For coding the recommendation quality and clarity, the sampling unit was the participants' responses to the first question for the topic. For the remaining codes, the sampling unit was the participants' responses to all four questions for a given topic. For each topic and set of codes, two researchers independently coded all of the data, agreement was calculated using Krippendorf's alpha (reported below), and the two researchers discussed all disagreements and resolved by consensus. The final analysis presented had full agreement by two researchers.

[3]Full text of questionnaire items available at https://bit.ly/crescenzi-chiir2021.

We assigned codes for four recommendation characteristics: 1) *specificity* of the recommended option or approach (α=.90), 2) the *accuracy* of the recommended option or approach (α=.69), 3) the *justification strength* (α=.83), and 4) the *clarity* (α=.49). We also report the number of mentions of 5) recommended options or approaches (α=.74), 6) options or approaches considered but not recommended (α=.87), 7) the total number of attributes mentioned (α=.83), and 8) the number of attributes identified as important (α=.89).

3.2.2 Quantitative Analysis. A sample size of 48 participants with 4 tasks per participant was indicated by power analysis. Assumptions regarding effect size were based on the results from a previous studies which used a similar method to induce time pressure [12].

To test for differences in dependent variables by time limit and decision time, marginal effects after multilevel mixed-effects models with a random intercept were estimated in Stata 15.1. Multilevel mixed-effects linear, negative binomial (count), ordered probit (ordinal), or logistic regression (nominal) models were estimated depending on the type of dependent variable. In the models for search behaviors, independent variables included time limit, topic, order, pre-task perceptions, and demographic characteristics. For models with recommendation characteristic dependent variables, an interaction of time limit and decision speed (slow vs. fast: median-split decision time) was also added. For post-task dependent variables, search behaviors, recommendation characteristics (i.e., specificity and accuracy), and interactions of time limit with search behaviors and recommendation characteristics were also included.

To identify differences in the dependent variables due to time limit condition, the average marginal effect (AME) of time limit condition was estimated, and the marginal effect (MER) of time limit condition at representative values of decision speed was estimated (and specificity and accuracy for post-task dependent variables). Similarly, the AME of decision speed and the marginal effect (MER) of decision speed at representative values for time limit conditions were estimated. Significant results are presented here; all marginal effects are reported in the online appendix.[4]

4 RESULTS

In our results, we present descriptive statistics and test for significant differences in search and decision behavior (RQ1), recommendation decisions (RQ2), and post-task perceptions (RQ3).[5] The effectiveness of the time limit manipulation was checked using the time to decision and felt time pressure. Tasks with a time limit were completed faster than those with no time limit (see 4.1). Greater time pressure was felt for tasks with a time limit than those with no time limit (see 4.3.1).

4.1 RQ1: Search and decision behaviors

RQ1 considers if there were overall effects of the time constraint condition on search and decision behaviors derived from system logs. Table 1 summarizes the means, standard deviations, and the statistical significance of the average marginal effect (AME) of time limit condition estimated after multilevel mixed-effects models (described in 3.2.2).

Table 1: Search and decision behaviors (RQ1): Mean, standard deviation, and *p*-value for AME of time condition.

	Overall	Time constraint		*p*
		None	5 min.	
dec. time (min.)	3.90 (3.98)	5.00 (5.35)	2.93 (1.69)	.02
if searched				
dec. time (min.)	4.10 (3.99)	5.25 (5.37)	3.09 (1.60)	
# queries	1.87 (1.43)	2.14 (1.66)	1.81 (1.11)	.23
query rate	0.83 (2.26)	0.69 (0.63)	1.03 (3.11)	.07
# result hovers	21.53 (23.32)	25.74 (28.49)	19.97 (17.45)	.63
hover max rank	5.26 (4.78)	5.67 (5.53)	5.42 (3.96)	.65
click max rank	4.04 (4.21)	4.42 (5.10)	4.10 (3.28)	.95
time per SERP (s.)	12.61 (19.65)	14.63 (27.03)	10.63 (6.87)	.33
# nonSERPs from SERP	2.97 (2.41)	3.20 (2.64)	2.77 (2.17)	.57
nonSERPs from SERP rate	.98 (1.35)	.84 (1.05)	1.08 (1.56)	.15

‡ p<.001, † p<.01, * p<.05

Decision tasks took about 4 minutes to complete on average (M=3.90, SD=3.98): 5 minutes if participants had no time limit (M=5.00, SD=5.35, Mdn=2.93) and almost 3 minutes if they had a 5-minute time limit (M=2.93, SD=1.69, Mdn=2.93). There was a significant average marginal effect of time limit condition on decision time: the model predicted a task time of 2.70 minutes less for tasks with a time limit than no time limit (AME=-2.70, p<.05).

A visual inspection of the mean search behaviors in Table 1 shows that time-limited tasks had a higher query rate (1.03 queries per minute of decision time vs. .69 with no limit), fewer results hovered (20 vs. 26), and fewer documents viewed from the SERP (# nonSERPS from SERP: 2.77 vs. 3.20). However, there were no significant differences in search behaviors between time limit conditions.

4.2 RQ2: Recommendation decisions

We report results from our qualitative analysis of the recommendations participants made in terms of their 1) specificity, 2) accuracy, 3) the strength of their justification, and 4) clarity and length in number of words. We also report 5) the number of options or approaches recommended, and 6) the number of attributes on which the options and approaches were considered. Our analysis of the four open-ended questions in the post-task questionnaire is described in detail in 3.2. We define and provide examples of each characteristic, and provide descriptive statistics. Unless otherwise noted, significant differences between time limit condition and decision speed were estimated after mixed-effects multilevel models using average marginal effects (AME), and interactions of time limit and decision speed using marginal effects at representative values (MER).

4.2.1 Specificity. Participants' recommendations varied in their specificity overall. 41% (n=74) of recommendations were for a *specific* and unambiguous option (e.g., buy a mesh-capable wifi router

[4] Available at http://anon.url

[5] As described in 3.2.2, average marginal effects (of time limit condition decision speed) and marginal effects at representative values (e.g., the levels of specificity, accuracy) were calculated after multilevel mixed effects models to test for significant differences.

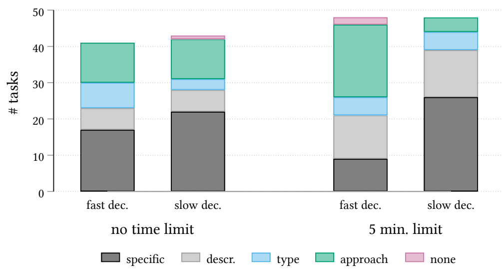

Figure 1: Recommendation specificity frequency by decision speed within each time condition.

specified by brand and product and/or model, board your dog at a specific kennel). In other cases, participants' recommendations *described* options that were ambiguous (21%, e.g., stay in an Extended Stay America but no location provided) or were for a *type of option* (11%, e.g., a brand of mesh wifi but not a product). Participants declined to make a recommendation in only 3 tasks (2%).

In 25% of tasks (*n*=46), participants recommended a *general approach* their friend might use to make their own decision rather than an option; these sometimes included a specific information source for their friend to use to get started. An approach was recommended most frequently for the housing topic (*n*=18).

> Looking on Craigslist for a short term sublet... I found one near the University of [ANON] *(p64, housing)*

In some cases, a participant recommended an approach although they also considered a specific option.

> I'd recommend my friend look at PC magazine's comparison and reviews... Wirecutter named one clear favorite, Netgear Orbi RBK50. If I knew anything at all about this stuff, I might have made this my top recommendation, but since I don't, I wouldn't feel comfortable making such a specific reccomendation [sic]. *(p44, mesh)*

We also explored the relationship between time limit, decision speed, and the interaction between time limit and decision speed on specificity. There was not a significant difference between time limit conditions in the likelihood of any level of recommendation specificity. However, there were differences in the likelihood of recommendation specificity between slow vs. fast decisions: slower recommendations were 22% more likely to be specific than fast recommendations (AME=22%, $p<.01$), 3% less likely to be for a type of option (AME=-3%, $p<.05$), and 17% less likely to be for a general approach (AME=-17%, $p<.01$).

Fig 1 shows the number of tasks at each level of specificity for each decision speed (fast vs. slow) within each time limit condition. With a time limit, recommendations made more slowly more likely to be specific (ME=32%, $p<.001$), less likely to be a type of option (ME=-4%, $p<.05$) or an approach (ME=-25%, $p<.001$). There was no difference of the likelihood of specificity levels between slow and fast tasks for tasks completed without a time limit (i.e., non-significant marginal effects of decision speed).

4.2.2 Accuracy. We also analyzed the accuracy of recommendations made by participants. The majority of the recommendations were *in line* with what was requested in the task description (82%, *n*=148). However, in 13% of tasks (*n*=24), participants made recommendations that were *intentionally different* than what was requested in the task description. Intentionally different recommendations were made for all topics but most frequently for the board dogs (*n*=14) and mesh wifi topics (*n*=5). For example, several participants recommended that their friend consider a pet sitter rather than board their dog. In an example below, the recommendation also mentioned situational factors from the task (i.e., the number and size of dogs) as justification for the intentionally different recommendation.

> Given that my friend has two, medium-large sized dogs, it might be best to consider a pet sitter, especially if two dogs does not change the sitter's rate. *(p50, board)*

Similarly, several participants recommended a regular router rather than a mesh-capable router for their friend, especially if they had previously recommended an apartment for the housing topic.

> I would recommend not wasting the money on mesh wifi for an apartment. Mesh wifi systems are only needed in large homes. A regular router will do just fine in an apartment. *(p51, mesh)*

In 4% of tasks, participants made a recommendation that was *wrong*: they either said their recommendation was wrong or they made a recommendation that did not meet the criteria without stating that it was intentional (e.g., recommended a wifi router that was not mesh-capable).

Given the infrequency of wrong/inaccurate recommendations, Fisher's exact test was used to test for difference in the relative distribution of recommendation accuracy between time limit conditions. There were no significant differences found between time limit conditions ($\chi^2(2)$=.69, p=.74), decision speed ($\chi^2(2)$=2.22, p=.38), or combinations of time limit and decision speed ($\chi^2(6)$=4.82, p=.54).

4.2.3 Justification strength. We analyzed the strength of the justification provided in the response to the open-ended question asking participants what they recommended and why. We assigned each response one of four levels of justification strength based on the extent to which the participant presented a compelling case for their recommendation that would be likely to convince their friend to adopt their recommendation: strong, moderate, low, or none.

In 15% of recommendations (*n*=27), a *strong* justification was provided in which participants provided a compelling case for their recommended option or approach. This included recommendations of a specific information source for their friend to use to find information. *Moderate* justification strength was included in 33% of recommendations (*n*=59); these included recommendations in which the participant recommended that their friend search for their own solution but identified possible options or approaches for them to consider. *Minimal* justification was offered in 35% of recommendation (*n*=63); these include recommendations in which the participant told their friend to search for information without suggesting a possible option or approach. *No justification* was provided in 17% of tasks (n=31), participants just stated the option(s) or approach they recommended or they declined to make a recommendation.

There was not a significant difference in justification strength between time limit conditions; the AME of time limit condition was not significant at any level of justification strength. However, we found an overall difference in justification strength based on decision speed: recommendations made slowly (vs. fast) were more likely to have strong (AME=11%, p<.01) or moderate (AME=8%, p<.05) justifications and less likely to have low quality (AME=-7%, p<.05) or no justification (AME=-12%, p<.01).

Looking closer, we found that the effect of decision speed on justification strength was significant for tasks with a time limit but was not significant for tasks without a time limit. In the time limit condition, recommendations made slower (vs. fast) were more likely to have a strong (ME=14%, p<.05) or moderate (ME=10%, p<.05) justification strength and less likely to have a low justification strength (ME=-8%, p<.05) or no justification (ME=-15.7%, p<.01).

4.2.4 Recommendation clarity and length. We categorized the recommendations by the extent to which we could clearly identify what was being recommended and the clarity of the accompanying justification. The vast majority of recommendations (90%, n=161) were clear and unambiguous, and only 10% of recommendations (n=19) were unclear or ambiguous.

Participants' recommendations contained 39 words (M=39.11, SD=46.67) on average in their written response to the question asking what they recommended and why. Tasks with a time limit had shorter recommendation text than those with no time limit (AME=-17.91 words, p<.05), and the slower recommendations had longer text than fast ones (AME=10.05, p<.05) as shown in Table 2.

4.2.5 Recommended and considered options/approaches. On average, participants recommended 1.12 items (SD=.48, range=0-3) and mentioned considering 1.34 additional items (SD=.96, range=0-5) in the open-ended responses. For 48 recommendations, participants said that they also considered "multiple" or "other" options; we counted this as one additional option or approach in our coding. In some cases, participants clearly stated multiple options or approaches for their friend to choose from:

> I think I've found three strong candidates for your short-term housing needs... *(p24, housing)*

As shown in Table 2, there were no significant differences in the number of items recommended or considered by time limit condition. There was no significant difference between slow and fast recommendations in the number of items recommended, but there was a difference in the number of items mentioned as considered: for slower recommendations, participants mentioned more items than for fast recommendations (AME=.48, p<.05). The marginal effect of decision speed was significant in the time limit condition (ME=.65, p<.05) but not in the no time limit condition.

4.2.6 Attributes mentioned. We also analyzed the number of attributes of options mentioned in the open-ended post-task questions. We identified an attributes as a dimension on which an option might be described (e.g., price, location, number of devices); values

Table 2: Contents of recommendation (RQ2): Marginal effects of time limit condition and decision speed.

marginal effects	# words in rec.	# rec items	# cons items	# total attr	# imp attr
time limit					
AME	**-17.91***	-0.10	-0.08	**-1.76***	**-.46***
MER decision speed					
if slow dec.	-14.57	-0.01	-0.26	-1.27	-0.46
if fast dec.	-21.36 (p=.05)	-0.19	0.11	**-2.30***	-0.48
decision speed (slow vs. fast)					
AME	**10.05***	-0.20	**0.48***	**1.95‡**	**1.12‡**
MER time limit					
in no limit	12.77	0.29	0.28	**2.51†**	**1.13†**
in time limit	6.97	0.12	**0.65***	**1.48***	**1.12‡**

‡ p<.001, † p<.01, * p<.05

of attributes might differ across options. We counted the *total number* of attributes mentioned and the number of attributes identified as most *important* to the participants when making the decision.

On average, participants mentioned 4.64 total attributes (SD=3.69, range: 0-32) and 1.87 attributes (SD=1.42, range: 1-11) were identified by participants as "most important." Recommendations made with a time limit (vs. none) mentioned significantly fewer total attributes (AME=-1.76, p<.05). Compared to fast recommendations, slower recommendations contained more attributes overall (ME=1.95, p<.001) and within each time limit condition. Similarly, fewer important attributes were mentioned for recommendations made with a time limit (vs. none) (AME=-.46, p<.05), and a higher number of important attributes were mentioned for slower recommendations (vs. fast) overall (ME=1.12, p<.001) and within each time limit condition.

4.3 RQ3: Impact of time limit and task adaptation on post-task perceptions

In Table 3 and below, we provide descriptive statistics for the post-task perceptions. To investigate how perceptions are impacted by the combination of time limits and task adaptations to the scope of the work task (i.e., specificity and accuracy), we estimated multi-level mixed-effects models as described in the Methods section and discuss the significant findings in terms of the marginal effects of the time limit condition (AME, ME at specificity, ME at accuracy), and decision speed (AME, ME at time limit) as shown in Table 4.

4.3.1 Time pressure. On average, participants slightly disagreed that they felt time pressure (M=3.22, SD=1.90). The model-predicted time pressure was about 1.5 points higher for tasks completed with a time limit than no limit (AME=1.54, p<.001). Higher time pressure was felt in the time limit condition for recommendations that were specific (ME=1.86, p<.001) or ambiguously described options (ME=1.46, p<.05), but the difference between time conditions was not significant for less specific recommendations (i.e., types of option, approaches, or no recommendation). Time pressure was also significantly higher in the time limit condition for recommendations that were in line with what was requested (ME=1.67, p<.001) or wrong (ME=3.19, p<.05), but the difference was not significant

Table 3: Post-task perceptions (RQ3): Mean, standard deviation.

	All	Time constraint	
		None	5 min.
time pressure	3.22 (1.90)	2.51 (1.28)	3.84 (1.88)
time inadequacy	3.85 (1.84)	3.09 (1.65)	4.52 (1.74)
fast pace	3.46 (1.80)	2.73 (1.56)	4.09 (1.75)
diff. search	2.58 (1.36)	2.78 (1.41)	2.41 (1.30)
dec. conf	5.31 (1.33)	5.43 (1.32)	5.20 (1.33)
n	*180*	*84*	*96*

Table 4: Post-task perceptions (RQ3). Marginal effects of time limit condition and decision speed.

marginal effect	time press.	time inadeq	pace	diff search	dec. conf
time limit					
AME	**1.54**‡	**1.69**‡	**1.36**†	-0.21	**-.42***
MER specificity					
specific	**1.86**‡	**1.94**‡	**1.72**†	-0.19	-0.50
described	**1.46***	**1.28***	**1.24***	0.29	**-1.03**†
type	1.18	**1.96***	**2.06**†	0.85	-0.54
approach	1.18	**1.42***	0.65	**-1.11***	0.27
none	2.55	**3.89***	0.11	-0.44	-0.82
MER accuracy					
in line	**1.67**‡	**1.87***	**1.45**‡	-0.34	-0.26
intent. diff	0.23	0.66	0.62	-0.15	**-1.31***
wrong	**3.19***	1.29	1.89	**3.12***	-1.06
decision speed					
AME	-0.06	0.40	0.23	0.27	-0.17
MER time limit					
in no limit	0.29	0.01	0.19	0.59	-0.03
in time limit	-0.39	0.78	0.27	-0.05	-0.29

‡ p<.001, † p<.01, * p<.05

if the recommendation was intentionally different. There were no differences in time pressure for slow vs. fast decisions overall or within either time limit condition: the average marginal effect of decision speed and the marginal effects of decision speed in each time limit condition were not significant.

4.3.2 Time inadequacy. On average, participants slightly disagreed that they felt time was inadequate (M=3.85, SD=1.84). Perceived time inadequacy was higher in the time limit condition overall (AME=1.69, p<.001), at all levels of recommendation specificity, and for recommendations that were in line with what was requested. There was not a significant difference in time inadequacy between time conditions for recommendations that were intentionally different or wrong. There were no differences in time inadequacy for slow vs. fast decisions overall or within either time limit condition.

4.3.3 Task pace. On average, participants slightly disagreed that they had to work at a fast pace (M=3.46, SD=1.80). Perceived task pace was higher in the time limit condition overall (AME=1.36, p<.01); if the recommendation specificity was specific, ambiguously described, or type of option; or if the recommendation was in line with what was recommended. There was not a significant difference in perceived task pace between time limit conditions for recommendations with specificity of general approach or no recommendation made or when recommendation accuracy was intentionally different or wrong. There were no differences in perceived fast task pace for slow vs. fast decisions overall or within either time limit condition.

4.3.4 Search difficulty. Overall, participants disagreed that it was difficult to search (M=2.58, SD=1.36). We found no significant difference between the two time conditions overall. There was lower search difficulty in the time limit condition (vs. no time limit) for recommendations that were a general approach (ME=-1.11, p<.05), and higher search difficulty for recommendations that were wrong (ME=3.12, p<.05). There were no differences in search difficulty for slow vs. fast decisions overall or within either time limit condition.

4.3.5 Decision confidence. Overall, participants were confident in their recommendation decision (M=5.31, SD=1.33). Recommender confidence was lower for tasks completed with a time limit than with no limit overall (AME=-.42, p<.05), for recommendations that were for an ambiguously described option (ME=-1.03, p<.01), or for recommendations that were intentionally different (ME=-1.31, p<.01). There were no differences in search difficulty for slow vs. fast decisions overall or within either time limit condition.

5 DISCUSSION

We conducted a user study to investigate adaptation in information search to support recommendation decision tasks under time constraints. Our results provide insights into the impact of time limits and decision speed on search behaviors, decision behaviors, recommendation characteristics, and users' perceptions about the tasks and their recommendations. In this section, we summarize our results and discuss implications.

RQ1: Impact of time limit on search behaviors. First, participants in the time limit condition reached the point of being ready to make a decision in less time than participants in the no time limit condition. Although this result is not unexpected, it is interesting since our tasks and study design allowed participants flexibility in deciding how much to search, yet this result is similar to prior IIR studies that have found an effect of time condition on task completion time [12, 33].

Second, we did *not* find a significant effect of time limit on the search interaction behaviors we investigated. Prior studies which have found adaptations in time-pressured search behavior adaptation (e.g., faster re-querying/acceleration and shallower results examination [12, 31]) have had both time limits and effort expectations (e.g., find 8-12 relevant documents). In contrast, in our study, the decision tasks were created to give participants considerable latitude in deciding when they had enough information. In these tasks, we observed an effect of time limit on decision time but did not detect an effect on search interaction measures.

RQ2: Impact of time limit and decision speed on recommendation decisions. Our results for RQ2 show several interesting trends. First, although participants were asked to recommend a specific option, the specificity of their recommendations varied.

Overall, 26% of the recommendations were for a general approach for how their friend might make their own decision rather than for a specific option. There was an interesting effect of decision speed (i.e., slow vs. fast) on recommendation specificity, especially when considered with the time limit condition: fast recommendations made in the time limit condition were more likely to be a general approach than those made slowly or without a time limit.

Second, most recommendations were in line with what the task requested; however, 13% of recommendations were intentionally different than what was requested suggesting that prior topic knowledge was considered during the decision tasks. We found no effects of time limit or decision speed on recommendation accuracy.

Third, participants' recommendations varied in the strength of their accompanying justification in both time conditions. This is another type of adaptation that our recommendation decision tasks allowed us to explore. As with specificity, there was effect of decision speed (i.e., slow vs. fast) on justification strength, especially for tasks with a time limit: fast recommendations made in the time limit condition were more likely to have no or minimal justification and less likely to be moderate or strong. We also found an effect of time limit and decision speed on recommendation length: recommendations were shorter in the time limit condition, or if the decision speed was faster.

Fourth, although the number of items considered and number of items recommended did not differ between the time limit conditions, the decision speed affected the number of items that participants considered: when the recommendation decision was made quickly, participants reported considering fewer items than when the decision was made more slowly. This suggests that it was the amount of time spent on the decision that impacted the size of the item consideration set (i.e., the number of items considered for the decision) rather than the time limit. In addition, there were differences in the number of *attributes* examined: participants mentioned fewer attributes if they had a time limit or if they made their recommendation decision quickly. This suggests that participants adapted by reducing the number of attributes considered but not items.

To summarize our results for RQ2, we found that time limit, decision speed, or an interaction of time limit and speed impacted the specificity, justification strength, and the number of items and attributes considered. These findings suggest that participants used various mechanisms to adapt the amount of "work" they needed to do to complete the task. These types of adaptation have not been found in prior IIR studies of the effects of time limits and time pressure on search [12, 31]. This study did not set any *a priori* effort expectations which enabled observing this type of adaptation which seems likely to be common in real-life tasks. Furthermore, our results suggest that context affords different types of adaptations. This is in line with Payne et al. [42] who suggested that their participants chose from a set of possible adaptations based on the task type and the time pressure felt; with a different task, they might have used different adaptation mechanisms.

RQ3: Impact of time limit and adaptation in scope of work on post-task perceptions. Participants felt greater time pressure, greater time inadequacy, and a faster task pace in the time limit condition overall, for tasks in which they made more specific recommendations (or recommendations of any specificity for time inadequacy), and for tasks in which their recommendation was in line with what was requested. Search difficulty was not impacted by the time limit condition overall; however, participants perceived searches as less difficult in the time limit condition when they recommended a general approach and more difficult when they made a recommendation that was inaccurate/wrong. Decision confidence was lower for decisions completed with a time limit overall, and especially when the recommendation was for an ambiguously described option, or an option or approach that was intentionally different option than what was requested. Unlike with recommendation characteristics, decision speed (i.e., slow vs. fast decisions) did not have a significant effect on time-, task-, or decision-related perceptions.

Implications. Our findings have implications for the design of search systems, the design of interactive IR studies, and for models and frameworks of information seeking. One of the key findings of this study is that there are multiple possible mechanisms for adapting search and decision processes under time pressure, but *context* can impact which adaptations can be observed. This finding suggests that search systems could better support users by understanding when they are making adaptations and by understanding what different types of adaptations may imply about the users' context and goals. An additional implication is that in the design of IIR user studies, the specified task outcome can influence which adaptations are observed or even which adaptations are possible. Our findings reinforce the recommendation by Wildemuth et al. [54] to clearly specify task goals at both the work task and search task level in simulated work task scenarios to avoid observing variability in task performance due to unintended adaptation.

Information-intensive tasks can have different phases in which different types of adaptations are possible, helpful, or potentially detrimental. If we know that different types of work conducted under different conditions (e.g., time pressure) is associated with certain types of adaptations, systems might deploy features to either support or combat those adaptations depending on the goals. For example, a system could assist time-pressured users in examining the most salient results, or it could alert users if an they were using a maladaptive strategy leading them to miss important information.

6 CONCLUSION

In this paper, we investigated adaptation in information search and decision-making under time pressure. We identified adaptations that participants made to complete assigned recommendation decision tasks, and examined how time constraints and decision speed affected search behaviors, adaptations, and user's perceptions about the task. Our study was novel in exploring the effects of time pressure in a task in which people have considerable flexibility in how to satisfy and adjust the task. These types of situations are common in everyday life and our results have implications for the design of search systems, methods for studying search, and for models of information seeking behaviors.

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