Earlier Seen, More Often Chosen: Image Loading Speed as a Potential Seed of Hidden Manipulation

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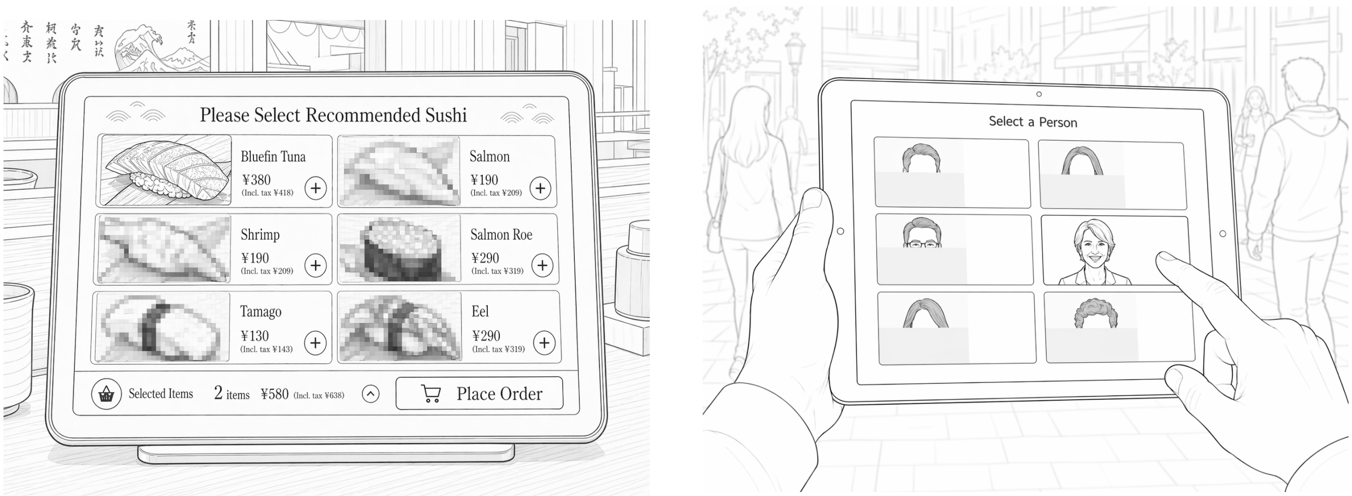


(a) A sushi ordering tablet interface in which one item (Bluefin Tuna) is fully loaded while the other items remain pixelated, illustrating how differential image loading speeds may influence user selection.

(b) A person-selection interface in which one candidate's image has fully loaded while others remain partially visible, illustrating how differential image loading speeds may bias selection toward the first available option.

Figure 1: Illustrative scenarios in which image loading speed differs across selectable options. This illustrative image was generated using DALL·E and was not used as an experimental stimulus.

Abstract

Choice interfaces may appear neutral even when subtle presentation differences bias user behavior. This paper investigates whether image loading speed can influence choices in image-based selection interfaces. We conducted two crowdsourcing experiments using different presentation formats: sequential top-to-bottom loading and progressive resolution improvement. In both experiments, multiple image options were shown in visually equivalent layouts, while one option became visually available earlier than the others. The results showed that earlier-loading options were selected more frequently than expected in both formats. Although the effects were modest, they were consistent across experiments. We also discuss how differences in image presentation timing that are difficult to distinguish from ordinary loading delays may influence users' choices without being perceived as intentional guidance.

CCS Concepts

• **Human-centered computing → Empirical studies in HCI**.

Keywords

Hidden manipulation, Dark pattern, Image format, Image display speed, User interface, Selection bias

ACM Reference Format:
Itsuki Kanaya, Takaya Miyama, Yuichiro Kinoshita, and Satoshi Nakamura. 2026. Earlier Seen, More Often Chosen: Image Loading Speed as a Potential Seed of Hidden Manipulation. In *Proceedings of the 14th Nordic Conference on*

NordiCHI '26, Vaasa, Finland

ACM ISBN 979-8-4007-2373-5/2026/10
https://doi.org/10.1145/3829807.3829877

Human-Computer Interaction (NordiCHI '26), October 03–07, 2026, Vaasa, Finland. ACM, New York, NY, USA, 15 pages. https://doi.org/10.1145/3829807.3829877

1 Introduction

In situations where users make choices on websites or smartphone applications, Dark Patterns, also referred to as Deceptive Patterns [3], have become a significant concern. These interfaces can steer users toward unintended actions, such as purchases, registrations, or subscriptions, and may cause economic or psychological harm [35]. Many well-known Dark Patterns rely on visually recognizable techniques, such as highlighting a preferred option with colors, borders, or layout emphasis, or making undesired actions difficult through confusing wording or interface structures. Because such designs are visually salient, they can often be recognized, criticized, and regulated as problematic.

However, not all forms of choice influence are visually obvious. Some interfaces may appear neutral and fair while still biasing user decisions through subtle interaction or implementation-level factors. For example, previous studies have suggested that the device used by the user [38] and progress bars displayed before options are presented [40] can affect users' choices. These findings suggest that user decisions may be influenced not only by explicit visual emphasis, but also by seemingly peripheral aspects of how an interface behaves. In this paper, we refer to such cases, where an interface appears neutral to users but can bias their choices through implementation-level characteristics, as *Hidden Manipulation*.

This issue is important because implementation-level differences may arise from both incidental system behavior and design decisions. In web interfaces, differences in display timing may arise from network latency, file size, caching, or rendering behavior. From the user's perspective, such differences may appear to be ordinary system behavior. From the provider's perspective, similar timing differences could also result from design choices, such as server-side delivery, response ordering, client-side rendering, animation timing, or placeholder removal. This asymmetry makes timing differences particularly relevant to the concept of hidden manipulation: a specific option may become visually available earlier than others without explicit visual emphasis, while the underlying cause of such timing differences may not be apparent to users.

As one implementation-level factor through which such hidden manipulation may occur, we focus on image loading speed in image-based selection interfaces. Images are commonly used as selectable options in contexts such as e-commerce, advertising, recommendation interfaces, subscription selection, and voting or ranking systems. In such contexts, even small shifts in selection probability may have practical consequences, especially when combined with other interface techniques. Therefore, understanding whether earlier visual availability can bias user choice is important for both identifying potential risks and designing fair choice interfaces.

In this study, we examine two image presentation formats: the baseline format and the progressive format. Wallace [39] identifies several JPEG image loading schemes; among them, we focus on two presentation behaviors. In the baseline format, an image is displayed sequentially from top to bottom. In the progressive format, the whole image is first displayed at low resolution and then gradually refined. Although these formats originate from JPEG compression schemes, we use the terms here to describe presentation behavior in the interface.

As shown in Figure 2, the baseline format incrementally reveals an image from top to bottom, whereas the progressive format initially presents the entire image at low resolution and gradually increases its clarity. In image-based selection interfaces, factors such as file size, communication delays, caching, and rendering behavior can create differences in when each option becomes visually available, as illustrated in Figure 3. We hypothesize that such timing differences can guide users' attention and influence their choices.

To investigate this hypothesis, we conducted two crowdsourcing-based experiments using a web system that we developed. In Experiment 1, we examined whether differences in image loading speed influence user selection behavior in the baseline format. In Experiment 2, we examined whether the same tendency appears in the progressive format, including two different resolution-improvement methods. Across both experiments, we investigated whether an option that becomes visually available earlier than the others is selected more frequently.

The contributions of this study are summarized as follows:

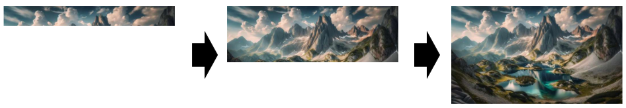
- We experimentally showed that differences in image loading speed can influence user selection behavior under controlled image-based choice conditions.
- We examined this effect across two image presentation formats, baseline and progressive presentation, and showed that earlier-loading options were selected more frequently in both formats.
- We identified image loading speed as a controllable implementation-level factor that can influence user choice even when the final interface layout remains visually equivalent across conditions.

2 Related Work

2.1 Dark Patterns and Hidden Manipulation

Dark Patterns are used in a wide range of services, including e-commerce websites [24, 28] and social networking services [25], and their use has been shown to correlate with the popularity of online services [10]. Prior work has shown that Dark Patterns can influence user behavior in practice [15, 20]. Although users often feel frustration when encountering such designs [21], many users do not notice their presence [7], and even when they do notice them, their behavior can still be influenced [2]. Accordingly, prior research has examined the detection of Dark Patterns [4, 23] as well as possible countermeasures [33, 37].

However, much of the existing research on Dark Patterns has focused on relatively static interfaces in which manipulative elements are visually recognizable, such as emphasized buttons, preselected options, or confusing wording. In contrast, less attention has been paid to manipulation that arises through dynamic and implementation-level properties of an interface. Such properties may not explicitly emphasize any option visually, yet they may still bias user choice in ways that are difficult for users to notice, interpret, or verify. This distinction is important in web interfaces,



(a) baseline format

(b) progressive format

Figure 2: Image presentation formats used in this study. The images were generated using DALL·E.

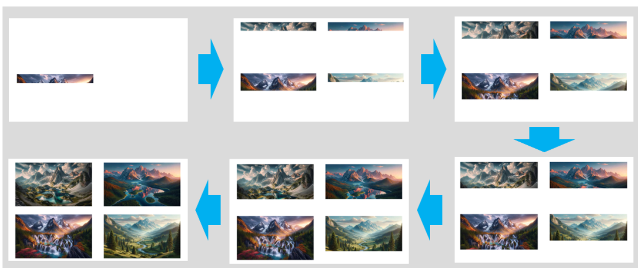


Figure 3: Example of differences in display timing among image options.

where apparent presentation timing may be shaped not only by visible design choices but also by underlying implementation.

From this perspective, we focus on image presentation methods whose apparent behavior changes dynamically depending on communication and rendering processes. Rather than treating image loading speed itself as a Dark Pattern, we examine whether controllable differences in image display timing can act as a potential seed of hidden manipulation in choice interfaces.

2.2 Choice Bias from Position, Order, and Visual Salience

It has been shown that the position of options affects their likelihood of being selected. In an experiment in which participants chose one item from four identical products arranged horizontally on a table, selection rates were 12%, 17%, 31%, and 40% from left to right, demonstrating the existence of a right-side bias [6]. Furthermore, in an experiment in which users selected one option from three choices on the web, the center option was more likely to be selected on PCs, whereas the rightmost option was more likely to be selected on mobile devices [38]. Studies have also shown that in U.S. elections, the order of candidates' names on the ballot can bias voting outcomes [17, 26], and that the order in which words are presented can affect recall rates [29]. These findings indicate that both spatial position and presentation order can influence human choice and memory.

Human visual perception also includes a phenomenon known as pop out, in which a single item that differs from a group of otherwise similar stimuli is immediately and effortlessly perceived. Previous work has shown that pop out cannot be intentionally ignored [22], and that visually salient options are more likely to be selected [12]. These findings suggest that visual salience can be used to bias user choice.

Earlier visual availability may function as a temporal counterpart to such salience. Even when multiple options are nominally presented together, one option may become perceptually available earlier than the others because of differences in loading speed, rendering timing, or placeholder removal. Such differences may attract attention or give users more time to process the earlier option, even when the final layout appears visually equivalent. In this sense, earlier visual availability may create a form of temporal salience that is difficult to notice at the static visual design level, yet still capable of biasing user attention and choice.

2.3 Limitations of Prior Work and Positioning

Prior work has established that Dark Patterns can influence user behavior, and that position, order, and visual salience can bias user choice. However, two limitations remain. First, much of the Dark Pattern literature has focused on relatively static and visually recognizable manipulations, leaving dynamic and implementation-level forms of hidden manipulation underexplored. Second, although prior work has shown that spatial position, presentation order, and pop out can affect selection, less is known about whether one option becoming visually available earlier than others can bias choice when the final interface appears visually neutral.

This gap is important because differences in visual availability timing are not merely incidental. In web interfaces, such timing can be influenced by server-side delivery, client-side rendering, caching, animation timing, or placeholder removal. From the user's perspective, such timing differences may be interpreted as natural consequences of file size, communication conditions, or system performance. From the provider's perspective, however, they can become controllable parameters that determine when each option becomes perceptually available. This asymmetry makes timing-based presentation differences difficult for users to detect or verify, while still making them potentially usable as part of a choice architecture.

From this perspective, we position controllable differences in image presentation timing not as a Dark Pattern in themselves, but as an implementation-level seed of hidden manipulation. This positioning is important because small timing-based biases may be combined with other interface techniques, such as option ordering, visual emphasis, default settings, recommendation labels, or pricing information. Based on this positioning, this study examines whether differences in image loading speed can influence user selection behavior across two image presentation formats.

3 Experimental Overview and Common Method

The research question of this study is ***how differences in the loading speed of image options influence user choice in an image selection interface that appears fair at first glance.*** To address this question, we conducted two experiments.

Experiment 1: We focused on the baseline image presentation format and examined whether differences in image loading speed affected user choice.

Experiment 2: We focused on the progressive image presentation format and examined whether differences in image loading speed affected user choice.

To examine timing-induced selection bias among image options, we recruited participants via Yahoo! Crowdsourcing (YCS) [5], which is widely used in Japan and offers high task completion rates and reliable accounts [36]. We conducted a web-based experiment in which participants selected one answer from four image options in response to simple questions.

In this study, we did not attempt to reproduce the exact technical processes of real-world image loading, such as network latency, caching, file transfer, or JPEG decoding. Instead, we abstracted these processes as controlled differences in the timing at which image options became visually available. This abstraction allowed us to isolate the effect of visual availability timing while keeping other factors constant. Accordingly, the baseline and progressive presentation formats used in our experiments should be regarded as controlled approximations of loading behaviors rather than exact reproductions of real-world image loading processes.

3.1 Task and Design

The experiment employed a four-alternative forced-choice format in which participants selected the most appropriate option from a set of image-based alternatives. All questions are provided in the Appendix. Examples include "Which cheetah looks the most natural?" and "Which orange do you think will sell the best?" These questions were designed to elicit subjective preferences, allowing participants to choose based on their immediate impressions.

To isolate the effect of image presentation format and loading speed on user selection, we minimized visual differences among the image options. Specifically, we controlled factors such as object size and color, and standardized image resolution and dimensions to reduce the influence of content-based differences on selection behavior. Because image generation models can produce visually similar images, we used DALL·E to generate candidate images and selected four images with minimal perceptual differences through discussion among the authors. All images used in the experiment were generated using DALL·E.

We used four options because prior studies have shown that a larger number of choices can increase users' cognitive load [1, 14, 34]. In addition, prior work reported that, in a 2×3 grid selection interface, the central column can be selected more frequently due to the influence of a button placed immediately before the selection screen [16]. Therefore, we arranged four options in a 2×2 grid so that the image options did not overlap with the position of the preceding button.

We prepared 15 questions to examine whether loading-speed differences biased selection behavior. In addition, because crowdsourcing-based experiments may include inattentive participants, we included five attention-check questions. For these attention-check questions, we designed items such as "Which image shows a unicycle?" and "Which image contains the most circles?" following [31], so that the correct answer could be easily determined by carefully reading the instructions. The full list of attention-check questions is provided in Appendix C. Therefore, the total number of tasks was 20.

3.2 Image Loading Speed Conditions

We defined image loading speed as the time required for an image option to become fully displayed. We prepared the following three speed conditions:

- **Synchronous Condition**: all four images were displayed in either 0.5 s or 2.0 s.
- **Early-priority Condition**: one image was displayed in 0.5 s and the remaining three images were displayed in 2.0 s.
- **Late-priority Condition**: one image was displayed in 2.0 s and the remaining three images were displayed in 0.5 s.

Hereafter, the condition in which all four images were displayed in 0.5 s is referred to as *Synchronous-fast*, and the condition in which all four images were displayed in 2.0 s is referred to as *Synchronous-slow*. We set the display times to 0.5 s and 2.0 s to examine whether selection bias would occur even when participants could clearly perceive differences in the time required for the images to become fully visible.

In each trial, the four image options began to be displayed simultaneously, but the time required for each option to become fully visible differed depending on the condition. The same presentation style was applied to both the main questions and the attention-check questions to avoid introducing noticeable artifacts specific to the experimental trials. Although the Early-priority and Late-priority Conditions were used to examine timing-induced selection bias, we also included the Synchronous Condition to provide trials in which all images were presented at the same speed.

In the Early-priority and Late-priority Conditions, the image option whose loading speed was manipulated was randomly selected from the four options in each question. In addition, the assignment of experimental conditions (Early-priority or Late-priority) to each main question was randomized across participants. All five attention-check questions were presented under the Synchronous Condition. To prevent biases caused by option position or question order, the presentation order of questions and the spatial arrangement of image options were randomized for each participant.

3.3 System Overview and Experiment Procedure

Participants who could complete the task on a PC first accessed the experimental system via a dedicated URL provided on the Yahoo! Crowdsourcing page. Because the experiment was conducted on participants' own computers, differences in screen size could lead to variations in the displayed size of the image options, potentially affecting the results.

To address this issue, we used a web-based experimental environment control system to standardize both the browser window size and the size of the image options. Before starting the experiment, participants were asked to match the size of a card image displayed on the screen with a physical credit card. This allowed us to estimate the display's pixel density and control the size of the on-screen stimuli [19, 27]. This calibration procedure was performed twice.

After calibration, participants proceeded to an instruction page where they confirmed the experimental procedure and precautions. They were instructed to use Google Chrome, Safari, or Firefox, and not to use the back button or reload button during the experiment. The experiment was restricted to PCs and could not be conducted on smartphones or other mobile devices.

After participants confirmed the instructions and began the experiment, a question was displayed as shown in Fig. 4(a). When participants pressed the "OK" button placed at the center of the screen, the image options were displayed according to the assigned presentation format, as shown in Fig. 4(b). Participants selected one answer from four alternatives and completed a total of 20 questions, consisting of 15 main questions and five attention-check questions.

Following Hoßfeld et al. [13], we intentionally controlled the timing of image presentation by preloading the images used in each trial before the experiment began and storing them in the browser cache. This minimized loading delays during presentation and allowed us to precisely control the onset time of each image.

Because the position of the "OK" button could potentially influence participants' choices, the button was placed between the four image options. After answering all questions, participants were redirected to a completion page displaying a common completion code and their participant ID, which they were required to enter on the Yahoo! Crowdsourcing page.

For each trial, we recorded the participant ID, gender, age group, trial number, time spent reading the question, selection time, question content, spatial arrangement of each option, selected option, and the position of the option whose loading speed was manipulated. The experimental system was implemented using Vue.js and PHP.

This study was approved by the university ethics review board for research involving human participants.

4 Experiment 1: Baseline Format

We investigated whether differences in image loading speed influenced user selection behavior in the baseline presentation format, in which images were incrementally revealed from top to bottom. We formulated the following hypotheses:

> **H1-1**: In the baseline presentation format, the earlier-loading option is more likely to be selected.
> **H1-2**: In the baseline presentation format, the later-loading option is less likely to be selected.

4.1 Task and Design

4.1.1 Baseline Format Condition. In this experiment, we reproduced the baseline presentation format by placing a white mask, with the same color as the background, over each image option and gradually reducing its vertical height. Specifically, the mask was divided into five horizontal segments and removed from top to bottom at equal time intervals, resulting in the incremental presentation shown in Figure 3.

Of the 15 main questions, 10 were presented under either the Early-priority Condition or the Late-priority Condition, while the remaining five questions were presented under the Synchronous Condition. In the Early-priority and Late-priority Conditions, the image option whose loading speed was manipulated was randomly selected from the four image options.

All five attention-check questions were presented under the Synchronous Condition. To prevent biases caused by option position or question order, the presentation order of the questions and the spatial arrangement of the image options were randomized for each participant.

4.2 Results

4.2.1 Data Preprocessing. We recruited 1,000 participants (500 male and 500 female) via Yahoo! Crowdsourcing. The experiment took approximately 3 minutes to complete, and each participant received 20 PayPay Points as compensation. PayPay Points are digital reward points that can be used for payments in Japan, with one point equivalent to one Japanese yen (JPY).[1] Because crowdsourcing-based experiments may include inattentive or unreliable responses, we applied several exclusion criteria before analysis.

First, participants whose screen-size calibration results fell outside the valid range, as well as those whose difference between the first and second calibration exceeded 20 pixels, were excluded from the analysis. These responses suggested that the participants had not properly performed the calibration using a physical credit card. In addition, participants were excluded if they failed to answer at least one of the five attention-check questions correctly, selected the same option position ten times in a row, had an average selection time of less than 1 second or greater than 8 seconds for the main questions, or did not follow the instructions provided in the crowdsourcing task.

The calibration criteria were intended to ensure that the displayed image size was appropriately standardized across participants, while the selection-time thresholds were adopted to conservatively exclude implausibly fast or slow responses that might indicate inattentive participation.

As a result, 589 participants were excluded, leaving 411 participants (220 male and 191 female) for analysis.

To ensure that the analysis focused on timing-induced selection bias rather than strong content-based preferences, we examined the selection rates of each option under the Synchronous Condition. We first calculated the option-level selection rates for all main questions under the Synchronous Condition, excluding the attention-check questions, and then computed the overall mean and standard deviation of these option-level selection rates. Questions that included an option whose selection rate exceeded the overall mean plus two standard deviations were excluded from the main analysis. Based on this criterion, three questions, "eraser," "cheetah,"

[1] https://paypay.ne.jp/point/

(a) Question page

(b) Selection page

Figure 4: Experiment pages

and "mountain," were excluded. This exclusion was intended to remove stimuli for which one image had a strong inherent preference independent of loading speed.

After preprocessing, the final dataset consisted of 4,932 selection trials in total, including 1,695 trials in the Early-priority Condition and 1,593 trials in the Late-priority Condition.

4.2.2 Selection Rate. To test the hypotheses, we analyzed the selection rates of the earlier-loading and later-loading options across all four positions, regardless of where the manipulated option was located. Specifically, we examined the proportion of trials in which the manipulated option was selected.

The probability that a specific option is selected at a rate of at least $a\%$ in n four-alternative forced-choice trials can be computed using a binomial distribution, as follows. We used this calculation to determine whether the observed selection rate was significantly higher than the chance level of 25%.

$$P(X \geq k) = 1 - \sum_{i=0}^{k-1} \frac{n!}{i!(n-i)!} \left(\frac{1}{4}\right)^{i} \left(1 - \frac{1}{4}\right)^{n-i} \quad (1)$$
$$\text{where } k = [\frac{n \times a}{100}]$$

In the Early-priority Condition ($n = 1,695$), the earlier-loading option was selected in 28.73% of trials. Based on Eq. (1), a one-sided exact binomial test against the chance level of 25% showed that this selection rate was significantly higher than chance ($p = .003$, 95% CI [26.63%, 30.93%]). These results indicate that the earlier-loading option was selected more frequently than expected by chance.

In contrast, in the Late-priority Condition ($n = 1,593$), the later-loading option was selected in 23.92% of trials. A one-sided exact binomial test against the chance level of 25% showed that this selection rate was not significantly higher than chance ($p = .834$, 95% CI [21.89%, 26.08%]). These results indicate that the later-loading option was not selected less frequently than expected by chance.

Thus, H1-1 was supported, whereas H1-2 was not supported.

To further examine the robustness of these results, we conducted an additional analysis including all 15 main questions. Specifically, the three excluded questions ("eraser", "cheetah", and "mountain"), which exhibited strong image preferences under the equal-loading baseline condition, were reintroduced into the analysis. Importantly, the same tendency was observed even when these three questions were retained. In the analysis including all 15 questions, the selection rate of the earlier-loading option was 28.40%, which was still higher than the chance level of 25%.

Next, we examined selection rates by position under the Synchronous, Early-priority, and Late-priority Conditions, as shown in Figure 5. In the Synchronous Condition, the upper-left position showed a lower selection rate than the expected value, while the lower-left position showed a slightly higher selection rate. The upper-right and lower-right positions were close to the expected value.

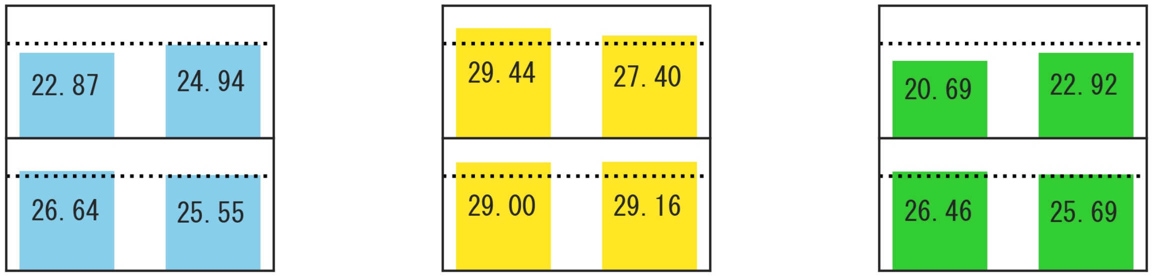
Panels (b) and (c) show the selection rates for each position when the manipulated option was assigned to that position. For example, in Panel (b), when the earlier-loading option was assigned to the upper-left position, the selection rate for that option was 29.44%. The same interpretation applies to the Late-priority Condition in Panel (c).

In the Early-priority Condition, selection rates exceeded the chance level by at least 2.40 percentage points across all positions. However, the selection rate was lower when the earlier-loading option was assigned to the upper-right position than when it was assigned to the other three positions.

In the Late-priority Condition, selection rates exceeded the chance level when the later-loading option was assigned to the lower row, whereas they fell below the chance level when it was assigned to the upper row. This pattern was similar to the position-based tendency observed in the Synchronous Condition.

4.2.3 Selection Time. Table 1 shows the mean selection time under each condition. Selection time was defined as the duration from when the selection page was displayed to when an option was selected.

The Synchronous-fast Condition, in which all four images were fully displayed in 0.5 s, yielded the shortest mean selection time among the four conditions (4.57 s). In contrast, the Synchronous-slow Condition, in which all four images were fully displayed in 2.0 s, yielded the longest mean selection time (5.71 s). A Mann–Whitney U test showed that this difference was statistically significant ($U =$



(a) Synchronous Condition **(b) Early-priority Condition** **(c) Late-priority Condition**

Figure 5: Selection rates by position under each condition. The 2×2 grid of graphs indicates the spatial arrangement of the image options as presented during the experiment. The dashed line in each plot represents the chance level of 25%, corresponding to the expected probability of each option being selected in a four-alternative forced-choice task. Note that the values in panels (b) and (c) do not sum to 100%, because each value represents the selection rate when the manipulated option was assigned to that position.

Table 1: Mean Selection Time by Condition and Selection of the Manipulated Option (s)

		Synchronous-fast	Synchronous-slow	Early-priority Condition	Late-priority Condition
Mean Selection Time		4.57	5.71	5.33	5.01
Manipulated option	selected	-	-	5.20	5.17
	not selected	-	-	5.39	4.96

$2, 357, 582.5$, $p < .001$). The mean selection time was 5.33 s in the Early-priority Condition and 5.01 s in the Late-priority Condition.

Table 1 also shows the mean selection time depending on whether participants selected the manipulated option. In the Early-priority Condition, selection time was slightly shorter when participants selected the earlier-loading option than when they did not. In the Late-priority Condition, selection time was slightly longer when participants selected the later-loading option than when they did not. However, these differences were small, and Mann–Whitney U tests revealed no statistically significant differences between trials in which the manipulated option was selected and those in which it was not in either the Early-priority Condition ($U = 282195.5$, $p = .190$) or the Late-priority Condition ($U = 236895.0$, $p = .443$).

4.3 Discussion

4.3.1 Selection Rates and Effects of Earlier and Later Loading. In the baseline format, the earlier-loading option was selected more frequently than the chance level, whereas the later-loading option was selected at approximately the chance level. These results suggest that earlier visual availability increased the likelihood that an option would be selected, while delayed visual availability did not clearly decrease the likelihood of selection.

One possible explanation for this asymmetry is the primacy effect. The primacy effect refers to the tendency for information encountered first to leave a stronger impression, and it has been reported to be prominent in visual evaluation tasks [18]. In the Early-priority Condition, there was a 1.5-second gap between the moment the earlier-loading option became fully visible and the moment the other three options became fully visible. During this interval, participants could inspect the earlier-loading option before comparing it with the others. This may have strengthened its memory representation or increased its attentional priority, leading to a higher selection rate.

In contrast, in the Late-priority Condition, although the later-loading option became fully visible 1.5 seconds after the other three options, participants could wait until all options were visible before making a decision. This may explain why the later-loading option was not clearly selected less frequently than chance.

Although baseline image preferences existed for several questions, their inclusion had little influence on the overall selection rate. Therefore, image preference alone is unlikely to explain the increased selection of earlier-loading options. Instead, loading order appears to have contributed independently.

4.3.2 Effects of Option Position. The effect of earlier loading also appeared to interact with option position. When the earlier-loading option was assigned to the upper-right position, its selection rate was lower than when it was assigned to the other positions. This may be related to eye movement patterns. Previous studies have reported that people tend to fixate first on the left and upper regions when viewing two-dimensional layouts [8, 9]. Therefore, the timing advantage of earlier loading may have been stronger when it aligned with participants' initial viewing tendencies.

In the Late-priority Condition, the selection rate for the upper-left option was substantially lower when it was the later-loading option. One possible explanation is that participants initially oriented toward the upper-left region, but their attention shifted to the other three options because those options became fully visible earlier. This suggests that presentation timing and spatial viewing tendencies may jointly shape selection behavior.

4.3.3 Selection Time. The mean selection times in both the Early-priority and Late-priority Conditions exceeded 5 seconds, even though all images became fully visible within 2 seconds. This suggests that many participants waited until all four options were visible and then compared them before making a selection.

The Early-priority Condition showed a slightly longer mean selection time than the Late-priority Condition. One possible explanation is that, in the Early-priority Condition, participants first saw the earlier-loading option and then waited for the remaining three options to become fully visible before comparing all options. This additional comparison process may have increased selection time. Nevertheless, the earlier-loading option was selected more frequently, suggesting that early visual availability may have influenced participants' impressions even when they waited until all options were visible before choosing.

5 Experiment 2: Progressive Format

We investigated whether differences in image loading speed influenced user selection behavior in the progressive presentation format, in which images gradually became clearer over time. In addition, we compared two resolution-improvement methods, the blur method and the pixel method, to examine whether the way in which image clarity improved affected selection time or the selection rate of the earlier-loading option. We formulated the following hypotheses:

> **H2-1**: In the progressive format, the earlier-loading option is more likely to be selected, regardless of the resolution-improvement method.
> **H2-2**: The blur method results in shorter selection times than the pixel method.
> **H2-3**: The blur method leads to a higher selection rate for the earlier-loading option than the pixel method.

H2-1 was based on the results of Experiment 1, which showed that the earlier-loading option was selected more frequently in the baseline format. H2-2 was based on the assumption that the blur method would allow users to perceive the overall shape of objects more easily than the pixel method, thereby enabling faster visual processing. H2-3 was based on the idea that, if the blur method supports faster perceptual processing, choices under the blur method may be more strongly influenced by earlier visual availability.

5.1 Design

5.1.1 Question and Option Selection. Although including or excluding these three questions (the "eraser," "cheetah," and "mountain" questions) did not substantially affect the selection rates under the early- and delayed-loading conditions, they were omitted in Experiment 2 as a precaution in order to eliminate any potential influence of the image options themselves. Instead, we created new questions so that the number of main questions and image options remained consistent with Experiment 1. The full set of question items is provided in the Appendix. All image options used in the experiment were generated using DALL·E.

5.1.2 Progressive Format Condition. In this experiment, image options were presented using two resolution-improvement methods in the progressive format: the blur method and the pixel method, as shown in Figure 6.

In the blur method, images were initially displayed with a 20 px blur using the CSS `filter` property. The blur was then gradually reduced over time in fixed steps until the images became fully clear, following the assigned loading-speed condition.

In the pixel method, images were initially displayed in a heavily pixelated state by reducing and re-rendering their resolution using the HTML Canvas element. The level of pixelation was then gradually decreased over time in fixed steps until the images became fully clear, following the assigned loading-speed condition.

Participants were randomly assigned to either the blur method or the pixel method when they accessed the experimental website. In each trial, the four image options began to be displayed simultaneously, but the time required for each option to reach full clarity differed depending on the speed condition.

The 15 main questions were evenly assigned to the Early-priority, Late-priority, and Synchronous Conditions, with five questions in each condition. Unlike in Experiment 1, the number of questions was balanced across the loading-speed conditions because Experiment 2 was designed to statistically compare the blur and pixel methods.

5.2 Results

5.2.1 Data Preprocessing. As in Experiment 1, we recruited 1,000 participants (500 male and 500 female) via Yahoo! Crowdsourcing. The experiment took approximately 3 minutes to complete, and each participant received 40 PayPay Points as compensation. Because crowdsourcing-based experiments may include inattentive or unreliable responses, we applied several exclusion criteria before analysis.

Participants were included in the analysis only when their screen-size calibration results satisfied both of the following conditions: (i) both the first and second adjustments were between 200 px and 500 px, and (ii) the adjustment error was less than 50 px. Unlike Experiment 1, the calibration tolerance was relaxed to 50 pixels because the calibration task was intended to provide an approximate standardization of stimulus size rather than an exact physical measurement.

In addition, participants were excluded if they answered at least one attention-check question incorrectly, selected the same option position ten times in a row, had extremely short or long mean selection times for the main questions based on the outlier criterion proposed by Rousseeuw [32], or did not follow the instructions provided in the crowdsourcing task. Unlike Experiment 1, response-time outliers were identified using Rousseeuw's criterion, which provides a more systematic distribution-based approach than fixed thresholds.

As a result, 475 participants were excluded, leaving 525 participants (259 male and 266 female) for analysis. The number of analyzed trials is shown in Table 2.

In Experiment 1, we also examined an additional exclusion criterion in which questions with a selection rate exceeding the mean + 2SD threshold were excluded in the synchronous condition. The results were consistent regardless of whether this criterion was applied, and the selection rate of the earlier-loading option remained

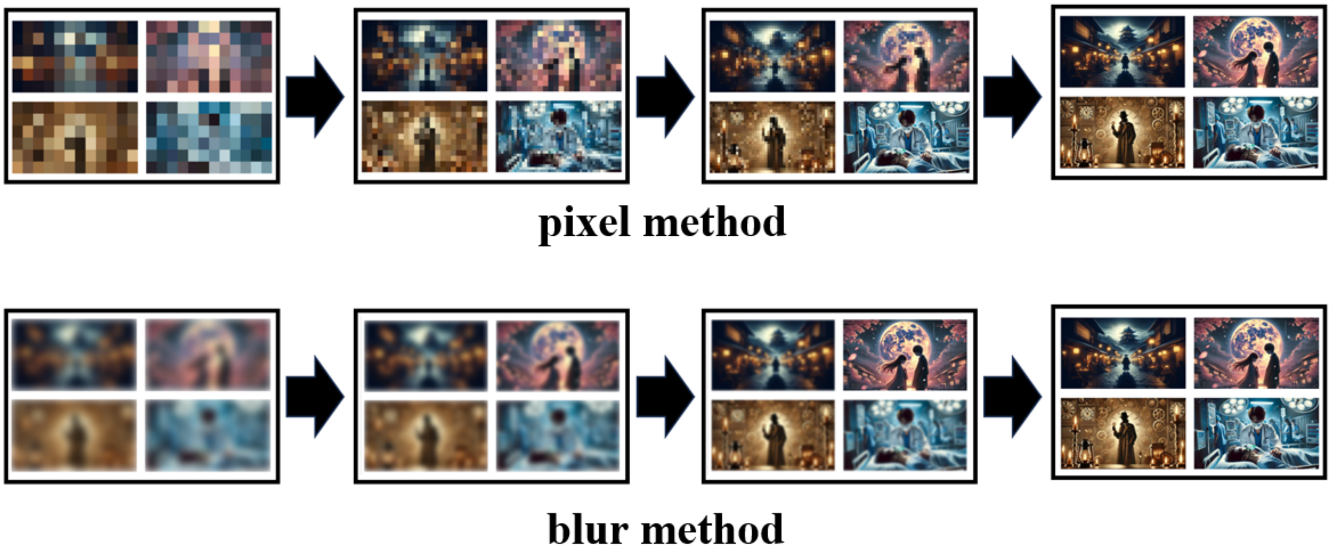


Figure 6: Two resolution-improvement methods used in Experiment 2. The upper row shows the pixel method, and the lower row shows the blur method.

significantly higher than the chance level in both cases. Therefore, in Experiment 2, we did not apply this mean + 2SD-based exclusion of questions in the synchronous condition in order to maintain consistency in the analysis of selection behavior under equal timing conditions.

5.2.2 Selection Rate. To test H2-1, we analyzed the proportion of trials in which the earlier-loading option was selected in the Early-priority Condition, combining the blur and pixel methods. As in Experiment 1, we used the binomial distribution shown in Eq. (1) to determine whether the selection rate exceeded the chance level of 25%.

In the Early-priority Condition (n = 2,625), the earlier-loading option was selected in 28.15% of trials, exceeding the chance level of 25%. Based on Eq. (1), a one-sided exact binomial test against the chance level of 25% showed that this selection rate was significantly higher than chance(p < .001, 95% CI [26.46%, 29.90%]). These results indicate that the earlier-loading option was selected more frequently than expected by chance, supporting H2-1.

When analyzed separately by method, the earlier-loading option was selected in 28.34% of trials in the blur method (n = 1,235). A one-sided exact binomial test against the chance level of 25% showed that this selection rate was significantly higher than chance (p = .004, 95% CI [25.90%, 30.92%]).

Similarly, in the pixel method (n = 1,390), the earlier-loading option was selected in 27.99% of trials. A one-sided exact binomial test against the chance level of 25% showed that this selection rate was significantly higher than chance (p = .005, 95% CI [25.69%, 30.41%]).

5.2.3 Selected Position. Figure 7 shows the selection rates by position under the Synchronous and Early-priority Conditions. In the Synchronous Condition, the selection rate of the upper-right position was approximately 1.0 percentage point lower than the chance level, while the lower-left position was approximately 1.6 percentage points higher. The upper-left and lower-right positions were close to the chance level.

Figure 7(b) shows the selection rates for each position in the Early-priority Condition when combining both the blur and pixel methods. These values represent the proportion of trials in which the earlier-loading option was selected when it was assigned to each position. For example, the value of 29.47% for the upper-left position indicates that the upper-left option was selected in 29.47% of trials when it was the earlier-loading option.

In the Early-priority Condition, the selection rates for three positions other than the lower-right position exceeded the chance level by at least 3.82 percentage points. In contrast, the lower-right position remained close to the chance level even when it was the earlier-loading option.

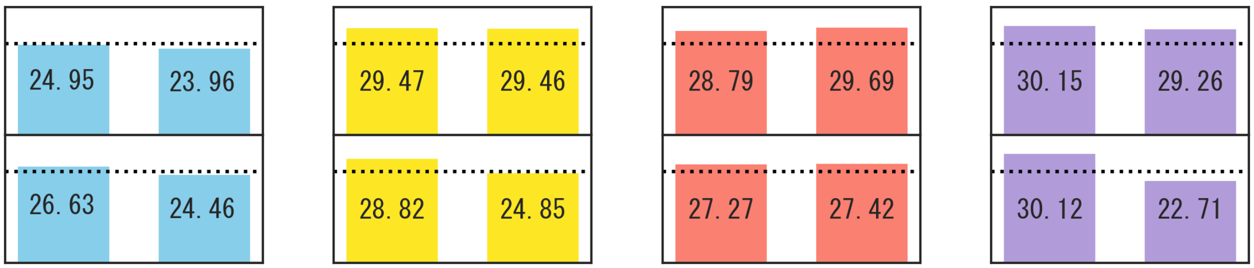
Figures 7(c) and (d) show the position-wise selection rates separated by method. In the blur method, the selection rates exceeded the chance level in all four positions. In the pixel method, the selection rates for three positions were around 30%, whereas the lower-right position was substantially lower at 22.71%, falling below the chance level.

5.2.4 Selection Time and Method Comparison. Table 3 shows the mean selection times for each method under the Synchronous and Early-priority Conditions, as well as the overall mean across the 15 main questions. Selection time was defined as the time from when the option display screen was presented to when a participant made a selection.

In both methods, the Synchronous-fast Condition yielded the shortest selection times, whereas the Synchronous-slow Condition yielded the longest selection times. In the Early-priority Condition, both methods yielded selection times in the six-second range, which

Table 2: Number of Trials per Condition After Exclusion

	Early-priority Condition	Late-priority Condition	Synchronous-fast	Synchronous-slow
Blur method	1,235	1,235	630	605
Pixel method	1,390	1,390	697	693



(a) Synchronous **(b) Early-priority(both)** **(c) Early-priority(blur)** **(d) Early-priority(pixel)**

Figure 7: Selection rates by position under the Synchronous and Early-priority Conditions. The 2×2 grid of graphs indicates the spatial arrangement of the image options as presented during the experiment. The dashed line in each plot represents the chance level of 25%, corresponding to the expected probability of each option being selected in a four-alternative forced-choice task. Note that the values in panels (b), (c) and (d) do not sum to 100%, because each value represents the selection rate when the manipulated option was assigned to that position.

Table 3: Mean Selection Time by Method and Condition (s)

	Synchronous-fast	Synchronous-slow	Early-priority Condition	Total
Blur method	5.19	6.60	6.19	5.86
Pixel method	5.27	7.09	6.78	6.32

were longer than those in the Synchronous-fast Condition but shorter than those in the Synchronous-slow Condition.

To test H2-2, we compared the overall selection times between the blur and pixel methods. Because the normality assumption was rejected, we conducted a Mann–Whitney U test. The result showed a significant difference between the two methods ($U = 30158$, $p = .016$), indicating that the blur method yielded shorter selection times than the pixel method. Thus, H2-2 was supported.

To test H2-3, we compared the selection rates of the earlier-loading option between the blur and pixel methods in the Early-priority Condition. The selection rate was 28.34% in the blur method and 27.99% in the pixel method. A two-proportion z-test showed no significant difference between the methods ($z = .202$, $p = .840$, $h = .008$). Thus, H2-3 was not supported.

5.3 Discussion

5.3.1 Selection Rate in the Progressive Format. Across the blur and pixel methods, the earlier-loading option was selected more frequently than the chance level in the progressive format. This result is consistent with Experiment 1 and suggests that earlier visual availability can increase the likelihood of selection across different image presentation formats. However, the selection rates of the earlier-loading option were similar between the blur and pixel methods, and H2-3 was not supported. One possible explanation is that both methods allowed participants to grasp the overall content of the images early enough for the difference between blurring and pixelation to have little influence on selection. In other words, while the speed at which one option became clear affected selection, the specific resolution-improvement method did not substantially change the strength of this effect.

5.3.2 Effects of Option Position. In the Early-priority Condition, both methods showed a relatively high selection rate for the upper-left position and a relatively low selection rate for the lower-right position. As discussed in Experiment 1, this pattern may be related to eye movement behavior. When viewing two-dimensional displays, users tend to fixate first on the left and upper regions [8, 9]. In addition, previous studies have reported that primacy effects are more likely to occur when information is presented simultaneously in parallel [41]. The interaction between these viewing tendencies and image loading timing may have influenced the observed position-based differences.

5.3.3 Selection Time. The blur method resulted in shorter selection times than the pixel method. One possible explanation is that the blur method allowed participants to perceive the overall shape of the image options more easily. Regions of interest in images tend to be concentrated near the center [11], and many stimuli in this experiment, such as oranges, diamonds, and doors, had their main objects located near the center. Under such conditions, the blur method may have facilitated earlier recognition of the object's overall shape compared to the pixel method, reducing the time needed to compare the four alternatives.

However, this shorter selection time did not lead to a significantly higher selection rate for the earlier-loading option in the blur method. This suggests that the resolution-improvement method affected how quickly participants made selections, but did not substantially change the degree to which earlier visual availability biased selection.

6 General Discussion

6.1 Interpretation and Integration

Across the two experiments, earlier-loading image options were selected more frequently than expected in both the baseline and progressive presentation formats. Although the observed effect was modest, with selection rates increasing from the chance level of 25% to approximately 28%, it was consistently observed across different presentation formats. These findings suggest that even seemingly neutral implementation-level factors, such as image loading speed and presentation timing, can systematically influence user choice in image-based selection interfaces. The purpose of this study was not to show that image loading speed alone strongly determines user choices, but rather that a subtle and controllable timing difference can systematically shift selection behavior.

The robustness analyses further strengthen this interpretation. Although several questions exhibited baseline image preferences under the equal-loading condition, the earlier-loading option continued to be selected more frequently even when these questions were included in the analysis. This finding suggests that the observed tendency cannot be explained solely by intrinsic image preferences and that loading order contributed independently to user choice. Thus, image loading speed should be understood as an implementation-level factor that can influence user choices rather than as an effect arising only from stimulus preference.

Here, "hidden" does not necessarily mean that users are unable to perceive differences in loading timing. Rather, differences in image loading speed can also arise from ordinary technical factors, such as network latency or image file size. Therefore, even when a timing difference itself is noticeable, users may not necessarily interpret it as an intentional mechanism for influencing their choices. In this sense, the potential influence on choice can be embedded within an interface behavior that otherwise appears technically neutral.

Experiment 2 further demonstrated that the earlier-loading option was selected more frequently in both the blur and pixel presentation methods, while no significant difference in selection rate was observed between the two methods. This result suggests that the observed bias is attributable to earlier visual availability rather than to a specific rendering technique. Although the blur method resulted in shorter selection times than the pixel method, this difference affected the speed of decision making rather than the direction of user choice. Together with the results of Experiment 1, these findings indicate that the influence of earlier image presentation is robust across different visual rendering methods.

These findings have implications for contexts in which images serve as selectable options, such as e-commerce websites, online advertisements, recommendation interfaces, subscription selection, and voting or ranking systems. As illustrated in Figure 8, in real-world interfaces such as e-commerce platforms or manga subscription services, providers could potentially guide users toward preferred items simply by rendering those images earlier than alternatives—without any explicit visual cue or persuasive content. In such contexts, even small shifts in selection probability may have practical consequences, especially when combined with other interface techniques such as option ordering, visual emphasis, default settings, recommendation labels, or pricing information.

6.2 Design Implications

Based on these results, designers of websites and applications should be cautious when implementing interfaces in which specific options become visually available earlier than others. Even when all options eventually appear in the same layout and with the same visual design, differences in visual availability timing may bias user decisions.

This concern is particularly important in choice interfaces where options are represented by images or thumbnails. Such interfaces are not limited to e-commerce websites. For example, in many restaurants in Japan, including family restaurants and sushi restaurants, customers select menu items using tabletop ordering terminals that display food photographs. In such contexts, a restaurant could potentially make certain menu items become visually available earlier than others, such as high-priced items or items that need to be sold quickly before disposal. From the service provider's perspective, this could increase sales or reduce waste. From the user's perspective, however, such timing-based steering may not align with their original preferences or interests, especially when the influence is difficult to recognize.

Similar concerns apply to content platforms such as video streaming services, manga applications, and other subscription-based services. These platforms often present movies, dramas, or comics as thumbnail-based choices. If a platform controls thumbnail loading speed so that sponsored, promoted, or strategically prioritized content becomes visually available earlier than other content, users' viewing choices may be subtly steered without explicit recommendation labels or visual emphasis. This could be beneficial for the platform or advertisers, but may reduce transparency and user autonomy.

These examples suggest that image loading speed should be considered part of the broader choice architecture of visual interfaces. Timing differences may arise unintentionally due to network latency, file-size differences, caching, or rendering behavior, but they may also be shaped through implementation-level decisions such as response ordering, rendering timing, animation timing, and placeholder removal. Therefore, fairness-oriented interface design should consider not only visible layout and styling, but also when each option becomes perceptually available to users.

In fairness-critical contexts, such as voting, ranking, recommendation, comparison, or subscription-selection interfaces, designers should ensure that all options are presented under equivalent timing and perceptual conditions. Practical approaches include synchronizing the presentation of all options, using placeholder rendering or

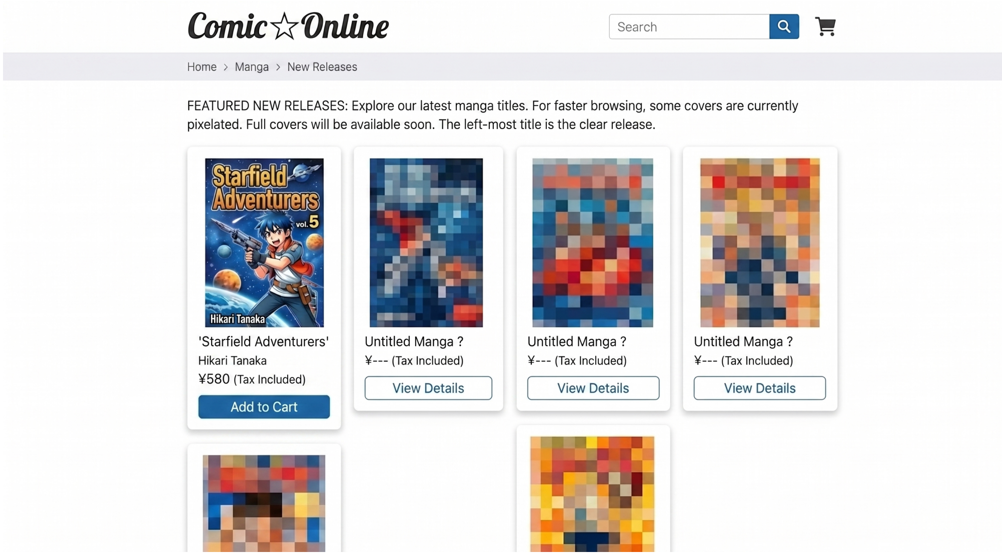


Figure 8: An illustrative example of a comic platform where only one title has fully loaded, with remaining covers pixelated and metadata unavailable, potentially directing user attention and selection toward the loaded item. This illustrative image was generated using DALL·E and was not used as an experimental stimulus.

skeleton screens, and preventing one option from becoming recognizable earlier than others. In other words, a visually fair interface may still be unfair at the level of perceived timing.

This study also suggests a broader caution for users and researchers. Seemingly ordinary interface behaviors, such as asynchronous image loading, may influence decision-making in subtle and non-transparent ways. Although we did not directly measure whether participants were aware of the loading-speed differences, the consistent selection bias observed across experiments suggests that such timing differences can affect choices even when they are not presented as explicit persuasive cues.

6.3 Limitations

This study has several limitations. First, both experiments were conducted on PCs and therefore differ from real-world service environments in terms of device characteristics, UI configuration, and interaction patterns such as scrolling. The effects observed in this study may differ on smartphones, where screen size, touch interaction, and scrolling behavior can change how users inspect visual options.

Second, this study used a relatively simple four-alternative image selection task. Although this design allowed us to isolate the effect of image loading speed, real-world decision-making often involves more complex information, including text descriptions, prices, ratings, rankings, labels, and prior preferences. Therefore, caution is required when generalizing the results to actual purchase decisions or other high-stakes choices.

Third, the image options were limited to 15 categories and were generated using DALL·E. Although we attempted to minimize content-based differences among options, subtle differences in image attractiveness or recognizability may still have influenced selection behavior. We addressed this issue by excluding questions that showed strong content-based preferences under the Synchronous Condition, but future work should further validate stimulus balance through pretests or larger stimulus sets.

Fourth, the range of presentation conditions was limited. We used two loading-speed levels, 0.5 s and 2.0 s, and examined two presentation formats: baseline and progressive. In the early- and delayed-loading conditions, the difference in loading time was fixed at 1.5 s (0.5 s vs. 2.0 s). Therefore, the present study does not allow us to determine whether the magnitude of the timing difference affects the strength of the observed effect. The boundary conditions of the effect remain unclear, including whether smaller timing differences, longer delays, or more complex combinations of loading behavior would produce similar or stronger effects. In addition, the present study implemented display formats that approximate baseline and progressive image loading behaviors. However, these implementations do not fully replicate the exact dynamics of real-world image loading processes, such as network latency or JPEG decoding behavior.

Finally, we did not directly measure participants' awareness or interpretation of the loading-speed manipulation. Because the timing difference between the earlier- and later-loading options was 1.5 s, it may have been noticeable to some participants, and we cannot rule out the possibility that awareness of this difference contributed to the observed effect. Future work should investigate whether participants were aware of the differences in image loading speed and whether the observed choice bias persisted despite such awareness.

Importantly, however, perceiving a difference in loading timing does not necessarily mean recognizing it as an intentional mechanism for influencing choice. Our study did not distinguish between awareness of the timing difference itself and awareness of its potential influence or intent. A simple post-task questionnaire may not be sufficient to capture this issue, because participants may retrospectively rationalize their choices [30] or fail to report subtle attentional influences. Future work should examine awareness and interpretation using complementary methods such as interviews, think-aloud protocols, eye tracking, or mixed-method studies with smaller but more closely observed samples.

6.4 Future Work

Future work should examine whether the observed effect generalizes to more realistic interfaces and decision-making contexts. One important direction is to conduct experiments using smartphones and real-world interaction patterns, including scrolling, touch input, and smaller displays. Another direction is to test more realistic services, such as e-commerce platforms, online advertisements, subscription-selection pages, and recommendation interfaces.

Future studies should also examine more complex decision-making tasks. For example, image loading speed may interact with product prices, recommendation labels, ratings, default selections, or visual emphasis. Investigating such combinations would clarify whether small timing-based biases can accumulate with other interface techniques and produce larger effects in realistic choice environments.

In addition, future work should explore a broader range of presentation conditions. This includes finer-grained variations in loading speed, different numbers of options, different layouts, combinations of baseline and progressive presentation, and different types of placeholders or skeleton screens. Such studies would help clarify when timing-induced selection bias emerges, when it disappears, and how designers can prevent it in fairness-critical interfaces.

7 Conclusion

In this paper, we investigated whether subtle differences in image loading speed can bias user choice in image-based selection interfaces that appear visually neutral. Specifically, we focused on two image presentation formats inspired by JPEG loading behavior: the baseline format, in which images are incrementally revealed from top to bottom, and the progressive format, in which the entire image gradually becomes clearer over time.

We conducted two crowdsourcing-based experiments to examine whether options that became visually available earlier than others were selected more frequently. The results showed that earlier-loading options were selected more frequently than expected in both presentation formats. In the progressive format, the blur method resulted in shorter selection times than the pixel method, although the selection rate of the earlier-loading option did not significantly differ between the two methods.

These findings suggest that image loading speed can act as a controllable implementation-level factor that biases user choice. Although the observed effects were modest, they were consistent across experiments and may become practically important when combined with other interface techniques. We therefore argue that timing differences in image presentation should be considered a potential seed of hidden manipulation, especially in visual choice interfaces where fairness, transparency, and user autonomy are important.

Acknowledgments

This work was supported by JSPS KAKENHI Grant Number JP22K12135.

The authors used ChatGPT solely to improve the clarity and readability of the English text. DALL·E was used to generate candidate images for the experimental options; however, the experimental conditions, option design, and final selection of stimuli were determined by the authors. Some figures in this paper, depicting illustrative use cases and hypothetical scenarios, were also generated using DALL·E. All scientific content, including the research design, experimental procedures, data analysis, interpretation, and conclusions, was created independently by the authors.

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A The main questions used in Experiment 1

Questions
Which aurora would you most like to see?
Which button would you most like to press?
Which diamond would you most like to have?
Which door looks the heaviest?
Which waterfall do you like the most?
Which fishing pond looks most likely to have fish?
Which tulip would you like to display at home?
Which lemon looks the sourest?
Which orange do you think will sell the best?
Which seaside view would you most like to visit?
Which food looks the spiciest?
Which person looks like a strong shogi player?
Which eraser would you like to use?
Which mountainous area would you like to visit?
Which cheetah looks the most natural?

B The main questions used in Experiment 2

Questions
Which aurora would you most like to see?
Which button would you most like to press?
Which diamond would you most like to have?
Which door looks the heaviest?
Which waterfall do you like the most?
Which fishing pond looks most likely to have fish?
Which tulip would you like to display at home?
Which lemon looks the sourest?
Which orange do you think will sell the best?
Which seaside view would you most like to visit?
Which food looks the spiciest?
Which person looks like a strong shogi player?
Which comic would you most like to read?
Which movie thumbnail would you choose?
Which song would you most like to listen to?

C The attention-check questions used in Experiment 1 and Experiment 2

Questions
Which image contains the largest number of people?
Which image contains the most circles?
Which image shows a unicycle?
Which image was taken at night?
Which image shows a three-story house?