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PASSIVE OR ACTIVE? BEHAVIORAL CHANGES IN DIFFERENT DESIGNS OF SEARCH EXPERIMENTS

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Passive or Active? Behavioral changes in different designs of search experiments *

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Abstract

While search experiments are available in several designs, accumulating experimental evidence suggests that individual search behavior depends on design details. This paper reports the first classification and comparison of several search experiment designs widely accepted in search studies. These designs can be categorized as passive, quasi-active, and active. We found individual- and aggregate-level significant differences in the results across designs, despite identical models. In the passive design, subjects tended to be more reluctant to search than in the active design, and risk-averse subjects quickly terminated their search. Our results highlight the importance and potentials of designing search environments in practice.

Keywords: search experiment, consumer search, labor search, experimental design, risk preference

JEL classification: C91, D12, D83, J60

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Daily economic behavior often entails sequential information search behavior with multiple options, such as purchasing goods, services or job-seeking. The seminal models of Weitzman (1979) and Lippman and McCall (1979) have proved to be a solid foundation for a growing corpus of experimental studies. The biggest advantage of these studies is that they connect and track individual characteristics with search behavior in many research fields (e.g., Schunk (2009); Schunk and Winter (2009) in general studies; Brown, Flinn and Schotter (2011); Miura et al. (2017) in labor studies; and Caplin, Dean and Martin (2011); Kittaka and Mikami (2020); Jhunjhunwala (2021); Casner (2021) in consumer studies).[1]

Depending on the research field and objectives, experimental designs often differ significantly, despite their identical theoretical models (e.g., differences in the process of action to obtain the information and conditions for termination of the search). However, surprisingly, there has been no consensus on the optimal design for search experiments of the proposed categories. Some experimental evidences shows that different experimental designs can lead to considerably different results (e.g., Pedroni et al. (2017); Holzmeister and Stefan (2021)).[2] [3] However, little attention has been paid to this issue in the field of search studies. Since search behavior is closely connected to our daily activities, the experimental results should be applied to real-world policy and management decisions. Hence, experimental results based on a variety of experimental designs that may yield substantially different results may cause confusion or even produce undesirable consequences. We address this gap in our study.

In this study, we investigate whether and what causes differences in subjects' search

[1] For other examples, see Rapoport and Tversky (1970); Schotter and Braunstein (1981); Hey (1987); Bearden, Rapoport and Murphy (2006) for general studies; Braunstein and Schotter (1982); Cox and Oaxaca (1989) for labor studies; and Kogut (1990); Zwick et al. (2003) for consumer studies. These studies differ in purpose and focus, but are based on the same theory and employ (almost) the same model.

[2] They showed that different experimental methods elicit different risk preferences.

[3] It is known that search behavior depends on individual risk preferences (cf. Nachman (1972); Lippman and McCall (1979)); thus, differences in search experiment designs may affect individual search behavior.

behavior among these designs through experiments. To this end, we categorize existing search experiment designs according to the degree of flexibility of the subjects' decision-making, which is the first attempt in search experiments. We focus on search experiments based on the theoretical work of Weitzman (1979) and Lippman and McCall (1979), such as those based on the "one-step-forward" strategy, and categorize the experiments into three categories: *passive*, *quasi-active*, and *active*. Passive search design is a relatively new design in search studies (e.g., Brown, Flinn and Schotter (2011); Jhunjhunwala (2021); Casner (2021)), in which the subjects choose a cut-off (reservation) value each search, and then the computer compares the value with a random suggested value. This design differs from the other two designs in that the subject cannot terminate the search until the computer suggests a value higher than or equal to the subject's choice; hence, we call this design (relatively) "passive."[4] Quasi-active search design is a major design in search experiments (e.g., Schotter and Braunstein (1981); Sonnemans (1998); Zwick et al. (2003); Schunk (2009); Miura et al. (2017)), wherein the subjects are offered *one* random value at each step, and they decide whether to continue or terminate the search based on that value. Active search design is motivated by Caplin, Dean and Martin (2011); Kittaka and Mikami (2020); Bhatia et al. (2021), wherein the subjects have *multiple* options (not knowing the values in advance) and are free to decide what options to choose or when to terminate the search.[5] Table 1 summarizes the designs mentioned in above arguments. Based on the findings of Pedroni et al. (2017) and Holzmeister and Stefan (2021), we suspect that such design differences might affect the results through risk preferences. Hence, we conduct an additional risk

[4] A similar experimental design is called the strategy method ("cold" in psychology), in which the subject describes only one value at the beginning. Sonnemans (1998) conducts a similar experiment in the fourth part of their experiments. In our experiment based on this design, although we find potential differences from other designs, we exclude it from our comparison because this design is not commonly used in recent search experiments.

[5] For other similar experimental design examples (regarding choices, but not exactly the same model), see Gabaix et al. (2006) and Reutskaja et al. (2011). We note that such multiple-choice designs are commonly used for decision-making in psychology, such as the Columbia card task (Figner et al. (2009)).

elicitation task using the multiple price list (MPL) based on Holt and Laury (2002).[6]

Table 1: Summary of designs

Design	Search decision	Offer	Timing of termination
Passive	state a cutoff (reservation) value	receive one offer	when the received offer exceeds the stated value
Quasi-active	accept or reject the current maximum offer	receive one offer	at any time when clicking the "Finish" button
Active	accept or reject the current maximum offer	select one from the potential offers	at any time when clicking the "Finish" button

We find that the results varied significantly at both the individual and aggregate levels across the designs (treatments). The average number of searches (search duration) was lower than the theoretically predicted value for all treatments. However, it was highest for the active search treatment and lowest for the passive search treatment. This result suggests that the search design is one of the causes of a well-known under-search problem (cf. Schotter and Braunstein, 1981; Hey, 1987; Cox and Oaxaca, 1989). As for the subjects' behavior, the prevalence of recall choosing a past option over a new one were twelve percent and almost constant for all treatments. Further, the termination rate (the probability that the subjects would terminate the search when they observed a new offer) was also constant within each treatment for most of the subjects. This suggests that most subjects followed a "one-step-forward" strategy with a constant reservation value, at least within the same experimental design. However, we find significant differences in the termination rates between the passive and active treatments. Risk preference, as measured by the MPL method, had a significant effect on the number of searches only in the passive search design; this may partly explain the difference in behaviors and results across the designs.

To the best of our knowledge, this is the first study to comprehensively examine

[6] In the context of risk and search, Schunk (2009) found that loss aversion, rather than subjects' risk preferences, affected search results, while Miura et al. (2017) and Bhatia et al. (2021) reported the opposite results. However, these studies differ in their setting, and hence the relationship between risk preference and search results is still unclear (our study is more similar to the latter model).

search experiments in order to analyze the effect of different designs which covers the literature. We contribute to the literature by illustrating that the differences in flexibility significantly affect subjects' search behavior even when using the same model; therefore, the choice of the experimental design is a crucial issue. Our results also provide rich comparisons of search experiments in various designs. We present several experimental design choices that can be used for different purposes and in different environments; we thus contribute to research related to search theory and experiments. Although many theoretical and experimental studies assume risk neutrality, our results suggest that individual risk preferences may potentially affect search behavior depending on the design. We argue that researchers should be very careful when designing search experiments, especially when investigating the relationship between subjects' risk preferences and their search behavior.

These findings may be applied to various market environments. Consider job search in the form that people search for multiple candidate firms one by one (i.e., active search), and another form of search includes the cases where people use agents to find firms (i.e., passive search). Similarly, in the marriage market, people search for a partner from multiple candidates or use a matchmaker for an arranged marriage (such as the traditional Japanese custom of Miai). Our results suggest that in such markets with multiple search forms, planners can control people's behavior by using different forms of search. When considering such a market, for example, variety of choice, price, and efficiency have been the main topics, we argue that the form of search is also important.

With regard to managerial and policy implications, we suggest that a passive search environment is not desirable from a search efficiency perspective because it could create (relatively) severe under-search problems. Of course, there are trade-offs between search efficiency and search cost; however, the under-search problem reduces the search efficiency in principle. Planners should avoid, as much as possible, search environments that reduce individuals' decision-making flexibility (such as delegating the search to others). For example, given cost efficiency or the benefit of specialization, people tend to delegate search to agents in a job matching or a matchmaking environment. However, such delegation may also reduce search efficiency by causing people to terminate the search more quickly; thus, total efficiency could be improved by designing the environment to make it easier for people to search discretion, for example, through search cost reduction. Conversely, this implies that such a passive search design might address important problems caused by lengthening searches, such as the unemployment problem, even at a slight cost of efficiency. We believe that these implications will be useful for practitioners.

The remainder of the paper proceeds as follows. Section 2 presents the theoretical model. Section 3 describes the experimental designs. Section 4 reports the results of the experiment. Section 5 concludes.

1 The model

We first describe a generalized form of a well-known standard search model (cf. Lippman and McCall (1979)) that can be addressed in both labor and consumer studies and all the search experiments we conduct.

Consider a scenario where an individual is searching for information (hereafter, we refer to it as "offers") that will positively affect their utility, such as "wages" or "match utilities." The settings are as follows. In each search, each individual obtains exactly one offer, denoted by w, and decides whether to accept the offer (or returns to previous offers, if any) or rejects it and continues the search. We assume that w is randomly drawn from the same twice differentiable cumulative distribution function $F(w)$ with an interval $[\underline{w}, \bar{w}]$ and that each individual is aware of the distribution. The individual incurs a time-independent positive cost c at each search period, which can be interpreted as a *search cost* (including trip costs and opportunity costs) to obtain new information. We suppose that both w and c are independent of each other and of any previous and remaining values of offers, time, and number of searches, as is common in search theory. A search problem is assumed to be an infinite horizon (i.e., the number of offers is infinite). We also assume that each individual search is in a random order.

Consider an individual who follows an optimal search policy to maximize their expected net surplus, given the maximum sampled offer x ($x_0 = 0$). For the moment, suppose that an individual has a liner utility function. Then, the value of the search (i.e., the value from rejecting offer x and performing another search) is given by

$$V(x) = -c + E\max[w,\, V(x)]. \tag{1}$$

The above expression can be written as[7]

$$V(x) = -c + \int_{\underline{w}}^{\bar{w}} \max[w,\, V(x)]dF(w) = -c + \int_{V(x)}^{\bar{w}} (w - V(x))dF(w) + V(x)$$

$$\Leftrightarrow c = \int_{V(x)}^{\bar{w}} (w - V(x))dF(w). \tag{2}$$

Expression (2) implicitly and uniquely defines a value of $V(x)$.

Now, consider a hypothetical maximum sampled offer x^* such that the individual is indifferent between accepting x^* and rejecting it. Then, as is well known, each individual's optimal search rule can be described as follows (cf. Lippman and McCall, 1979; Weitzman, 1979): (i) they should further search if $w < x^*$; (ii) otherwise, they should stop and accept w, where x^* is uniquely and implicitly defined by the following expression:

$$c = \int_{x^*}^{\bar{w}} (w - x^*)dF(w). \tag{3}$$

Hereafter, we refer to x^* as a *reservation value*. The expression (3) and an optimal search policy imply that, in each period of the search, an individual compares the search cost (the left-hand side of (3)) and benefits from an additional search (the right-hand side), and then decides whether to search further based on the time-independent

[7] Here, we use $E\max[w,\, V(x)] = V(x)\int_{\underline{w}}^{V(x)} dF(w) + \int_{V(x)}^{\bar{w}} wdF(w) = V(x) + \int_{V(x)}^{\bar{w}}(w - V(x))dF(w)$.

variable x^*. Therefore, each individual's search behavior is *myopic*. Hence, we refer to this rule as "one-step-forward" search rule with a constant reservation value.

Here, we consider that each individual with an arbitrary, concave, and non-decreasing utility function $u(\cdot)$ follows an optimal search policy that maximizes $Eu(\cdot)$. Then, from the arguments above, we have

$$u(x) = F(x)u(x - c) + \int_x^{\bar{w}} u(w - c)dF(w), \tag{4}$$

and this expression implicitly determines the individual's reservation value x^*. It is known that the solution of (4) has the same constant reservation property as seen above; therefore, the "one-step-forward" search rule will persist (cf. Schunk, 2009).

The reservation value x^* described above is a good approximation for capturing individuals' search behavior. Here, we consider another more easily observable (and widely used) measure, such as the number of searches (duration of the search). Since each individual stops with probability $1-F(x^*)$ (in which $w > x^*$), the expected search duration can be simply summarized by the following expression:

$$E[N] = \frac{1}{1 - F(x^*)}, \tag{5}$$

where N is the number of searches. Notably, Nachman (1972) showed that more risk-averse individuals have lower x^*, requiring them to terminate the search sooner than less risk-averse individuals.

We emphasize that, in this setting, given that an individual follows such an optimal search policy with a constant reservation value, they never choose a *recall* option through which they can return and accept previously rejected offers (cf. Lippman and McCall, 1979). More importantly, as long as the experimental design follows this model, the theory predicts that an individual's search behavior will be characterized by the same reservation value x^* and the same number of searches, regardless of the experimental design.

2 Experimental design

We conducted an experiment consisting of two parts. Part 1 is a search task consisting of three treatments and Part 2 is a risk elicitation task.

The experiment was conducted entirely online at Osaka University, Japan, in July and August 2021 using oTree (Chen, Schonger and Wickens, 2016); the subjects participated in the experiments using their own computers.[8 9] The total number of subjects was 103, consisting of undergraduate and graduate students aged 18 to 32 years (average age: 21) from various departments of Osaka University. They were recruited through the ORSEE platform (Greiner, 2015). We employed within-subject design, and each of the three search treatments in Part 1 was repeated 20 spells (plus five practice spells per treatment). The order of the treatments was randomized by sessions to remove learning effects. The average time required for the experiment was about 60 minutes. The subject's reward was the sum of one randomly selected payoff (times 60) from each of the three search treatments and the payoff of the Part 2, and the average earnings was 2,000 JPY (about \$18.24).[10] The subjects were informed of their reward for completing the entire session.

Before each treatment, a pre-recorded instruction clip was played, and the subjects could start their tasks at their own time after they thoroughly understood the details.

[8] Common concerns in online experiments include lack of attention and increased noise because of the participation of various subjects (Snowberg and Yariv (2021); Gupta, Rigott and Wilson (2021)). Snowberg and Yariv (2021) showed that observations involving university-student subjects are less noisy than those collected using other methods (such as MTurk). In addition, Li et al. (2020) showed that online experiments on individual decision-making tasks perform equally well as lab experiments, especially when subjects are observed via webcam. Given their findings, we recruited university students and asked subjects to turn on their webcams and share their computer's screen during the experiment to ensure their complete concentration.

[9] To ensure a unified environment for the subjects, we only permitted them to use personal computers (not tablets or smartphones)and the same software (Google Chrome and Zoom). We set up several personal computers and assigned each participant a room using the Zoom room feature. During the experiment, we stayed connected with the participants via a zoom chat and over the phone.

[10] We adopted this random incentive system in which a single random outcome is chosen to avoid risk hedging behavior. See Heinemann, Nagel and Ockenfels (2009); Charness, Gneezy and Halladay (2016) for more details. Note that in many search experiments, the reward is the sum of all the spells.

In addition, the subjects could read the instructions at any time during each treatment. After the experiment, we administered a questionnaire to determine whether the subjects had understood the experiment correctly on an eight-point Lickert scale. Ninety one percent of the subjects answered seven or eight point (the average point was 7.74). All experiments were conducted in Japanese (the instructions and screens provided in this paper were translated into English). As is often the case with search experiments, through the instructions, each subject was informed that they would participate in an experiment designed to investigate how they search for wages or prices.

In each of the three search treatments, subjects make sequential decisions based on offers, simulating typical information search behavior. For consistency, the offer the subjects received was displayed as a number on the card for all designs. This card design was motivated by Caplin, Dean and Martin (2011), Sugden, Wang and Zizzo (2019), and Kittaka and Mikami (2020).[11] As is common in search treatments, each offer is an independent random draw from a discretized exponential distribution with $\lambda = 0.15$, truncated at 20. At the beginning of the session, using a graph and a table, we explained to the subjects that the offers were drawn from the same distribution across the three search experiments (the subjects could access the details of the distribution at any point). Table 2 shows distribution we used in Part 1.

Table 2: Probability of drawing each value (Always available to subjects)

Value	1	2	3	4	5	6	7	8	9	10
Prob.	14.66%	12.62%	10.86%	9.35%	8.05%	6.92%	5.96%	5.13%	4.42%	3.80%
11	12	13	14	15	16	17	18	19	20	Total
3.27%	2.82%	2.42%	2.09%	1.80%	1.55%	1.33%	1.14%	0.99%	0.85%	100%

Subjects had to pay one search cost to obtain information on one offer. Our design potentially allowed subjects to search infinitely, and the presence of search costs could

[11] In addition to search experiments, there are other examples where boxes or images are used to indicate multiple options, such as in Reutskaja et al. (2011) and Deck et al. (2013).

lead to negative rewards. However, the expected number of searches was 4.537; with a few exceptions, no subjects conducted an extensive search, and they all received positive rewards. The payoff for each search spell equals the maximum offer that the subject found during each spell minus the total search cost paid (i.e., the total number of searches) during the spell. After each search spell was terminated (conditions for termination are described below), the payoff for that spell was displayed at the bottom, which signaled the subject to proceed to the next spell by clicking on the "Next" button. When the subject clicked on the "Next" button after the spell was repeated 20 times, they were led to the next treatment instruction screen (if any).

A feature of our experiment is that the process of information acquisition and the conditions for terminating the search differ across the three search treatments. In the following subsections, we describe the design of each of the three search treatments.

2.1 Passive search

The "passive" search design is popular in more recent search experiments (e.g., Brown, Flinn and Schotter (2011); Casner (2021); Jhunjhunwala (2021)). Unlike in the other two designs, in this design, the subjects select the reservation value directly at each search period.[12] Compared with the active or quasi-active search, this design can be considered as mimicking a real-life situation where the principal delegates the search to an agent (e.g., a recruitment consultant).

Figure 1 is the screen shot of the passive search treatment. The number of spells is displayed at the top, and the current offer is shown as a card number at the center (the initial offer is zero). Subjects selected a cutoff value (i.e., a reservation value) from a list of numbers from 1 to 20. When a subject selects a reservation value and chooses to continue ("ask to search" button on the screen), a new offer is presented, incurring a search cost. If the offer is higher than or equal to the reservation value selected, the

[12] This type of procedure is called the BDM procedure by Becker, DeGroot and Marschak (1964).

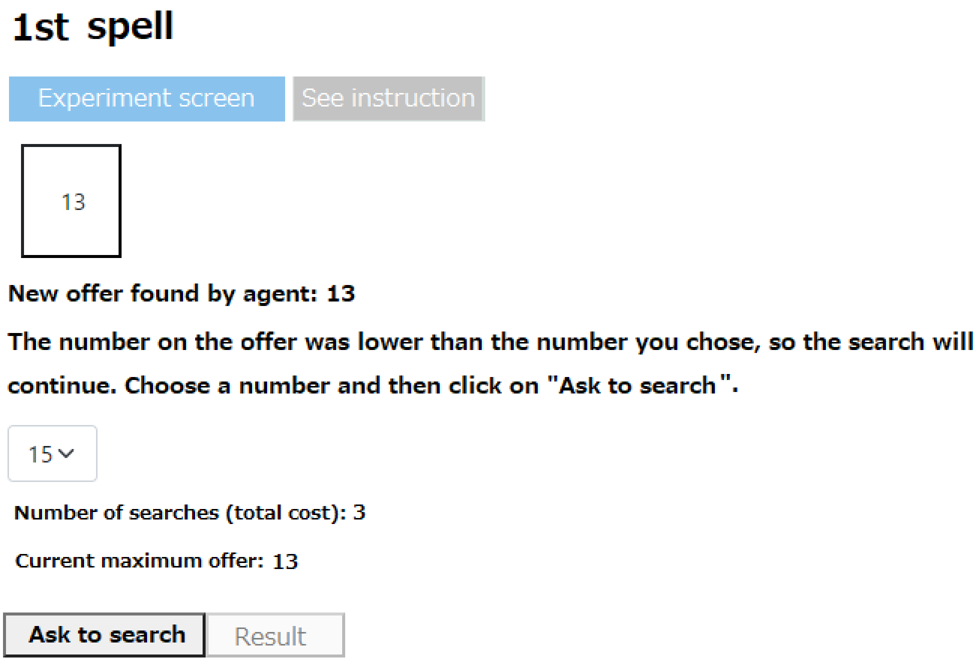


Figure 1: The main screen of the passive search design

search is terminated. Conversely, if the offer is strictly lower than the reservation value, the search continues, and the subject is required to select the reservation value again (which can be different from the previous values). Unlike some previous studies, we allow recall. That is, the subject's payoff is not the offer that exceeds the reservation value at the time, but the maximum value up to that point.[13][14]

[13] Casner (2021) allowed subjects to recall, which is similar to our study. In contrast, Brown, Flinn and Schotter (2011) explicitly prohibited recall options, and Jhunjhunwala (2021) also partially excluded recall. The latter two designs are appropriate for their purposes; however, the reservation value may differ under no recall setting. Hence, we allow recall to compare the results among three designs.

[14] Unlike in the other two treatments, recall is costly in the passive search design. The costly recall setting could lead to a different (and possibly not constant) reservation value. We emphasize that, because we (potentially) allow subjects to search infinitely numerous times, the reservation value may be constant (cf. Janssen and Parakhonyak (2014)). Moreover, as subjects never choose the recall option theoretically described at the model section, and the intuition is identical, although the costly recall complicates the problem, similar to all previous studies mentioned above, we employ this design to compare the design to others.

2.2 Quasi-active search

To our knowledge, the "quasi-active" search design is the most popular among the experiments in search theory. In this treatment, one offer is always available on the screen. The offer is randomly determined according to a predefined distribution, and the subjects choose to continue the search or accept the offer. When a subject clicks on the "Continue" button, a new offer is presented. Once they choose to terminate the search (clicked on the "Finish" button), the maximum offer minus the total search cost equals the payoff for that spell. In terms of a retained maximum value, the subject can return to the previous offers (i.e., recall is allowed). This design (and the active search design) differs from the passive search design in that subjects do not have to choose a reservation value, and they can terminate the search at any time even if the current offer displayed is lower than the current maximum value. This design corresponds to real-world situations, such as job matching, and the design is often used in the context of labor search (e.g., Miura et al. (2017)).

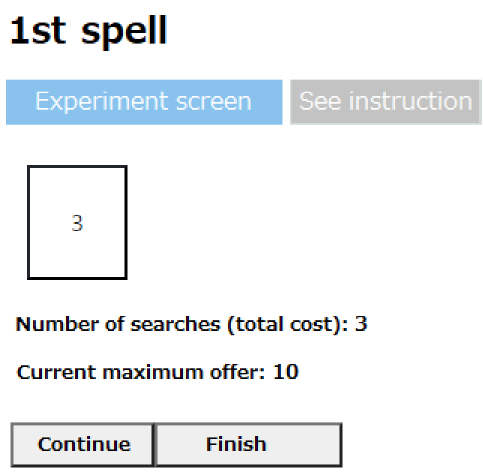


Figure 2: The main screen of the quasi-active search design

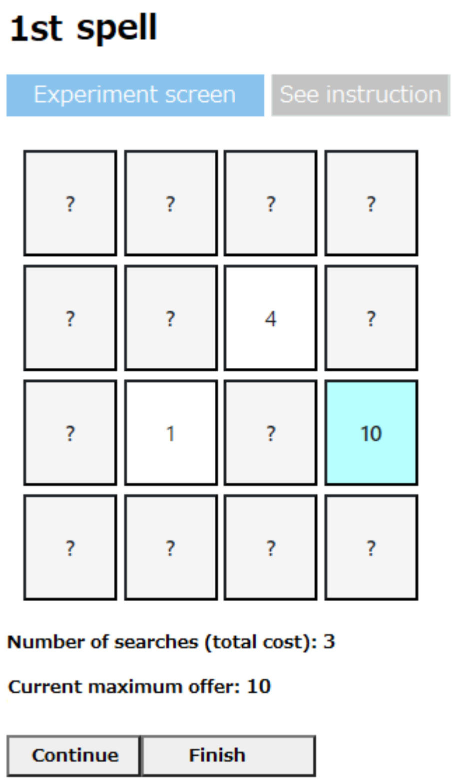


Figure 3: The main screen of the active search design

2.3 Active search

The "active" search design is inspired by the works of Gabaix et al. (2006); Caplin, Dean and Martin (2011); Kittaka and Mikami (2020); Bhatia et al. (2021). The difference between a quasi-active search and an active search is that, if a subject decides to search, multiple options (values are written on the back of it) are displayed, and they are free to choose one. Specifically, in the active search design, each subject is presented with 16 available offers and a terminating option on the display. If the subject chooses all 16 offers, they obtain a new set of 16 offers, while the previous maximum offer is recorded. Therefore, subjects can draw as many offers as they want. The value of each offer is not initially known, and subjects can discover the value of their chosen offers by incurring a search cost per offer (they are informed that all offer values will be realized independently from the same distribution). Subjects are also free to choose to terminate their search with the current offer(s) at any point, without any cost. We call this design “active” as subjects are free to decide which offers they want to know the value of and under what conditions they want to terminate their search.

Figure 3 is the screen of the active search treatment. When a subject clicks on the “Continue” button and chooses one of the cards (offers), the value of the chosen offer is displayed, incurring one search cost. When the subject clicks on the “Finish” button, the search process is terminated, and the maximum current offer minus the total search costs is displayed and recorded as the payoff for that spell (recall is allowed). Although consumer search experiments often employ quasi-active or passive designs as described above, we believe that this active search design is the closest to the context of consumers’ choice behavior.

2.4 Risk elicitation task

We also elicited subjects’ risk preferences in the Part 2 by MPL based on Holt and Laury (2002). MPL is one of the risk elicitation methods which is widely used not only in search experiments but also in various research for measuring individual risk aversion (e.g., Tversky and Kahneman (1992); Andersen et al. (2008); Beauchamp et al. (2020)).

Figure 4 displays a part of contents of the questionnaire. There are 20 pairs of two lotteries, and subjects choose between ”Lottery A” and ”Lottery B”. The payoff depends on the probability p that the higher value of each lottery is realized. If subjects choose lottery A (safe lottery), they receive 600 JPY with probability p or 300 JPY with probability $1 - p$; if they choose lottery B (risky lottery), they receive 900 JPY with probability p or 0 JPY with probability $1 - p$. The probability p, beginning with five percent, increases by five percent from the first row to the twentieth row. Thus, in the first row, the expected payoff for the risky lottery becomes greater than that

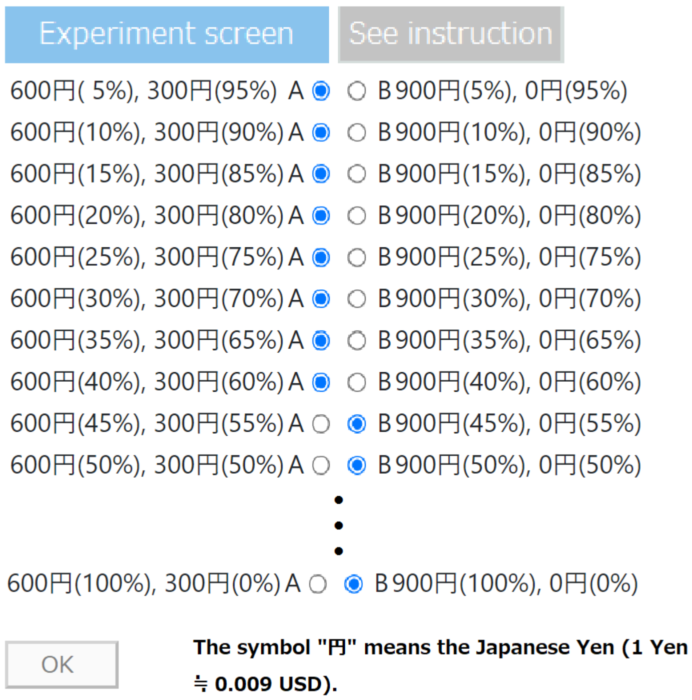


Figure 4: The screen of the multiple price list task (We add a note and omit some parts)

for the safe lottery (315 JPY and 45 JPY, respectively). In the MPL we utilized, the top nine rows, the expected payoff of the safe lottery is greater than the risky one. The expected payoff of the safe lottery is equal to the risky one in the tenth row, so the risk-neutral subjects switch from Lottery A to B on tenth or eleventh rows. Since risk-averse subjects tend to choose a more safe lottery, they would switch A to B earlier than the tenth row. Hence, we use the number of safe lotteries chosen as a proxy for each subject's risk aversion.

3 Results and discussion

3.1 Main result

Since we are interested in determining whether there is a difference among the designs, we first compare the results at the aggregate level analysis to verify the presence of a

Table 3: Summary of data

	Passive	Quasi-active	Active	Theoretical
Average payoff	8.298	8.437	8.413	9.028
	(0.028)	(0.026)	(0.028)	
Average number of searches	3.095	3.133	3.380	4.537
	(0.027)	(0.022)	(0.022)	
Number of observations	2060	2060	2060	-

Note: The "Theoretical" column presents theoretical values for a risk-neutral player. Standard errors are presented in parentheses. In the passive treatment, the top 10 spells with the highest number of searches is very high (the average number is 26.00 in the passive treatment, while it is 18.30 in the active treatment and 19.90 in the quasi-active treatment); the average number of searches in the passive treatment is 3.006 when removing the data that exceed the maximum number of searches in other spells (21 in both active and quasi-active treatments).

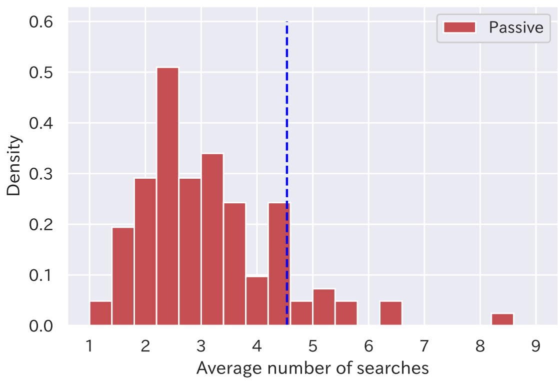
difference. Table 3 reports the summary static for each treatment.

The average payoff (the maximum offer found minus the total search cost in each spell) was slightly lower in the passive treatment, but there were no statistical differences across treatments. However, we find that the average number of searches differed significantly across treatments. Specifically, the average number of searches in the active search treatment was significantly higher than in the other treatments at the 1% significance level.[15]

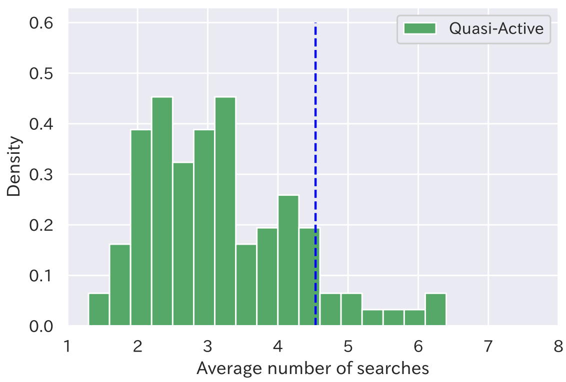
At the individual level analysis, the average number of searches was also different in the active and both the quasi-active and passive treatments at the 5% level.[16] This implies that the design of the information acquisition process is a crucial aspect in search experiments, and that making one's own decision regarding potential offers affects the search decision.

[15] We also conduct a non-parametric test for the number of searches. The Mann–Whitney U (Wilcoxon rank-sum) test for differences between the active and quasi-active treatments was significant at the 5% level. It was further significant at the 1% level in the active and passive treatments. Conversely, there was no significant difference between the quasi-active and passive treatments ($p = 0.1001$).

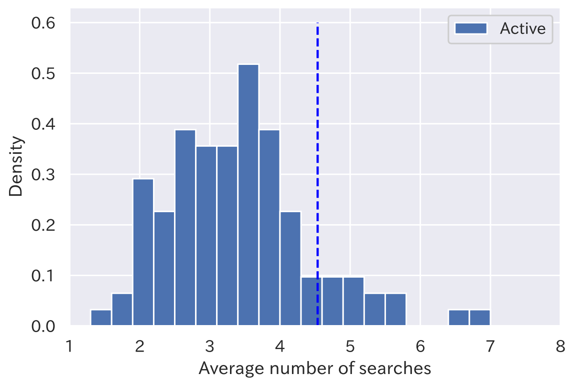
[16] The Wilcoxon signed-rank sum test for differences in the active and quasi-active (passive) treatments was significant at the 5% level, while it was not significant in the quasi-active and passive treatments.



(a) Passive treatment



(b) Quasi-active treatment



(c) Active treatment

Figure 5: Histograms of the average number of searches for each treatment (the dashed line represents the theoretically predicted number of searches).

Figure 5 illustrates the distribution of the number of searches averaged by subject. The dashed line represents the theoretically predicted number of searches for risk-neutral subjects. The figure shows that the distribution trend of the average number of searches also seemed to differ among the treatments. The peak of the average number of searches was around 3.6 in the active treatment and 2.3 and 3.3 in the quasi-active treatments, while it was around 2.3 in the passive treatment. These results suggest that, among all experimental designs, the passive treatment suppresses the number of searches the most overall.

As in previous studies, we observe an "under-search" problem, where subjects searched less than the theoretically predicted number of searches. Further, subjects' behavior was the closest to the theoretical predictions in the active search treatment. We thus argue that adjusting the degree of flexibility of subjects' decision-making may be an effective remedy to partially solve the under-search problem.

Discussion The recall is costly only in the passive search treatment, so subjects may potentially search more excessively in this treatment than in other treatments. As we note in the table, there were some spells in which the number of searches was longer only in the passive treatment. And in fact, some subjects may have carried out an additional search in which they selected an extremely low reservation value to terminate the search.[17] Therefore, the average number of searches in the passive treatment may be in excess of the number of actual searches carried out by the subject to obtain the information.

3.2 Behavioral differences

In this section, we consider what might have caused the differences in the results between the designs, as seen in the previous subsection, from the perspective of subjects' behavior.

Spell-to-spell transitions and learning Before considering search behavior in detail, we briefly examine whether there was a learning effect. As mentioned in Section 3, each treatment was conducted in a random order to eliminate learning effects across the treatments. In addition, Figure 6 shows that there was no significant trend in the average number of searches across spells. These results suggest that the learning effect is not the underlying factor in the different results across the treatments.

[17] In Section 3.3, we discuss the possibility of heuristics, which tend to appear in the passive treatment, possibly leading to a higher number of searches.

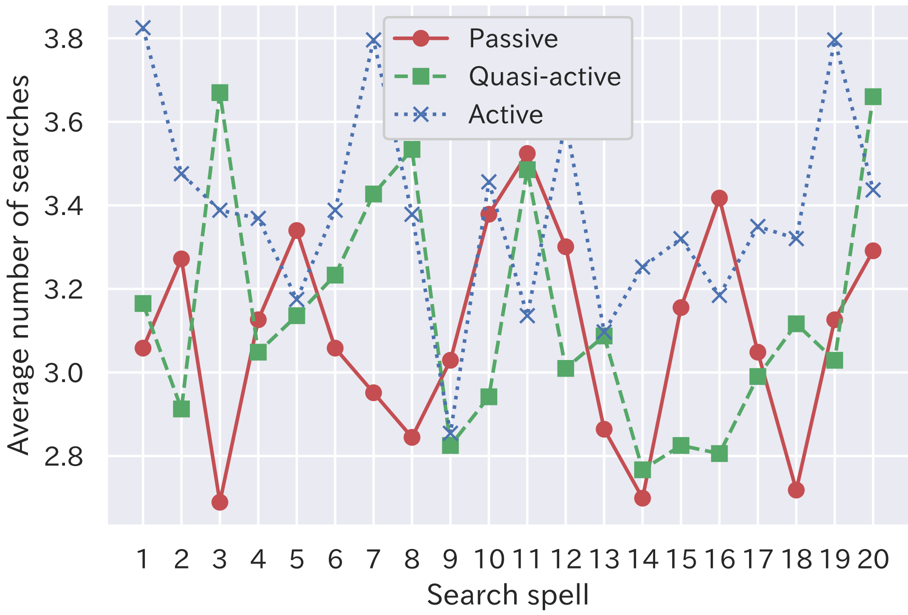


Figure 6: The relationship between experience and the average number of searches

Search strategy Some previous studies (e.g., Brown, Flinn and Schotter, 2011; Casner, 2021) based on the passive design suggest that subjects exhibit a downward trend in reservation value, rather than following a search strategy based on constant reservation value, as described in Section 2.

Here, we investigate whether or not subjects' search strategies are based on the constant reservation value in all designs. We further explore whether the tendency of search strategies differs across designs, that is, whether it drives differences in the average number of searches across designs.

First, we consider the subjects' search strategies from the viewpoint of recall behavior. The reason is as follows. Consider a subject who follows the optimal search strategy with a constant reservation value. If she decided to continue the search instead of terminating the search at the previous drawn offer value, then she would never choose the past offer value again. We define a subject as exhibits "recall" if the subject terminates the search even though the last offer is equal or less than the previous maximum offer.

Table 4: Summary of data regarding recall

Treat.	Number of Recall	Number of Obs.	prevalence of recall (%)
Passive	245	2060	11.9%
Quasi-active	264	2060	12.8%
Active	231	2060	11.2%
Total	740	6180	12.0%

Table 4 reports a summary of our data regarding recall. The prevalence of recalls was not large throughout the three search treatments, and the trends were similar across the treatments. This suggests that a search strategy based on a constant reservation value is likely to be consistent with subject behavior; therefore, we analyze the subjects' search strategy in more detail below.

Termination rate Here, we consider the trend of the termination rate of the search because the rate should be almost constant throughout the game if subjects employ the constant reservation value strategy.

Figure 7 shows the percentage of subjects who terminated the search among those who continued to search until a particular duration at the aggregate level up to the 10th search (Note that less than 15% of the spells lasted for six or more searches and less than 4% lasted for 10 or more).[18] The termination rate of the subjects was approximately 30% for the active and quasi-active treatments. This result suggests that, irrespective of how long the search lasted, the variance in the reservation value is not large enough in these treatments under the condition that all subjects obey their own constant reservation value strategy. In the passive search process, the termination rate was constant for a spell with up to six searches and decreased slightly for spells with six or more duration in a row. That is, the variance in the reservation value was relatively large compared with the other treatments.

[18] The number of observations after the 10th search was too small ($N < 60$) and was thus excluded.

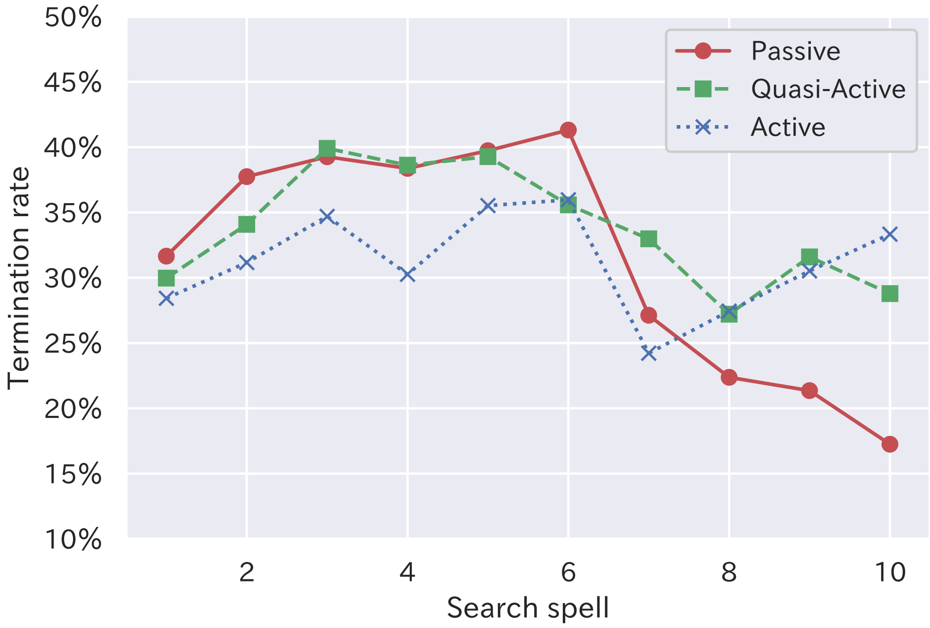


Figure 7: Percentage of subjects terminating the search per period across treatments

Table 5 shows the fraction of subjects whose termination rate changed with the search duration compared with the initial (baseline) termination rate. Regarding whether there was a difference in the termination rate, we found no significant difference for the search duration up to the fifth search within treatments at the individual level, except for a few subjects. This suggests that, at least for the first couple of searches, most subjects may employ a search strategy based on a constant reservation value.

However, for 13.5% of the subjects, we found significant differences in the baseline termination rate across treatments within individuals (calculated by Fisher's exact test at the 5% significance level). To investigate the causes of the low termination rate of search in the passive treatment, we analyze the relationship between risk preferences and termination rate.

The effect of risk preferences We create "termination rate" as a dependent variable, which takes the value of 0 if the subject continues the search in each search decision

Table 5: Termination rate change among subjects ($N = 103$)

Treat.	Termination rate (first search)	Number of subjects who differed in termination rate by search duration			
		Second search	Third search	Fourth search	Fifth search
Passive	31.6%	12	7	6	8
Quasi-active	29.9%	8	8	5	6
Active	28.4%	9	8	4	7

Note: The "Termination rate" column indicates the average probability that the subjects terminated the search on the first search. Columns 3 to 6 shows the number of subjects who would change the termination rate from the value of the first search in the number of searches, by using Fisher's exact test at the 5% significance level. Searches beyond the sixth search were not included because of the small sample size and difficulty of testing.

and takes the value of 1 if the subject terminates. We analyzed this dependent variable by the five regression models, using three types of dependent variables, which are described below. We used an active search treatment as a baseline and created "Passive" and "Quasi-active" as treatment dummy variables. "Number of safe lottery" is the number of safe options that subjects choose in the risk elicitation task (taking values between 1 and 20), which is a time-invariant variable within individuals. "Number of searches" is the number of searches by the subject in each spell.

Table 6 reports the results of a logistic regression regarding the termination rate. Using two treatment dummy variables, Column (1) in Table 6 shows that the passive and quasi-active treatments positively affected the probability of termination at the 1% and 5% levels of significance. We then carried out an analysis to see the impact of the umber of searches is in Columns (2) and (3). From Column (2), we could not confirm an overall trend that people changed their search strategy throughout the search, which is consistent with previous arguments. By treatments, Column (3) shows that the coefficient was negative and significant only in the passive treatment, but the magnitude was relatively small. Finally, using the number of safe lottery, we investigated the effect of risk preferences on the termination rate in Columns (4) and (5). Column (4) is consistent with the theoretical prediction that more risk-averse subjects tend to terminate the search quickly, although Column (5) shows that this result was not common across all designs. More specifically, in the passive search design, more risk-averse subjects tended to be more reluctant to search, unlike in the other designs. Given the statistical difference in the termination rates between the active and passive treatments, this result implies that the reason for the lower average number of searches in the passive treatment is that more risk-averse subjects are more likely to terminate their search in each search decision.

3.3 Discussion: consistency with previous studies

Thus far, we found no evidence that subjects had a decreasing reservation value trend at an individual level, unlike previous studies (e.g., Brown, Flinn and Schotter (2011); Casner (2021)). There were no significant differences in the termination rates for the first couple of searches. Furthermore, Figure 7 and Column (3) in Table 6 show that the termination rate is lower later in the search, which is inconsistent in the case of a long-term decreasing reservation value trend. We then pose a pertinent question: Does our study yield different results from previous studies?

Here, we used the passive design to investigate the changes in the reservation value in detail. We believe this to be a superior design for this purpose in that it allows us to directly observe the subject's reservation value. According to Brown, Flinn and Schotter (2011), we compared the reservation value selected at the beginning of each spell with the last value selected to determine if they were the same or showed an increasing or decreasing trend, at an aggregate level. Although we found some patterns indicating that the trend changed mid-spell or was random, we only considered the first and last values because such patterns were found for all the three trends.

Table 7 shows the trend of the reservation values excluding the 652 spells that were terminated with only one choice. In approximately 30% of the spells, subjects followed a rigorous, constant reservation value strategy; that is, they continued choosing only

Table 6: Estimates of the Decision to terminate using logistic regression with random effect model

Covariates	Coefficients (SE)				
	(1)	(2)	(3)	(4)	(5)
Passive	0.102***		0.188***		−0.229
	(0.036)		(0.052)		(0.145)
Quasi-active	0.083**		0.094*		−0.062
	(0.036)		(0.054)		(0.142)
Number of safe lottery				0.012*	0.001
				(0.007)	(0.010)
Passive × Number of safe lottery					0.025**
					(0.011)
Quasi-active × Number of safe lottery					0.011
					(0.010)
Number of searches		−0.005	0.007		
		(0.005)	(0.009)		
Passive×Number of safe lottery			−0.027**		
			(0.012)		
Quasi-active×Number of safe lottery			−0.003		
			(0.013)		
Constant	−1.202***	−1.124***	−1.225***	−1.306***	−1.215***
	(0.033)	(0.101)	(0.044)	(0.030)	(0.130)
Observations	25,981	25,981	25,981	25,981	25,981

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels. Standard errors (SE) are in parentheses. We used active search treatment as the baseline treatment. Passive and Quasi-active variables are dummy variables. Number of safe lottery is the number of safe options that subjects choose in the risk elicitation task (taking values between 1 and 20). We use this variable as a proxy for measuring the subject's risk aversion. Number of searches is the number of searches by the subject in each spell.

one value within the same spell, which is consistent with the observation that the termination rate was constant.

Conversely, we also found a trend of decreasing the reservation value in some spells, similar to Brown, Flinn and Schotter (2011) and Jhunjhunwala (2021). Further, the

Table 7: Trend in the reservation value in the passive treatment

Trend	Num.	Percentage	Avg.Rsv.Value
Only one choice	652	31.6%	7.12
Same value	651	31.6%	8.91
Decreasing	593	28.7%	9.87
Increasing	164	7.9%	9.97
Total	2060		

average reservation value selected in those spells was significantly higher than in spells where the reservation value was constant (significant at the 1% level).

Table 8: Difference in the reservation value selected in the beginning and in the end in the passive treatment

	Num.	Mean	SE	t-value
Difference	2060	1.19	0.10	16.23
Difference (search number ≤ 4)	1673	1.10	0.10	14.81
Difference (search number ≤ 2)	1160	0.72	0.09	9.31

Table 8 presents the differences in the reservation value from the first offer to the accepted offer within a spell (we assigned a value of 0 to spells in which the first offer was accepted). A positive difference indicates that the subject later chose a lower value than the initial one, and the opposite is true for a negative difference. The results show that, as the search continued for a longer period, the last reservation value selected tended to be slightly lower overall than the first one. However, most of these declines were observed immediately at the beginning of the search.

Table 9 represents the number of spells in which the second or last chosen value fell significantly relative to the first chosen value. Overall, in the trend of decreasing reservation values, there was a tendency to set a higher reservation value at the beginning, and then lower the value (recall that the expected reservation value for the risk-neutral subject was 9.03). In approximately 20% of the spells, the reservation value was initially set at 10 or higher, but at the end, the reservation value dropped to less than half

Table 9: Observation of spell with sharp decreases in the reservation value in the decreasing trend in the passive treatment

First chosen value	Number (percentage)	Difference in the	
		second search	last search
20	41 (1.9%)	9.80	16.41
≥ 13	201 (9.7%)	4.22	7.92
≥ 10	825 (20.2%)	1.64	3.38
< 10	1235 (59.9%)	0.20	0.19

in approximately half of the spells.[19] Such observations of behavior in some spells are consistent with the observation in Figure 7 that termination rates are higher in earlier searches and lower thereafter. Note that, in the present study, such a behavior was not pronounced at the individual level and did not have a significant influence. And although it cannot be stated with certainty whether this trend is unique to the passive treatment, Figure 7 shows a similar trend of low termination rates for the first search for all treatments.

4 Conclusion

Accumulating experimental evidence suggests that individual search behavior depends on experimental design details, in contrast to theory. In the present study, we disentangle the effect of design details by employing three treatments to cover the previous studies, Passive, Quasi-active, and Active, according to the degree of flexibility of the subjects' decision making.

We found a significant difference in the results at both the individual and aggregate levels across the designs. The average number of searches was highest for the active search design and lowest for the passive search design. prevalence of recall and termination rate analysis results support that most subjects search according to a constant

[19] A heuristic in which the subject chooses a reservation value higher than the theoretical value for the first few times, and later lowers it, is similar to the heuristic detected by Casner (2021). Interestingly, in the researcher's experimental design, subjects had to acquire information about the distribution of offers. In our experiment, we found similar heuristics even without learning.

reservation value strategy within treatments. However, there was a difference in the termination rate between the passive and active treatments. Unlike the quasi-active and active treatments, more risk-averse subjects tend to be more reluctant to search in the passive treatment, which may explain the difference between the designs. We, therefore, argue that researchers should be very careful in designing search experiments. These findings that people's search behavior may depend on the form of search can be applied to various market environments that can potentially take multiple forms of search (e.g., job market, matchmaking market, shopping). We believe that our results will be helpful to practitioners.

There are several caveats to our results. First, we showed that the passive design causes the most severe under search problems, but this does not mean that the design is inferior. The passive design is suitable for studying search heuristics, as it allows the direct elicitation of the subject's reservation values, which will contribute to the study in economics and management. Hence, improving the passive design to mitigate the under-search problem is a challenge for the future, and our results will help build a suitable design. Second, we found a significant impact of the risk preferences measured with the MPL method only in the passive design. However, search theory and Bhatia et al. (2021)'s result predicted that the preferences affect subjects' behavior in any design. This result shows that, despite the widespread use of the MPL method, it may not be adequate to elicit risk preferences in subjects' search behavior or at least requires great care. Addressing this issue will lead to fruitful future research.

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Appendix A (For Online Publication)

We conducted our experiment using oTree (Chen, Schonger and Wickens, 2016) and web-server(Heroku and oTree hub). After the subjects gained access to Zoom, we shared the URL (using Zoom's room feature) via chat. The instructions were recorded in a video, and the subjects could view it at their own pace and convenience. At the beginning of each experiment, subjects were required to enter passwords that could only be found by reading each instruction carefully. First, we explained the common instructions, and then conducted each experiment. The order of treatments was changed in each slot. The instructions, including the common ones, could be referred to at any point during each experiment. The details of the instructions are described below.

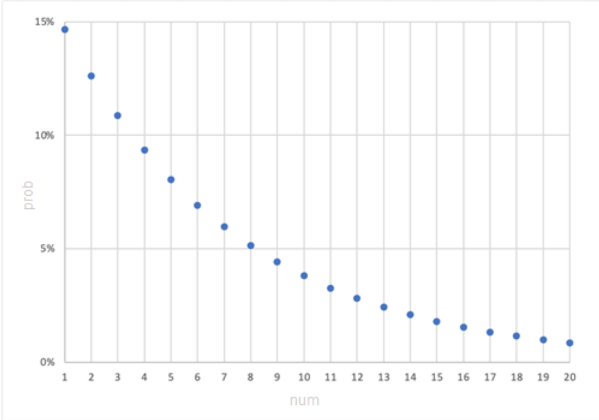
Common instructions

In parts 1 to 3 of the experiment, you will make 20 decisions each. During the experiment, the following cards will appear.

The cards have numbers on them, and the results of each session depend on the numbers you find during the experiment.

Regarding the numbers on the cards The numbers on the cards follow the following probabilities in the interval [1–20]. The number on each card is independent to the number of previous cards found.

num	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	計
prob	14.66%	12.62%	10.86%	9.35%	8.05%	6.92%	5.96%	5.13%	4.42%	3.80%	3.27%	2.82%	2.42%	2.09%	1.80%	1.55%	1.33%	1.14%	0.99%	0.85%	100%



Rewards After all experiments are completed, the computer randomly selects one out of the 20 times. The result of the chosen spell will be multiplied by 60 yen to give you a reward for that part of the experiment.

Part 1 (Passive search)

Experiment overview

Assume a situation in which you are paying someone (an agent) to find what you want. For example, you might ask someone to buy a product for you in a shop, or you might ask an agent to help you find a job. The experiment is carried out 20 times in total. Assume that you are looking for something you want 20 times.

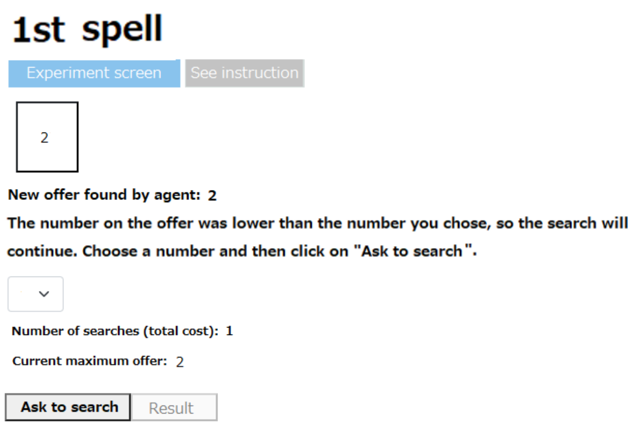
Experiment description

You tell the agent your “cut off value.” The agent looks for a card each time a cutoff value is given. The cost of drawing a card is 1 each time, and you pay the agent at the end. The cards have numbers on them, and the highest number the agent finds on a card is recorded as the maximum point for that spell. If your maximum points are above the cut-off value set, the spell will end automatically, and you will proceed to the next spell. If the maximum points are less than the cut-off value set, you will have to pay again to have an agent find a card for you. (You can set a different cut-off value). The result for each spell is the maximum point for that spell minus the cost of paying the agent (total cost).

Example

At the beginning, you set the cut off value to 10. Then, the agent finds a value of 5. The maximum point is updated to 5. At this time, 5 is less than the cut-off value you had set (10); therefore, you cannot complete this spell. The total cost you will incur is 1. Next, you set the reservation value as 15. Then, the agent finds a value of 6. The maximum point is updated from 5 to 6. At this time, 6 is less than the cut-off value that you had set (15); therefore, you cannot complete this spell. The total cost you incur is 2. Next, you set the cut off value as 6. Then, the agent finds a value of 6. The maximum points remain at 6. At this time, 6 is greater than or equal to the standard value set by you (6); therefore, you can finish this spell. The total cost to you is 3. The result of the spell is 3 (=6[maximum point]–3[total cost]).

Display on the screen



The number of times the agent has searched for a card (total cost) is shown below the card, and each time the agent searches for a card, a cost of 1 is added. The maximum points at this time are the highest number of cards that the agent has found.

Part 2 (Quasi-active search)

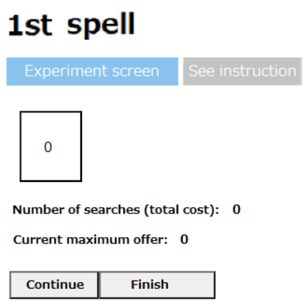
Experiment overview

Assume a situation where someone proposes something to you. For example, consider a shop assistant offering a recommendation or a job offer. You will be asked to make a decision. The experiment is carried out 20 times in total. Assume that you are looking for something you want 20 times.

Experiment description

There is one card on the screen. You can ask for this card to be changed to another card. The higher the number, the better the goods or the company you have found. The cost of drawing a card is 1 each time. You can choose to draw any card from the ones you have not yet drawn. You can draw as many offers as you want. The payoff for each search spell is recorded as the maximum value that you find during each spell minus the total search cost paid (i.e., the total number of searches) during the spell. After each spell, the results are displayed.

Display on the screen

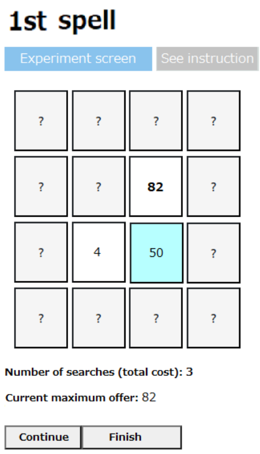


The number of times you changed the card (total cost) is shown below the card, and the maximum point (current maximum offer) for this spell is the highest number of cards.

Part 3(Active search)

The cards are presented on the screen. You can turn over the cards one at a time. Each card has a number on it, and the highest number on the cards you turn over is recorded as the maximum point for that session. The higher the number, the better the goods or the company you have found. The cost of drawing a card is 1 each time. You can choose to draw any card from the ones you have not yet drawn. You can draw as many offers as you want. The payoff for each search spell is recorded as the maximum value that you found during each spell minus the total search cost paid (i.e., the total number of searches) during the spell. After each spell, the results are displayed.

Display on the screen



There are 16 cards on the screen. When you draw all the cards, a new card will be set automatically. Card [?]: it has not been drawn yet. Card [number]: it has already been drawn. The card you have just drawn will be displayed in light blue.

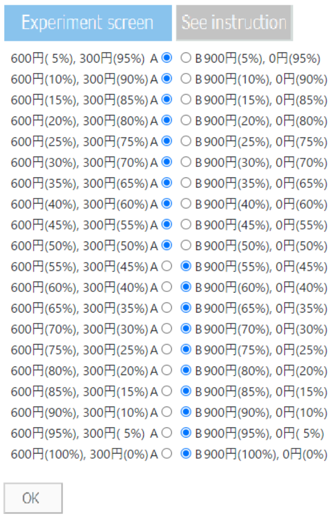
Part 4 (Risk elicitation task by multiple price list:MPL)

In this part of the experiment, you will be asked to decide at which point you will switch to A or B for a total of 20 questions. Each question is a choice between A and

B. A and B are lotteries. Example. A: 10% chance of getting 600 yen and 90% chance of getting 300 yen. B: 10% chance of getting 900 yen and 90% chance of getting 0 yen. Please choose which lottery you prefer, A or B.

Display on the screen

There are 20 questions on the screen.



Operation description

Click on one button anywhere, and A or B will be set automatically. The other choices, apart from the one you selected, will be the same. You can then choose again for each question. Once you have made your decision, click on the “Next” button.

Rewards

At the end of the experiment, you will be asked to choose one of the questions from 1 to 20. The reward for this part of the experiment is determined according to the probability of the lottery of the question you had chosen. You will be rewarded for this part of the experiment. At the end of Experiment 4, the rewards for all the experiments are determined.