**Exploring the Potential of Online Webcam-based Eye Tracking
in Decision-Making Research and Influence Factors on Data Quality**

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Abstract

Recent developments of open-source online eye-tracking algorithms suggests that they may be ready for use in online studies, thereby overcoming the limitations of in-lab eye-tracking studies. However, to date there have been limited tests of the efficacy of online eye-tracking for decision-making and cognitive psychology. In this online study, we explore the potential and the limitations of online eye-tracking tools for decision-making research using the webcam-based open-source library *Webgazer* (Papoutsaki et al., 2016). Our study had two aims. For our first aim we assessed different variables that might affect the quality of eye-tracking data. In our experiment ($N = 210$) we measured a within-subjects variable of adding a provisional chin rest and a between-subjects variable of corrected vs uncorrected vision. Contrary to our hypotheses, we found that the chin rest had a negative effect on data quality. In accordance with our hypotheses, we found lower quality data in participants who wore glasses. Other influence factors are discussed, such as the frame rate. For our second aim ($N = 44$) we attempted to replicate a decision-making paradigm where eye-tracking data was acquired using offline means (Amasino et al., 2019). We found some relations between choice behavior and eye-tracking measures, such as the last fixation and the distribution of gaze points at the moment right before the choice. However, several effects could not be reproduced, such as the overall distribution of gaze points or dynamic search strategies. Therefore, our hypotheses only find partial evidence. This study gives practical insights for the feasibility of online eye-tracking for decision making research as well as researchers from other disciplines.

Keywords: online-studies, research methods, data quality, intertemporal discounting, multi-attribute choice

Practical Implications of Online Eye-Tracking

As a preemptive summary, we list five major lessons we learned from applying online eye-tracking for decision making research. Our suggestions, which are further detailed in the discussion section, provide practical guidelines for the design and procedures of online eye-tracking studies in the field of decision-making and other disciplines.

1. One of the greatest challenges currently facing this tool is the large degree of variability in data quality, both with-in and between-subjects. Frequent validation and calibration of the eye-tracking data is suggested, particularly for participants with insufficient data quality. As a robust data quality measure for validation, we recommend the hit ratio, which is detailed in the Methods section (Yang & Krajbich, 2020).
2. Giving clear and specific instructions to the participant can have a positive effect on the data quality. If possible, the participants should keep a natural but still head position, wear contact lenses instead of glasses, and use a desktop computer and an external monitor.
3. Online eye-trackers are best suited for testing relatively simple relationships between gaze and choice behavior, such as the last fixation. More subtle effects, such as gaze transitions, may be more difficult to assess.
4. Default settings of eye-trackers should be considered before data collection (Orquin & Holmqvist, 2018). The current version of Webgazer enables a Kalman filter, which, if turned on, makes the gaze prediction of fast gaze saccades more difficult.
5. Because of the lower accuracy of online eye-tracking, areas of interest (AOIs) should be larger than 15% of the total screen size. The most reliable gaze data could be achieved for a binary choice design with one stimulus for each choice option. These

choice options should be horizontally aligned the choice options to ensure a large distance between the AOIs and compensate for inaccurate gaze predictions.

Exploring the Potential of Online Webcam-based Eye Tracking in Decision-Making Research and Influence Factors on Data Quality

Eye-tracking Studies Help Understanding of Human Decision-Making Behavior

Eye-tracking is an important research tool for understanding human decision-making (Meißner & Decker, 2010; Orquin & Mueller-Loose, 2013) and the role of visual attention, i.e., how humans recognize and select visual information (Bundesen, 1990). It has been applied to understand everyday decisions in various areas, such as finance (Krol & Krol, 2019), medicine (Al-Moteri et al., 2017), and nutrition (Gidlöf et al., 2013). Compared to other methods (e.g., fMRI), eye-tracking is less intrusive and enables a more naturalistic research environment (Schulte-Mecklenbeck et al., 2017).

Benefits of online eye-tracking studies

Computer scientists have recently developed Open Source computer algorithms that can predict gaze locations based on the user's interaction images from the user's webcam (Papoutsaki et al., 2016). This enabled researcher of various fields to combine the benefits of eye-tracking and online studies, which can result in more affordable, demographically diverse, and representative research samples (Goodman et al., 2013; Goodman & Paolacci, 2017; Henrich et al., 2010; Peterson, 2001). Moreover, in times of crisis, such as the COVID-19 pandemic in 2020, research labs were closed and online eye-tracking methods appeared as a last-resort alternative for many researchers (Yang & Krajbich, 2020).

Online Eye-Tracking Tools

For this study, we will focus on the open source JavaScript based library Webgazer (Papoutsaki et al., 2016), which is one of the most popular online eye-tracking tools of this

kind. In addition to the eye-images from the user's webcam, Webgazer uses user's mouse movements and clicks as training data, assuming an alignment between eye- and cursor-movements (Huang et al., 2012). Webgazer is an advancement of prior webcam-based eye-trackers (Huang et al., 2012; Lu et al., 2012; Xu et al., 2015) in such that it works remotely, requires a low amount of calibration, and focuses on predicting gaze points. Webgazer is still being actively developed and maintains an active discussion board on the GitHub repository page (Papoutsaki et al., 2020).

Online Eye-Tracking Tools Have yet to see use

Despite the benefits that online eye-tracking promises to bring, only a few behavioral researchers have made use of it so far (but see Federico & Brandimonte, 2019; Hsu et al., 2018; Madsen et al., 2019; Robal et al., 2018; Zhao et al., 2017). Only one methods-focused study replicated a simple binary decision task using Webgazer (Yang & Krajbich, 2020). A plausible reason for these reservations is uncertainty regarding the quality of the data obtained in the online context. Online participants could be worse at concentrating (Arechar & Rand, 2020; Goodman et al., 2013), and more likely to drop out because of data protection concerns (Semmelmann & Weigelt, 2018), high calibration effort—which can take up to 50% of the total study time (Semmelmann & Weigelt, 2018)—or because they do not meet the technical requirements, such as computer processing power (Yang & Krajbich, 2020).

Study Aims & Hypotheses

For this study we specifically tested two major aims with five hypotheses as detailed below. The first aim concentrates on influence factors on data quality of online eye-tracking, which could indicate efficient improvements for the setup of future eye-tracking studies. The second aim concentrates on testing the feasibility decision-making studies with online eye-

tracking by replicating a choice task where eye-tracking data was acquired using offline means (Amasino et al., 2019).

Study Aim 1: Influence Factors on the Data Quality of Online Eye-Tracking

While previous studies showing the general feasibility for simple cognitive tasks (Papoutsaki et al., 2016; Semmelmann & Weigelt, 2018; Yang & Krajbich, 2020), there remain unresolved issues concerning the influence of participant-related factors on the data quality. The literature on in-lab eye-trackers suggests head movements and glasses as potentially efficiently controllable influence factors on the spatial resolution of online eye-tracking.

Head Movements

First, eye-tracking data becomes less accurate and precise when the participant moves their head (Hessels et al., 2015; Niehorster et al., 2018; Wass et al., 2014). Moreover, remote eye-trackers that allow a participant's head to remain in a natural position, show relatively worse data compared to tower-mounted eye-trackers, where the participant's head is fixated on a frame (Holmqvist et al., 2011). The current release of Webgazer (Papoutsaki et al., 2020) cannot distinguish eye- from head movements, which can result in different gaze estimations, even if the participant looks at the same point on the screen. Semmelmann and Weigelt (2018) proposed that a provisional chin rest might improve the data quality of Webgazer. We therefore hypothesize that such a chin rest could help against the negative effects of head movements:

H1a: A chin rest instruction positively affects the eye-tracking data quality.

Glasses

Second, in-lab eye-tracker show a lower accuracy (Paulus et al., 2017) (but see Nyström et al., 2013) and precision (Nyström et al., 2013) for participants with glasses. This could be due to two reasons: First, reflections from the glasses can distort the eye-images obtained from the webcam. Second, the frame of glasses could occlude the participant's eye and impair its detection on the webcam images, which could result in data loss and poor calibration. We therefore hypothesize that glasses have a negative effect on the spatial resolution of webcam-based online eye-tracking. If the hypothesis holds true, participants with visual impairment, where possible, could easily be instructed to switch to less reflective visual aids (e.g., contact lenses), or none if they are short-sighted:

H1b: Wearing glasses negatively relates to eye-tracking data quality.

Study Aim 2: Relationship Between Eye-Movements and Choice Behavior Online

Our second Study Aim is to explore the feasibility of online decision-making research with online eye-tracking tools on multi-attribute choice tasks by replicating an intertemporal discounting paradigm where eye-tracking data was acquired using offline means (Amasino et al., 2019). Like in the original study, we attempt to find associations between gaze distribution, gaze movement, and choice.

Choice Outcomes Relate to the Relative Distribution of Gaze Points

Across diverse choice paradigms, participants' choice behavior can be predicted by their relative distribution of gaze on the respective choice option, such as the last fixation (Franco-Watkins et al., 2016), the total number of fixations (Franco-Watkins et al., 2016) and the number of gaze points (Amasino et al., 2019). Possible explanations for this so-called

utility effect (Orquin & Mueller-Loose, 2013) are underlying preferences (Shimojo et al., 2003) (but see Glaholt & Reingold, 2009), comparison processes (Glaholt & Reingold, 2011), evidence accumulation (Krajbich et al., 2010) or a causal biasing effect of attention on choice (Gwinn et al., 2019). In an online eye-tracking study with a binary choice task, Yang and Krajbich (2020) found relationships between choice behavior and eye-tracking measurements, such as dwell time and fixations. Following this line of research, we hypothesize to find similar associations between gaze distribution and choice:

H2a: Participants' choices can be predicted by the number of gaze points on the respective choice option.

Intertemporal Choice Behavior

Intertemporal choices are choices between smaller but immediate (smaller-sooner; SS) and larger but delayed (larger-later; LL) rewards. Most studies on intertemporal discounting use choice tasks with four information attributes, i.e., one amount and time attribute for each option (**Figurec**) (Ainslie, 1975; Grune-Yanoff, 2015; Mazur, 1987; Odum, 2011; Samuelson, 1937). Two types of models were used to understand how humans integrate these two types of information (Payne et al., 1988): Option-wise integration models (Ainslie, 1975; Grune-Yanoff, 2015; Mazur, 1987; Odum, 2011; Samuelson, 1937) state that the subjective value (SV) of the reward of a choice option A decreases depending on the time delay and the discounting parameter k for participant i for the respective option. The relative value (RV) of a choice option A against choice option B could be formalized as the difference in SV. In contrast, attribute-wise integration models state that amount and time information are integrated separately (Ericson et al., 2015), for example by integrating the difference in monetary reward and the difference in time across the choice options (Amasino et al., 2019).

These two intertemporal choice models imply distinct information search patterns, which can be empirically tested using eye-tracking (Amasino et al., 2019; Franco-Watkins et al., 2016; Liu et al., 2021; Reeck et al., 2017). Two of those implications are highlighted below.

Choice Outcomes Relate to More Gaze Points on Amount Information

First, participants who have more gaze points on amount rather than time information tend to make more patient decisions in intertemporal choice tasks (Amasino et al., 2019; Reeck et al., 2017). Possible explanations for this are that the relative gaze indicates a lower subjective value for time information as the discounting factor (Scholten et al., 2014) or a causal effect of attention to time information on impatient choices (Ebert & Prelec, 2007; Radu et al., 2011).

H2b: Participants' choices for immediate over delayed options negatively relate to the relative number of gaze points on amount versus time attributes.

Choice Outcomes Relate to Attribute-Wise Gaze Transitions Between Information Attributes

Second, participants make more patient choices when they show more attribute-wise gaze transitions, i.e., gaze transitions between attributes of the same kind across different options, than option-wise gaze transitions, i.e., gaze transitions within a choice option (Amasino et al., 2019; Khaw et al., 2018; Reeck et al., 2017). Attribute-wise gaze transitions search pattern might draw attention to the time information and therefore the costs of consumption for the respective option (Ebert & Prelec, 2007). It should be noted that Amasino et al. (2019) could only find this effect in the main sample but not in the replication sample of their publication.

H2c: Participants who show more attribute-wise gaze patterns also prefer the delayed over the immediate choice option.

Methods

We used two tasks to test each of our major aims. For Study Aim 1 we used a fixation task to explore influential factors of eye-tracking data quality. For Study Aim 2 we used a binary choice task to test the relationship between choice behavior and eye-tracking data collected using an online eye-tracker.

Sample

264 participants were recruited via the online participant recruitment platform Prolific (www.prolific.co). An a-priori power simulation with the R package *simr* (Green et al., 2016) with a mixed-effects model and estimated effect sizes based on literature (Nyström et al., 2013; Paulus et al., 2017; Stuart et al., 2016) showed that it requires a sample of $N > 225$ to find a significant fixed effect of 2% of screen size of an influence factor on data quality with a power of at least .82 ($\alpha = .05$, 95% CI = .81 to .83). This sample would contain more than twice as many participants as in previous studies on intertemporal choice paradigms (Amasino et al., 2019; Reeck et al., 2017). Participants were required to have a webcam and understand the English language. As a basic payment, participants received \$3,00 for completing the study. As an additional bonus payment, one of the chosen options from the intertemporal choice task was randomly selected (50 cent to \$5) and sent to the participant on the respective delay (e.g., \$5 in 10 days). The experiment was approved by the ethics committee of the Freie Universität Berlin. Participants gave informed consent before entering the experiment.

Demographics

54% of the participants were male (45% female, 1.4% diverse). Mean age was 34.4 years ($SD = 13.06$ years, range = 20 years to 80 years). Most of the participants were Caucasian (65.9%; Asian: 19.4%; Hispanic: 7.8%; Black: 6.9%) and resided in the US (84%; Poland: 4.6%, United Kingdom: 4.2%; other: 9.2%). Participants with residency in the United States did not differ from participants with international residency in terms of eye-movements data, choice behavior, and eye-tracking data quality. Almost all participants had Webcams with a frame rate of 30 Hz, only one participant had 25 Hz. Participant's screen width ranged from 1024px to 2560px ($M = 1557.4$ px, $SD = 300.3$ px) and screen heights range from 615 px to 1024px ($M = 898.9$ px, $SD = 163.8$ px). Average monitor diagonal size was 1798.89px diagonal ($SD = 338.27$ px, range = 1255.01 to 2939.21 px). Half of the participants (52%) wore visual aids (11% contact lenses, 41% glasses).

Data Cleaning Procedure

Fixation Task

The participants who were excluded from the fixation task analysis as well as the reason for exclusion are described in **Table 1**. Data from around a fifth (20.5%) of the total number of 264 participants who completed the study was excluded. The most common reasons were of technical nature, such as an inconsistent time measure, where the time data as indicated by Webgazer excessively exceeded the time limit of the task (>5500 ms), incomplete eye-tracking data, or a low frame rate of the eye-tracking data. Interestingly, those three participants who were excluded based on extreme offset scores, were the only ones who used the Safari browser. The fact that seven participants had no variation in gaze points, i.e., all gaze points

on one specific coordinate, indicates a calibration error. In total, $N = 210$ participants were included in the fixation task analysis.

Table 1*Number of Excluded Participants for the Fixation Task*

Reason for exclusion	<i>n</i>	%
Inconsistent time measure ^a	17	6.4
Incomplete eye-tracking data	16	6.1
Frame rate < 3Hz	16	6.1
Did not follow instructions ^b	12	4.5
No variance in gaze points ^c	7	2.7
Offset > 50% of screen size	3	1.1
Long eye-sight but did not wear visual aids	2	0.8
Total	54	20.5

Note. The raw dataset before data cleaning includes 264 participants. The reasons for exclusion are not mutually exclusive, i.e., a participant could be excluded for multiple reasons. Therefore, the total number of participants does not represent the sum of the number of excluded participants by reason.

^a had more than three trials that were longer than 5500ms

^b indicated that they moved their head or did not try to use the chin rest

^c eye-tracking data was recorded but the gaze points remained exactly at a specific position.

Choice Task

Of those 210 participants who were included in the fixation task, we additionally excluded data from 22 (10.5%) participants who only chose the LL option. Moreover, 22 (10.5%) participants showed inconsistent choice behavior that could not be fitted to a hyperbolic discounting model and could be plausibly explained by random choices (Amasino et al., 2019). Furthermore, we adapted three selection criteria applied by Yang and Krajbich (2020). First, reaction times must be larger than 400ms and less than 10000ms, which led to the exclusion of ten trials but no participants. Second, four (1.9%) participants were excluded because of a low frame rate of the eye-tracking data of <5 Hz. Third, participants were

required to have at least 6 out of 9 valid fixation dots in the fixation task. A fixation dot is defined as valid if more than 80% of all gaze dots are within a range of 15% screen size around the target stimulus. This criterion ensured that when the participant looked at the information attributes of the choice task, the far majority of the recorded gaze points would have been within the respective AOI (Yang & Krajbich, 2020). 158 (75.2%) participants did not fulfill these criteria, which resulted in a total sample of $N = 44$ participants for the choice task analysis.

Software and Materials

The experiment was programmed with the open-source JavaScript library JsPsych and hosted on cognition.run (www.cognition.run). The eye-tracking algorithm Webgazer.js was retrieved from Papoutsaki et al. (2016) (www.webgazer.cs.brown.edu). We setup Webgazer with the Facemesh face tracker and a ridge regression model to predict the gaze coordinates. Because gaze points are predicted locally in the participants browser, no sensitive identifiable video data was transmitted to our server.

Design

A within-subject design was used with one factor (*chin rest*: yes, no; **Figure 1**). The participants performed two blocks in subsequent order, one block with the chin rest condition, the other block with the control condition. Both blocks contained a calibration task to setup Webgazer and a fixation task to measure data quality (Simmelmann & Weigelt, 2018). In the chin rest block, participants also performed the choice task (Amasino et al., 2019). Overall, each participant performed the calibration and the fixation task two times and the choice task one time. The order of the blocks was randomized between the participants in order to reduce

position and carry-over-effects. The participants were randomly assigned to the two experimental groups.

Figure 1

Within-Subject Design

Note. The effect of the chin rest instruction will be examined in a within-subject design with two conditions for each group. After receiving basic instructions in order to prepare for the Eye-Tracking tasks, participants are randomly assigned to one of the groups. Condition 1 contains tasks that are performed with the chin rest instruction. Condition 2 contains task that are performed without the chin rest instruction. After completing both conditions, participants answer demographic questions and receive a debriefing about the experiment.

Procedure

To prepare for the eye-tracking tasks, participants were instructed to only use one monitor, turn their mobile phone into airplane mode and close all CPU-intensive programs and websites. In addition, they received further instructions on how to position themselves and adjust the light based on experiences from our pilot study and previous studies (Semmelmann & Weigelt, 2018; Yang & Krajbich, 2020). In the chin rest condition, the participants were instructed to rest their head on one of their arms. In the control condition, they were instructed to not rest their head on their arm but to keep a natural and upright position. In both conditions, the participants were instructed to keep the head at the same position and only move the eyes. These instructions are detailed in **Appendix A**. Between each task and within one block, the participant was additionally instructed to not move and stay in the instructed position. During these instructions, the participants could see themselves in the video stream on the top left corner framed by a rectangle box. The rectangle appeared green if the face could be detected and red if the participant had to adjust the position.

At the end of the experiment, the participants answered demographic questions and provided information about the visual aids (*perfect sight, glasses, contact lenses, not corrected*), the kind of visual impairments (*not corrected, near sighted, far sighted, and progressive*), any makeup they are currently wearing (*Eye-Shadow, Mascara, Eyeliner, Brow-Liner*) and about the relative vertical position between them and the computer screen. As a manipulation check at the end of the study, participants were asked if they have actually tried to use the provisional chin rest and if they moved their head during the eye-tracking tasks.

Stimuli and Tasks

Calibration

In the calibration, the participants clicked 13-times on one of 27 dots (50x50px; RGB: 0, 191, 255) that appeared randomly on one of 13 possible positions on the screen (**Figurea**), which generated training data of 351 mouse clicks per participant as well as the mouse movements between the dots. During the task, the participants were instructed to always follow the mouse with their eyes. The total calibration time of ca. 6 minutes was still above the minimum calibration time recommended by Yang and Krajbich (2020). In contrast to previous studies (Semmelmann & Weigelt, 2018), we did not exclude subjects with bad calibration or sent them back for recalibration because we aim to compare data quality across participants with the same calibration effort.

Fixation Task

The quality of the eye-tracking data and influence factors on data quality were measured in the fixation task (**Figureb**) (Semmelmann & Weigelt, 2018; Yang & Krajbich, 2020). In each trial, participants looked for 2000ms at a fixation cross in the center of the screen, followed by 500ms black screen, and then for 5000ms at a 50 x 50px dot (RGB: 0, 191, 255). This procedure is repeated in a randomized order for each of the 9 possible dot positions on the screen.

Figure 2*Interface of the Tasks*

a)

c)

c)

Note. For the calibration (a) and the fixation task (b) The x- and y-coordinates of the stimuli positions are shown as percentage of the screen size starting from the top left corner of the screen. Only one dot is shown at a time. The dots are presented to the participant in a randomized order. The intertemporal choice task (c) is comprised of delayed (LL; top) and immediate (SS; bottom) choice options. Left values show the reward in US-\$, right values show the temporal delay for the respective choice option in days.

Choice Task

The intertemporal choice task (**Figure c**) was adapted from the replication study of Amasino et al. (2019). The participants made repeated choices between two options on the top and the bottom of the screen by pressing the up- and down arrow keys on the keyboard. The SS-option contained a small reward (50cent to \$4.5 in 50 cent intervals) that is immediately

available (at the same day the study was completed), the LL-option contained a larger reward (\$4, \$4.5, or \$5) that will be delivered with a time delay (1, 3, 7, 15, 30, 90 and 180 days). For example, a participant can decide between \$5 in 180 days versus \$2 today. The top and bottom positions of the SS- and LL-options are randomized, and the left and right side is switched after half of the trials to account for cultural bias towards the top-left option (Amasino et al., 2019). The options were presented after 1500ms blank screen and a 1500ms fixation cross. For each trial, data was collected on choice behavior, response time, and gaze points.

We made several modifications to the original procedure by Amasino et al. (2019) to account for the online setting. Instead of \$10 maximum bonus payment with a maximum delay of 365 days, participants could win \$5 with a maximum delay of 180 days. To increase attention to the LL-reward, we slightly varied the values between \$4, \$4.5, and \$5 to increase visual attention. Moreover, we did not present all choice pairs but randomly selected 80 out of 141 possible choice combinations with a medium level of difficulty, where biased answers towards either the SS- or LL-option are least likely (**Appendix B**). We chose a lower number of trials in order to adjust to the low motivation and concentration participants indicated in our pilot study. Moreover, no time limit was set for the responses.

Measurements

Fixation Task

In order to discuss the data quality of online eye-tracking, we will focus on the spatial resolution, which is measured by *accuracy* and *precision* (Holmqvist et al., 2012; Nyström et al., 2013). In addition, we will measure the *hit ratio* as a data quality outcome, which is a major criterion for selecting participants for the choice task analysis and will be explained below.

Accuracy

The accuracy is measured by the *offset*, which is the average Euclidian distance d_i (1) between the recorded gaze coordinates $x_{i, \text{recorded}}$ and $y_{i, \text{recorded}}$ and the true gaze coordinates $x_{i, \text{target}}$ and $y_{i, \text{target}}$ for each gaze point i across gaze points n (2). Because the true gaze coordinates are unknown, in practice, the fixation dot where the subject is supposed to look is used as a reference point (Nyström et al., 2013). A large offset between predicted and recorded gaze points indicates a low accuracy.

$$d_i = \sqrt{(x_{i, \text{target}} - x_{i, \text{recorded}})^2 + (y_{i, \text{target}} - y_{i, \text{recorded}})^2} \quad (1)$$

$$\text{offset} = \frac{1}{n} \sum_{i=1}^n d_i \quad (2)$$

Hit Ratio

The *hit ratio* is defined as the relative number of gaze points within a range of 15% of the screen size around the target stimulus, i.e., with a Euclidean distance (1) $< 15\%$, for the respective trial j (3). While every gaze points are included in the analysis, this measure of hit ratio only describes how many of them are close to the target stimulus. A maximum hit ratio of 1 indicates that all gaze points are within a range of 15% around the target stimulus. A minimum hit ratio of 0 indicates that all gaze points are larger than 15% away from the target stimulus.

$$\text{hit ratio} = \frac{n_{d < 15\% \text{ screen size } j}}{n_j} \quad (3)$$

Precision

The precision is the consistency of the gaze points and calculated as the *root-mean square* (RMSE) of the Euclidean distances (4) between the gaze points i and the average of all gaze points n (5). High values of *RMSE* indicate a high variance of the gaze points and therefore a low consistency and low precision.

$$d_i = \sqrt{(\bar{x} - x_{i, \text{recorded}})^2 + (\bar{y} - y_{i, \text{recorded}})^2} \quad (4)$$

$$RMS = \sqrt{\frac{1}{n} \sum_{i=1}^n d_i} \quad (5)$$

Choice Task

Intertemporal discounting model

focus on the hyperbolic discounting model (Ainslie, 1975; Grune-Yanoff, 2015; Mazur, 1987; Odum, 2011; Samuelson, 1937), which states that the subjective value (SV) of the reward of a choice option A decreases depending on the time delay and the discounting parameter k for participant i (6).

$$SV_A = \frac{\text{reward}_A}{1 + k_i * \text{time delay}_A} \quad (6)$$

Areas of Interest

To measure eye-movements during the choice task, we establish four AOIs for each information attribute: the amount for the SS, the amount for the LL, the time for the SS, and the amount for the SS. A gaze point is defined as within the AOI, if the gaze coordinate is within a box of 40% of the maximum screen height and width around the attribute relative to the participant's screen. The AOI size is larger than in the original study (Amasino et al.,

2019) to account for the low accuracy and precision of online eye-tracking data (Semmelmann & Weigelt, 2018; Yang & Krajbich, 2020).

Fixations

A fixation is an event during the eye-tracking task where the gaze remains relatively still around an object on the screen (Holmqvist et al., 2011; Larsson et al., 2015), and where the participant is assumed to uptake the visual information of that object (Rayner, 1998). We define a fixation as a consecutive sequence of gaze points within an AOI. A new fixation starts when the gaze enters an AOI and ends when it leaves the AOI. In the original study (Amasino et al., 2019) fixations were calculated based on an implicit algorithm provided by the eye-tracker (Tobii T60). To compare the fixations between the two studies, we recalculated the fixations based on the raw eye-tracking data that were published by the authors (www.osf.io/2p3dj/files/).

Eye-Tracking Indices

Gaze distribution and gaze movements were described by three indices that are adapted from Amasino et al. (2019): The Option Index, Attribute Index, and Payne Index. All three indices are calculated based on gaze points within the AOIs. For the Option Index and Attribute Index, we defined that an AOI must contain at least 3 gaze points to be considered in the calculation. All indices range on a scale from -1 to 1. The indices are first calculated on trial level and then averaged for each subject.

Option Index

The *Option Index* measures the relative number of gaze points on the LL- versus the SS-choice option (9). A positive value indicates more fixations on the SS-option; a negative value indicates more fixations on the LL-option.

$$\text{Option Index} = \frac{\text{Gaze points in SS option AOIs} - \text{Gaze points in LL option AOIs}}{\text{Gaze points in SS option AOIs} + \text{Gaze points in LL option AOIs}} \quad (9)$$

Attribute Index

The *Attribute Index* measures the relative number of gaze points on the amount versus the time attributes (10). A positive value indicates more fixations on the amount attributes; a negative value indicates more fixations on the time attributes.

$$\text{Attribute Index} = \frac{\text{Gaze points in Amount AOIs} - \text{Gaze points in Time AOIs}}{\text{Gaze points in Amount AOIs} + \text{Gaze points in Time AOIs}} \quad (10)$$

Payne Index

The *Payne Index* (Payne, 1976) measures the relative numbers of gaze transitions between the same attribute across options (e.g., from the amount AOI of the LL-option to the amount AOI of the SS-option) versus the number of transitions within options (e.g., from the amount AOI of the SS-option to the time AOI of the SS-option) (11). A positive value indicates more transitions within the options; a negative value indicates more transitions within attributes. The direction of the transitions is ignored in this calculation.

$$\text{Payne Index} = \frac{\text{Option wise transitions} - \text{Attribute wise transitions}}{\text{Option wise transitions} + \text{Attribute wise transitions}} \quad (11)$$

Statistical Analysis

Every hypothesis was tested using mixed-effects models that were programmed with the R package *lme4* (Bates et al., 2015). The parameters of interest were added step-wise in several blocks, including the null-model, the experimental parameters, and random slopes. The goodness-of-fit was compared among the models with a likelihood-ratio-test against the null-hypothesis that the additional factors have no explanatory power against $p > .05$.

Fixation Task

Participant responses to the kind of visual aid were dichotomized into *no-glasses* (0; perfect sight, contact lenses, not corrected) and *glasses* (1; glasses). The x- and y-position of the stimulus were centered as -1 (left/top side, respectively), 0 (center), and 1 (right/bottom side). Data quality indices were calculated based on gaze data between 1000ms to 5000ms to account for gaze transitions within the first 1000ms (Orquin & Holmqvist, 2018; Semmelmann & Weigelt, 2018). Because the monitor sizes vary across participants, offset and RMSE were standardized as percentage of the screen size (Semmelmann & Weigelt, 2018), so that high value indicates a high offset and RMSE. Following the example of Semmelmann and Weigelt (2018), we report both percentage screen size and pixels whenever possible.

H1a and H1b were tested with mixed-effects general linear models to predict the data quality indices hit ratio, offset, and RMSE. Compared to a multiple regression, mixed-effects models allow the estimation of effects on trial level while controlling for homogeneity of the trials within participants and heterogeneous effects across participants. The null model contains the control variables as fixed effects and the participant as a random effect. The control variables are eventually recoded and included based on their contribution to the model fit (AIC) with the R package *lmerTest* (Kuznetsova et al., 2017): the diagonal monitor size,

webcam resolution, and frame rate were z-standardized; the ethnicity, browser, make-up, educational degree, and the sitting position of the participant were dummy-coded; the x- and y-positions of the target stimuli were codes as -1 (left/top), 0 (center), 1 (right/bottom); and the trial number as added without recoding. The square of the x-coordinate of the stimulus was added as a predictor since we expect a u-shaped relationship with data quality outcomes. For the second block, chin rest (H1a) and glasses (H1b) were added. For the third block, random slopes were added for the chin rest effect. The contribution of chin rest and glasses for reducing the unexplained variance was estimated by calculating Pseudo- R^2 (Snijders & Bosker, 2012).

Choice Task

In line of the replication efforts for the choice task and for manipulation checks, we fitted a participant-specific discounting parameter k based on the participants choice behavior in a hyperbolic discounting model, using maximum likelihood estimation. Because k is not normally distributed, it was log-transformed for further analysis. Pearson correlations were calculated between the discounting parameter and the eye-tracking indices.

H2a-c were tested with mixed-effects logistic regression models to predict participant's choices. The null model includes the control variables trial number and response time (z-standardized) as fixed effects and the participant as a random-effect. For the second block, the Option Index, Attribute Index, and Payne Index on the trial level were added. Due to significant correlations between the eye-tracking indices and choice outcomes on the participant level, the average eye-tracking indices on participant level were added in a third block. For fourth block, random slopes were tested for the eye-tracking indices.

To further investigate H2a, we partitioned all gaze points after stimuli onset into five time-bins for each trial and measured the proportion of gaze points within top AOIs versus

bottom AOIs. We compared this proportion across the choice outcomes within each time-bin. Furthermore, we examined the relationship between the last fixation of each trial and choice outcomes. All group differences were tested with a one-sided Welch's paired t-test against $p < 0.01$. In contrast to the original study, no cluster correction methods were used on the eye-tracking data because AOIs could not be identified clearly based on the raw gaze points (Amasino et al., 2019).

Results

Results are reported separately for the major aims of this study. The fixation task was used to explore influential factors of eye-tracking data quality (Study Aim 1). The choice task was used to test the relationship between choice behavior and eye-tracking data collected using an online eye-tracker (Study Aim 2).

Fixation Task

Descriptive Statistics

Data Quality Outcomes

Across participants, the hit ratio distribution was left skewed around $M = 60\%$ ($SD = 24.3\%$, range = 4.5% to 99.1%). On average, participants had 4 out of 9 valid fixation dots ($SD = 2.9$, range = 0 to 9). The offset distribution was right skewed around $M = 15.6\%$ (184 px, $SD = 7.1\%$ (102.6 px), range = 5.4% (63.3 px) to 44.7% (831.7 px)). The RMSE distribution was right skewed around $M = 7.2\%$ (86.2 px, $SD = 2.6\%$ (37.5 px), range = 3.3% (31.7 px) to 27.1% (384.9 px)). Frame rate was normally distributed around $M = 15.1$ Hz ($SD = 5.5$ Hz, range = 3.9 Hz to 32.5 Hz).

Manipulation Checks

The t-tests did not show any difference between the randomized groups for hit ratio ($t(208) = -0.27, p = 1.000$) and offset ($t(208) = 0.57, p = 1.000$). However, the RMSE was less for the group where the chin rest was introduced first ($M = 6.7\%$, $SD = 3.3\%$ vs. $M = 7.6\%$, $SD = 4.8\%$; $t(208) = 2.43, p = .048$, Cohen's $d = 0.36$). Additionally, by plotting the distribution of gaze points along the trials and across the screen, we could show that participants' gaze transition from the fixation cross at the center of the screen to the target stimulus and that most gaze points are distributed around the fixation stimuli (**Appendix C**).

Correlations Among Data Quality Outcomes and Predictors

Correlations among the continuous data quality outcomes and predictors are shown in **Table 2**. Offset and RMSE strongly correlate ($p < .001$), such that those participants with less offset also have less RMSE. Moreover, offset is almost deterministically correlated with the hit ratio. Glasses show a negative correlation with hit ratio ($p = .01$), and positive correlations with offset ($p = .028$), and age ($p = .03$). Furthermore, frame rate is correlated with monitor size ($p < .001$), such that those participants with larger monitors had a higher frame rate.

Main Findings

H1a and H1b were tested with linear mixed-effects models. Intraclass correlation coefficients (ICC) showed that a more than a third of the variance in data quality outcomes on trial level can be attributed to the variance across participants (hit ratio: ICC = 37.3%, 95% CI = 32.6% to 42.7%; offset: ICC = 40.6%, 95% CI = 35.7% to 46%; RMSE: ICC = 35%, 95% CI = 30.3% to 40.2%). Moreover, for all three data quality outcomes, the SDs of the random intercepts on participant level, which estimates the variance of the data quality scores across participants, are more than two times larger than the fixed effects on the trial level. This

suggest that data quality varies more among than within participants and that mixed-effects modeling is required for analyzing influence factors on data quality on trial level while considering the nested structure within participants. In the following, we discuss the effects for chin rest and glasses.

Table 2*Descriptive Statistics and Correlations for the Fixation Task Variables*

Measure	<i>M</i>	<i>SD</i>	Hit ratio	Offset	RMS	Frame rate	Age	Glasses	Monitor size
Hit ratio	0.60	0.24	-						
Offset	0.16	0.07	- .94***	-					
RMS	0.07	0.03	- .61***	.69***	-				
Frame rate	15.09	5.53	.07	- .08	.09	-			
Age	34.04	12.64	- .14	.11	.00	- .13	-		
Glasses ¹	0.42	0.49	- .18**	.15*	.07	.02	.21**	-	
Monitor size ²	1794.17	340.15	.13	- .05	.01	.39***	- .07	- .07	-
Webcam resolution ³	822.29	140.12	- .03	- .01	.00	- .10	.05	- .04	- .04

Note. $N = 210$.¹ 1 = wearing glasses, 0 = not wearing glasses² measured as diagonal screen size [px]* $p < .05$, ** $p < .01$, *** $p < .001$.

Hypothesis 1a: Chin Rest

Against H1a, the mixed-effects regression shows negative effects of chin rest on data quality (**Table 3a-c**). Compared to the trials in the control condition, participants in the chin rest condition had more than 1% higher offset ($M = 16.3\%$, $SD = 11.9\%$ vs. $M = 15\%$, $SD = 9.5\%$). There was no significant effect for hit ratio and RMSE. Estimations of Pseudo R^2 showed a small contribution of the chin rest effect to the mixed-effects model: Compared to a model that only contains the control variables, the chin rest effect reduces the unexplained variance on trial level for offset by 0.75%.

For all three outcome models, random slopes for chin rest were added, which estimates the variance of the fixed chin rest effect across participants. Random slopes significantly improved the model fit compared to other models without random slopes (**Appendix D**), as can be seen on lower AIC and BIC scores, higher Log-Likelihoods, and Chi²-tests for models comparisons for all three outcomes (**Table 4**). For all data quality outcomes, the SD of the random slope for chin rest is more than twice as large as the estimated fixed effect of chin rest (**Table 3Table 3a-c**). This suggests that, while on average, there is evidence for a negative effect of chin rest on data quality, the direction of the effect varies greatly among participants.

We found negative correlations between the random intercept for the participant and the random slope for chin rest for the outcomes hit ratio ($r(208) = -.31$ and offset ($r(208) = -.15$), which means that the larger the hit ratio and offset, the lower the magnitude of the effect of the chin-rest. There was no correlation between the random elements of the model for RMSE ($r(208) = -.05$).

Table 3

Estimates from Linear Mixed-Effects Models for Control Variables the Chin Rest Intervention and Glasses as Predictors for the Data Quality Outcomes

a) Hit ratio

	<i>B</i>	<i>SE</i>	95% CI		<i>t</i>	<i>df</i>	<i>p</i>
			LL	UL			
Intercept	74.80	2.50	69.54	79.31	29.91	343.9	< .001
Trial	- 1.05	0.18	- 1.39	- 0.69	- 5.96	3359.4	< .001
x-Position ¹	- 6.89	0.96	- 8.77	- 5.14	- 7.16	3359.0	.001
Frame rate	1.89	1.51	- 0.93	4.71	1.26	303.6	.212
Chin rest ²	- 3.15	1.65	- 6.31	- 0.02	- 1.90	209.9	.058
Glasses ³	- 8.81	3.31	-14.87	- 2.18	- 2.66	210.1	.008
Random parts							
$u_{\text{Participant}}$	23.30		20.97	26.39			
σ_{ϵ}	28.05		27.20	28.48			
$u_{\text{Chin rest}}$	19.95		17.11	22.49			
$N_{\text{Participant}}$	210						
Observations	3779						

b) Offset

	<i>B</i>	<i>SE</i>	95% CI		<i>t</i>	<i>df</i>	<i>p</i>
			LL	UL			
Intercept	11.56	0.68	10.21	12.95	17.12	320.6	< .001
Trial	0.24	0.05	0.15	0.35	5.25	3359.4	< .001
x-Position ¹	1.91	0.25	1.38	2.38	7.55	3358.9	.001
y-Position	- 0.41	0.15	- 0.70	- 0.11	- 2.81	3358.9	.005
Frame rate	- 0.92	0.42	- 1.74	- 0.05	- 2.17	311.5	.031
Chin rest ²	1.37	0.55	0.33	2.48	2.52	210.0	.013
Glasses ³	2.19	0.93	0.34	4.18	2.36	209.6	.019
Random parts							
$u_{\text{Participant}}$	5.86		5.66	7.05			
σ_{ϵ}	7.37		7.13	7.49			
$u_{\text{Chin rest}}$	7.11		6.32	7.84			
$N_{\text{Participant}}$	210						
Observations	3779						

c) RMSE

	<i>B</i>	<i>SE</i>	95% CI		<i>t</i>	<i>df</i>	<i>p</i>
			LL	UL			
Intercept	6.67	0.22	6.27	7.13	29.84	306.6	< .001
Trial	0.08	0.02	0.05	0.12	4.33	3359.3	< .001
y-Position	- 0.56	0.06	- 0.68	- 0.43	- 9.30	3358.9	< .001
Frame rate	0.24	0.15	- 0.04	0.50	1.61	283.9	.108
Chin rest ²	- 0.12	0.20	- 0.55	0.24	- 0.60	210.0	.551
Glasses ³	0.38	0.33	- 0.32	1.00	1.16	209.9	.247
Random parts							
$u_{\text{Participant}}$	2.00		1.63	2.35			
σ_{ϵ}	3.02		2.95	3.09			
$u_{\text{Chin rest}}$	2.58		- 0.03	0.45			
$N_{\text{Participant}}$	210						
Observations	3779						

Note. Estimates of the fixed and random effects in a generalized linear mixed model. Trial-specific variables (e.g., stimulus position, chin rest) are modelled on level 1, participant-specific variables (e.g., glasses) are modeled on level 2. Random intercepts are specified for the participant. This table represents the estimates for Block 3, where random slopes are specified for the chin rest variable. Other models without random slopes (Block 1 and Block 2) can be found in **Appendix D**. The random effects $u_{\text{Participant}}$, and $u_{\text{Chin rest}}$ are reported as SD. σ_{ϵ} represents the standard deviation of the residuals. The dfs for the t-tests are estimated based on the Satterthwaite method.

¹ square transformed

² 0=trials without chin rest, 1=trials with chin rest

³ 0=participants without glasses, 1=participants with glasses

Table 4*Model Comparison for the Mixed-Effects Model on Data Quality Outcomes*

	AIC	BIC	Log-Likelihood	χ^2	df	P
<i>Hit-Ratio</i>						
Block 0	36974.0	36993.0	-18484.0			
Block 1	36903.0	36940.0	-18445.0	77.27	3	< .001
Block 2	36889.0	36939.0	-18437.0	17.18	2	< .001
Block 3	36688.0	36750.0	-18334.0	205.75	2	< .001
<i>Offset</i>						
Block 0	27272.0	27290.0	-13633.0			
Block 1	27202.0	27246.0	-13594.0	77.50	4	< .001
Block 2	27175.0	27231.0	-13578.0	30.96	2	< .001
Block 3	26705.0	26773.0	-13341.0	474.41	2	< .001
<i>RMS</i>						
Block 0	20337.0	20356.0	-10165.6			
Block 1	20255.0	20293.0	-10121.6	87.99	3	< .001
Block 2	20257.0	20307.0	-10120.4	2.29	2	.318
Block 3	19889.0	19970.0	- 9931.4	378.05	2	< .001

Note. Block zero only contains an intercept only model on the respective criterion with a random effect for participants. Block 1 adds the control variables. Block 2 adds the experimental predictors chin rest and glasses. Block 3 adds the random effects for chin rest. Table 2 represents the estimates for Block 3. The model estimates for Block 1 and Block 2 can be found in **Appendix D**.

Hypothesis 1b: Glasses

In support of H1b, the mixed-effects regression showed a negative effect of glasses on the data quality. Compared to participants without glasses, participants with glasses have an 8.8% lower hit ratio ($M = 37.9\%$ $SD = 29.8\%$ vs. $M = 47.5\%$, $SD = 32.6\%$) and a 2.2% lower offset ($M = 16.9\%$ $SD = 7.3\%$ vs. $M = 14.7\%$, $SD = 6.9\%$) (**Table 2a-c**). There was no significant effect for RMSE.

Estimations of Pseudo R^2 showed a slightly larger contribution of the glasses effect to the mixed-effects model than the chin rest effect: Compared to a model that only contains the

control variables and the chin rest, glasses reduce the unexplained variance of the intercept of hit ratio by 3.4%, of offset by 2.28% and of RMSE by 0.54%.

A fixed effects one-way ANOVA analysis did not show any effect of the specific types of visual aids (contact lenses, glasses, none because of perfect sight, and none but uncorrected) (hit ratio: $F(3, 206) = 3.34, p = .020$; offset: $F(3, 206) = 2.43, p = .066$; RMSE: $F(3, 206) = 1.12, p = .343$) or the type of correction (long sight, short sight, progressive, no correction) on data quality outcomes (hit ratio: $F(3, 206) = 1.21, p = .307$; offset: $F(3, 306) = 1.13, p = .338$; RMSE: $F(3, 206) = 0.67, p = .569$).

Other Factors

The mixed-effects models showed additional effects for the trial number, the frame rate and the stimuli position (**Table 2a-c**). There were significant effects of trial number on data quality, such that with each trial, the hit ratio decreases by around 1%, the offset and RMSE increase by around 0.2% to 0.1% of screen size respectively. This is a large effect, considering that the tasks involve up to 89 trials before recalibration. Moreover, we found that frame rate positively predicts offset, such that those trials with a higher frame rate of 1 SD have 0.9% less offset. Furthermore, we found a positive effect of the x- and y-position of the stimulus on data quality, such that the right side and the lower side of the screen has a better data quality. Compared to the center of the screen, the right side had 1.9% more hit ratio and 0.5% less offset, and the lower side had 0.4% less offset and 0.6% less RMSE.

Additional Analysis

In addition to the main findings, we were interested in the reliability of online eye-tracking, i.e., to what extent the data quality outcomes vary across participants and environment. Therefore, one of the authors conducted the study five subsequent times under

lab conditions with artificial room light. Results show that while the frame rate remained steady around $M = 13.07$ Hz ($SD = 0.12$ Hz), there were large variations in regards to hit ratio ($M = 75.6\%$, $SD = 18.3\%$), offset ($M = 9.5\%$ (90 px), $SD = 1.7\%$ (15.2 px)), and RMSE ($M = 6.3\%$ (60 px), $SD = 0.4\%$ (5.1 px)).

Choice Task

Descriptive Statistics

Eye-Tracking Indices

The average Option Index on participant level was normally distributed around zero ($M = -0.06$, $SD = 0.07$, range = - 0.22 to .02). On average, participants had positive Attribute Indices ($M = 0.12$, $SD = 0.25$, range = - 0.38 to 0.79), which means that they looked slightly more on amount than time attributes. On average, participants had positive Payne Indices ($M = 0.13$, $SD = 0.33$, range = - 0.70 to 0.86), which means that they showed more option-wise gaze transitions than attribute-wise gaze transitions.

Choice Behavior

On average, the participants preferred the LL-option on 74% ($SD = 20\%$) of all trials. Average response time ($M = 2305.1$ ms, $SD = 1152.2$ ms, range = 463ms to 9847ms) was slightly higher compared to the original study (Amasino et al., 2019). The mixed-effects regression showed a negative effect of reaction time on choice (**Table 6**), such that choice for the LL-option decreases by factor 0.67 with 1 standard deviation increase in reaction time. Furthermore, we found similar distributions of the discounting parameters and relations between the estimated Subjective Value (SV) of the choice options and the proportion of choice, response time, and the number of fixations as in the original study (**Appendix E**).

Correlation Among Choice Variables and Eye-Tracking Indices

Correlations among choice variables and eye-tracking indices are shown in **Table 5**. Intertemporal discounting is correlated with response time indicating that less patient participants, who more often chose the SS-option, responded faster ($p = .047$). The Option Index is also strongly correlated with the location of the choice options ($p = .001$) such that participants looked more often on a choice option when it was presented on top. Moreover, intertemporal discounting is negatively correlated with the Attribute Index ($p = .001$) and is positively correlated with Payne Index ($p < .001$). Therefore, more patient participants look more on amount attributes and show more attribute-wise gaze transitions.

Main Findings

H2a-c were tested with mixed-effects models on the choice outcomes with the eye-tracking indices as predictors (**Table 6**). Mixed-effects models facilitate analyzing the effects of eye-tracking related variables on choice on trial level while considering the nested structure within participants. Approximately 40% ($ICC = 0.40$, calculated based on Wu et al., 2012) of the variance in choice outcomes on trial level can be attributed to the variance across participants. Similar to the main analysis for Study Aim 1, logistic mixed-effects models are required for modeling choice outcomes on trial level while considering the homogeneity of choices within participants. Model comparisons with AIC, BIC and Log-Likelihood scores and Chi²-tests showed the best model fit for the model with fixed effects for eye-tracking indices on trial as well as participant level but no random slopes for the eye-tracking indices (**Table 7**). The other models (Blocks 1, 2, and 4) that were compared against this model are described in **Appendix F**. The results for the specific hypotheses are detailed below.

Table 5*Descriptive Statistics and Correlations for Choice Task Variables*

Measure	M	SD	Proportion of LL-choices	Discounting parameter k	Response time	LL-option on top	Option Index	Attribute Index
Proportion of LL-choices ¹	0.74	0.20	-					
Discounting parameter k ²	- 5.43	1.74	- .87***	-				
Response time [ms]	2334.69	779.68	- .14	.30*	-			
LL-option on top	0.50	0.04	.14	.03	.14	-		
Option Index ³	- 0.06	0.07	- .03	- .10	- .32*	- .50***	-	
Attribute Index ⁴	0.14	0.27	.33*	- .47**	- .36*	- .14	.30*	-
Payne Index ⁵	0.12	0.34	- .39**	.54***	.27	.06	.01	- .59***

Note. $N = 44$. Correlations are calculated on participant level

¹ Choice as average for each participant with 0 = chose SS option and 1 = chose LL option

² Log-transformed

³ The Option Index measures relative gaze distribution for the larger-later option (index>0) vs. the shorter-sooner-option (index<0).

⁴ The Attribute Index measures relative gaze distribution for amounts (index>0) versus times (index<0).

⁵ The Payne Index measures gaze transitions between options (index>0) versus between attributes (index<0).

* $p < .05$, ** $p < .01$, *** $p < .001$.

Table 6

Estimates from Generalized Mixed-Effects Models for Control Variables and Eye-Tracking Indices as Predictors for the Choice Outcome

	<i>B</i>	<i>SE</i>	95% CI		<i>z</i>	<i>p</i>
			LL	UL		
Intercept	1.00	0.33	0.43	1.54	3.02	0.003
Level 1 variables						
Trial	0.01	0.00	0.00	0.01	4.06	0.000
Reaction Time ¹	- 0.39	0.05	- 0.51	- 0.29	-7.39	0.000
Option Index	- 0.06	0.07	- 0.19	0.09	-0.82	.414
Attribute Index	0.10	0.09	- 0.08	0.28	1.23	.218
Payne Index	- 0.01	0.09	- 0.18	0.16	-0.07	.942
Level 2 variables						
Option Index ²	- 0.86	2.61	- 4.93	2.95	-0.33	.743
Attribute Index ²	1.13	0.86	- 0.44	2.90	1.31	.189
Payne Index ²	- 1.21	0.66	- 2.48	0.01	-1.83	.068
Random parts						
$u_{\text{participant}}$	1.06		0.76	1.29		
$N_{\text{participant}}$	44					
Observations	3241					

Note. Estimates of the fixed and random effects in a generalized mixed model with the hypothesized models. The eye-tracking indices Option Index, Attribute Index, and Payne Index are modeled on trial level (level 1) and participant level (level 2). The random intercept $u_{\text{participant}}$ is reported as SD. Other models without random slopes (Block 1, 2, and 4) can be found in **Appendix F**.

¹ z-scaled

² averaged for each participant

Table 7*Model Comparisons for the Mixed-Effects Models on Choice Models*

	AIC	BIC	Log-Likelihood	χ^2	df	P
Block 0	3321.8	3333.9	- 1658.9			
Block 1	3236.3	3260.6	- 1614.1	89.5	2	< .001
Block 2	3239.3	3281.9	- 1612.6	3.0	3	.393
Block 3	3234.4	3295.3	- 1607.2	10.8	3	.013
Block 4	3251.1	3366.7	- 1606.6	1.3	9	.998

Note. Block zero only contains an intercept only model on choice outcomes with a random effect for participants. Block 1 adds the control variables. Block 2 adds the trial-specific eye-tracking as experimental predictors. In Block 4, the eye-tracking indices are added as level 2 effects. In Block 4, adds random slopes for the eye-tracking indices on trial level. The parameter estimates for Block 1, 2 and 4 can be found in **Appendix F**.

Hypothesis 2a: Prediction of Choice Outcomes by Gaze Distribution

H2a states that choice behavior can be predicted by the gaze point distribution. Against H2a, the mixed-effects logistic regression did not show a significant effect for the Option Index (**Table 6**). Therefore, we could not find evidence that relative gaze on the LL-choice option predicts choice. However, in support of H2a, the analysis of time-bins and the last fixation show that the gaze distribution at the end of a trial predicts choice (**Figure**).

Figure 3a shows the proportion of gaze points on top versus bottom AOIs for trials with top choice versus trials with bottom choice across five time-bins. In contrast to the original study, where participants already started to direct their gaze towards the chosen option in the second time-bin, we did not find significant differences in gaze point location in the first four time-bins (Welch's paired t-tests: $-1.10 \leq t(43) \leq 1.59$, $.12 \leq p \leq 0.69$). However, for the last time-bin, participants' choice could be predicted by gaze data (Welch's paired t-test: $t(41) = 8.12$, $p < .001$, Cohen's $d = 0.59$, 95% CI = 0.43 to 0.74). Like the original study, the first time-bin shows a strong bias towards the top option.

Figure b compares the last fixations on top versus bottom AOIs between the two choice outcomes. In approximately 60-65% of all trials, participants chose the last fixated option. Although this effect is slightly smaller compared to the original study (Amasino et al., 2019), we also found a significantly higher proportion of top choices for the trials where the last fixation was on the top option (Welch's paired t-test: $t(41) = 9.83, p < .001$; Cohen's $d = 2.37$, 95% CI = 1.43 to 3.31).

Hypothesis 2b: Choice Outcomes Relate to More Gaze Points on Amount

Information

Against H2b, which states that more relative gaze on amount versus time attributes relate to more patient choices, the mixed-effects models did not show a significant effect of Attribute Index on choice behavior, neither on trial- nor on participant level (**Table 6**). Therefore, we did not find evidence that participants who more often chose the LL- than the SS-option also looked more at the amount attributes of the choice task.

Hypothesis 2c: Choice Outcomes Relate to Attribute-Wise Gaze Transitions Between

Information Attributes

Against H2c, which states that more attribute-wise than option-wise gaze transitions relate to more patient choices, we could not find an effect of Payne Index on choice behavior, neither on trial- nor on participant level (**Table 6**). Therefore, we did not find evidence that participants who more often chose the LL- than the SS-option show more gaze transitions between the same kind of attributes across options than gaze transitions between different kinds of attributes within the same choice option.

Figure 3*Distribution of Gaze Points and Last Fixation versus Choice Outcome*

Note. a) Proportion of gaze points on top AOIs across five time-bins for top versus bottom choice: Trials were split into five time-bins for each trial separately. b) proportion of top choices for the last fixation on top versus bottom choices: Trials were split according to whether the final fixation was to the top or bottom choice option. Plots on the left side are calculated based on data from the original study (Amasino et al., 2019). Plots on the right side are calculated based on data from this study. Violin plots show data density. Horizontal lines show mean. $N = 44$. * $p < .05$, ** $p < .01$, *** $p < .001$.

Discussion

In this online study, we explored the potential and the limitations of online eye-tracking tools, using the JavaScript based open-source library Webgazer (Papoutsaki et al., 2016). Our first Study Aim was to explore influence factors on the data quality. Therefore, we replicated a fixation task (Simmelmann & Weigelt, 2018) to examine the influence of a provisional chin rest and glasses on three data quality outcomes. In contrast to H1a, we found a negative effect of the chin rest intervention on the spatial resolution. In support of H1b, we found a lower spatial resolution for participants with glasses. Our evidence suggests that while using contact lenses instead of glasses seems like an effective intervention for improving the eye-tracking data, implementing a chin rest intervention could have a detrimental effect on the data quality.

Our second Study Aim was to explore whether decision-making findings from high-performance eye-trackers in a controlled lab environment can be reproduced online with an online eye-tracking tool. Therefore, we replicated a multi-attribute choice task (Amasino et al., 2019). While participants showed the expected choice behavior, the eye-tracking data differed in several ways from the lab data. Out of 264 participants, who completed the study, only $N = 44$ (16.6%) had sufficient data quality to be included in the choice task analysis. H2a finds mixed evidence: Although the overall gaze distribution did not predict choice, the time-bin analysis and the last fixations suggest that eye-tracking data could predict choice at the moment right before the participant reveals the decision. H2b and H2c must be rejected because choice could not be predicted by gaze distributions towards amount information (H2b) or gaze transitions between the same kind of attributes across options (H2c).

In the following, we will discuss the findings for the two study aims in more detail, as well as practical implications for future online eye-tracking studies.

Study Aim 1: Influence Factors on the Data Quality of Online Eye-Tracking

The goal of our fixation task was to identify influence factors on data quality in a large sample size. Moreover, results from this task give insight into the data quality that could be generally expected when doing online eye-tracking studies and what requirements participants must meet in order to provide meaningful data. For discussing the influence factors on eye-tracking data quality, we specifically focused on a provisional chin rest and glasses.

Chin Rest

Against H1a, we found that participants had lower accuracy and hit ratio when using the chin rest. We conclude that, while it still seems plausible that head movements do have a negative effect on data quality (Hessels et al., 2015; Niehorster et al., 2018; Wass et al., 2014), the chin rest intervention failed to control them. The large variance of the chin rest effect among participants, which is more than twice as large as the estimated fixed effect, implies that the direction of the chin rest effect differs among participants. For some participants, the chin rest had a positive effect on data quality; for others, the chin rest had a negative effect on data quality. At lower levels of hit ratio or accuracy, the magnitude of the chin-rest effect (positive and negative) was larger. Behavioral factors, such as the participant's concentration (Niehorster et al., 2018), could explain this variance. However, no moderating factor for the chin rest effect on trial- and participant levels was found in this study.

We propose two possible reasons for these findings: First, by following the instructions, several participants could have taken an unnatural and uncomfortable pose (e.g., by leaning forward to get the elbow on the table), which also explains why ten participants did not comply with the chin rest instruction at all. Second, as suggested by Robal et al. (2018) the hand on which the head rested could have obscured the face and interfered with the face

detection. The face tracker used in this study (Facemesh; Lugaresi et al., 2019) should greatly reduce the distorting effects of hands on the face. It might be possible that other types of chin rests, such as a plastic bar, contribute to fixating the participant's head without obscuring the face. Such chin rests would also be more robust against changing positions, for example when the participant relaxes the body position throughout the study.

Due to the large unexplained variability of the effect of the chin rest on data quality and the absence of a professional chin rest apparatus in the online setting, interventions other than controlling head movements seem more practical for improving the data quality of online eye-tracking. Future research should follow previous studies who instructed participants to keep the head still in a natural position (Hsu et al., 2018; Robal et al., 2018; Semmelmann & Weigelt, 2018; Zhao et al., 2017).

Glasses

In support of H1b, we found evidence for a negative effect of glasses on hit ratio and accuracy. Our findings are in line with previous research by Paulus et al. (2017). In contrast to Nyström et al. (2013), we did not find any effect on precision. These findings suggest that glasses increase the bias in the estimation of gaze points based on eye-tracking data but do not increase the unsystematic variation in gaze points. Another reason for the absence of an effect on precision could be the generally low variance of the precision measure in this study, which is further discussed in the limitations section.

It is yet unclear whether reflections from the glasses distort the eye-image (Holmqvist et al., 2012; Nyström et al., 2013; Stuart et al., 2016) or whether the frames of the glasses obscure the eye. Because we did not find an effect of glasses on precision, there is no evidence for any unsystematic distortions of the eye-image. Consequently, it seems like an efficient way to improve the data quality is by asking participants to wear contact lenses

instead of glasses. By doing that, the demographic diversity of the sample should be considered because the exclusion of non-contact wearers might also exclude certain demographic groups, e.g. participants of older age, who are less likely to wear contact lenses (Cope et al., 2015).

Study Aim 2: Relationship Between Eye-Movements and Choice Behavior Online

By replicating an intertemporal choice task, we attempted to reproduce findings regarding the relationship between participants' gaze patterns and choice behavior. The task design belongs to an established paradigm in decision-making research and was internally replicated in the original study (Amasino et al., 2019). Moreover, the multi-attribute choice task tests the potential of online eye-tracking in a more complex setting than the simple task designs of previous studies (Simmelmann & Weigelt, 2018; Yang & Krajbich, 2020).

We found partial evidence for H2a. We could not reproduce findings regarding the relation between choice and the distribution of the number of fixations (Franco-Watkins et al., 2016) the number of gaze points in in-lab studies (Amasino et al., 2019), and dwell time in an online study (Yang & Krajbich, 2020). However, choice could be predicted by the last fixation and the distribution of gaze points right before the participant reveals the decision, which was also found in previous research (Amasino et al., 2019; Franco-Watkins et al., 2016).

Against H2b and H2c, we could not confirm the associations between choice outcomes and the gaze on amount information as well as attribute-wise gaze transitions that were found with in-lab eye-trackers (Amasino et al., 2019; Khaw et al., 2018; Reeck et al., 2017), using online eye-tracking. While there was no significant fixed effect of any eye-tracking variable, the model with the best fit included the eye-tracking indices on trial level and participant level alike. Future research should examine the difference between trial-wise

variations in gaze distribution and participant-specific gaze patterns regarding their relationship with choice outcomes.

Our manipulation checks gave reason for us to rule out other explanations for the findings. Most of the participants followed our instructions and directed their true gaze towards the information attributes of the choice options. It is possible that online participants pay less attention to studies, especially during the COVID-19 pandemic (Arechar & Rand, 2020). However, a lack of visual attention would relate to inconsistent choices that would be detected in our data cleaning procedure. The distribution of the discounting parameter was comparable to the original study and predictive for the choice outcomes, response time, and the number of fixations on the choice options (Amasino et al., 2019). This is in line with previous findings that intertemporal choice behavior could be described by a hyperbolic model (Ainslie, 1975; Grune-Yanoff, 2015; Mazur, 1987; Odum, 2011; Samuelson, 1937). Moreover, choosing the relevant options was incentivized with a real monetary reward of up to \$5.

The similarity of choice preferences between online and in-lab participants (Goodman et al., 2013) and successful implementations of online eye-tracking in previous studies (Simmelmann & Weigelt, 2018; Yang & Krajbich, 2020) suggest that associations between eye-movement and choice behavior do exist in the online setting, such as the utility effect (Orquin & Holmqvist, 2018), the effect of attribute-wise search strategies on patience choice, and the effect of visual attention to amount information (Amasino et al., 2019; Reeck et al., 2017). However, those associations are overlayed by a high level of noise in the eye-tracking data, which makes it is more difficult to dynamically track the choice process online compared to lab conditions. In other words, current online eye-tracking tools might not be accurate enough to measure more complex effects, such as associations between choice and gaze transitions between specific kinds of information attributes, but they suffice to measure

strong effects, such as associations between choice and the gaze distribution right before the participant enters the decision into the computer.

The negative effect of trial-number on data quality suggests that the spatial resolution of the eye-tracking data in the choice task is worse than when it was originally measured in the fixation task. A linear extrapolation of this effect across 80 trials would mean that the accuracy and precision could decrease by 16% of screen size. Possible reasons are shifting head poses or an insufficient calibration at the beginning. This contradicts the finding of Yang and Krajbich (2020) who found a stable spatial resolution over time.

Practical Implications – (how) can Online Eye-Tracking be used for Decision-Making Research?

Our findings revealed several restrictions to the feasibility of decision-making research with online eye-tracking. The data quality outcomes obtained in our study, which are comparable to previous studies (Semmelmann & Weigelt, 2018; Yang & Krajbich, 2020) and other online eye-tracking tools (e.g., iTracker; Krafka et al., 2016), show that task stimuli and AOIs should be larger than 15% of the screen size to accurately measure gaze. In addition, future research must consider factors such as (re-)calibration, participant selection, and participant compliance, without which associations between eye-movements and decision making behavior cannot be efficiently examined in the online context.

Calibration and Participant Selection

As in previous research (Yang & Krajbich, 2020), more than two-thirds of the participants who completed the study had to be excluded from further analysis, mostly, because of a low hit ratio. To meet the required data quality scores, online eye-tracking studies should measure the data quality and eventually recalibrate throughout the task. As a

criterion for recalibration, the hit ratio (Yang & Krajbich, 2020) seems more suitable than average accuracy (Simmelmann & Weigelt, 2018) or precision because it is more robust against outliers. In this study, no recalibration was used because our study aims required us to compare data quality among participants with the same amount of calibration.

When selecting participants based on technical equipment or demographics, researchers must consider the eventual trade-off between demographic inclusivity and data quality and be sensitive about any possible discrimination against demographic groups. The low data quality of certain groups of participants, such as older participants who wear glasses (see this study), or non-Caucasian ethnicities (Blignaut & Wium, 2014) should be compensated with a more intense calibration instead of exclusion from the study.

The Eye-Tracking data was Smoothened by Default Settings of the Eye-Tracker

The eye-tracking algorithm in our study differed from previous studies (Papoutsaki et al., 2016; Semmelmann & Weigelt, 2018; Yang & Krajbich, 2020) by using a Kalman Filter, which smoothens the data on-the-fly and reduces the unsystematic variation and the influence of outliers (e.g., blinks). The artificial gaze points, which were introduced by the filter, impeded the analysis of natural gaze saccades. This was one of the reasons, which prevented the use of a cluster correction algorithm on the choice task data, which could have helped associating clusters of gaze points with AOIs and separating them from gaze saccades (Amasino et al., 2019). Moreover, contrary to the original purpose of measuring the unsystematic variation of the raw gaze points, the RMSE outcome is likely artificially diminished by the filter. This might explain why several predictors, which were found to influence other data quality scores, did not show any effect on precision and why no evidence was found for any relationships between gaze transitions and choice.

This illustrates the influence of default settings of eye-trackers on the study results (Orquin & Holmqvist, 2018). Future research should explore post-hoc data analysis methods for improving the quality and interpretability of raw eye-tracking data. Examples are the correction of systematic offsets with the help of clustering algorithms (e.g., agglomerative clustering) to detect AOIs or the use of machine learning algorithms (e.g., neural network classifiers) to detect fixations.

Large Areas of Interest and Vertical Alignment of the Choice Options

The vertical alignment of the choice options could have increased the noise of some of the eye-tracking measures. On typical 16:9 monitors, vertically aligned AOIs are spatially closer together than horizontally aligned AOIs. Because the size of each AOI was set to 40% of the screen size, there was only 10% of the screen size between the AOIs (e.g., 90 px on the average monitor height in our sample). As a result, the more inaccurate the eye-tracker the higher the chance that true gaze points on the bottom AOIs are wrongly assigned to top AOIs and vice versa. This could have distorted the effects of eye-tracking measures that relied on an accurate separation of top and bottom gaze points, such as the Option Index. Future research should replicate the choice task with a horizontal alignment. It might also be useful to instruct participants to, instead of laptops, use a desktop computer with an external monitor, which is generally larger and, moreover, more likely to be on eye level with the participant.

Participant Compliance and Technical Feasibility

Overall, we found that online participants are generally disciplined enough and technically equipped to contribute to online eye-tracking studies of less than 30 minutes. Most participants who completed the study looked at the fixation stimuli and only 12 participants indicated that they did not follow the instructions. Note that our participants had the option to take a break before the recalibration in the second task, which might have promoted their motivation in the long run. Moreover, only a minority of participants dropped out during the eye-tracking initialization. Those participants could have experienced long waiting times for the initialization due to a low computer performance or technical problems (e.g., a missing Webcam). Therefore, long waiting times and the required hardware should be clearly communicated to the participants beforehand. Moreover, it should be noted that because of the low frame rate of around 15 Hz, online eye-tracking is not suitable for tasks that involve fast gaze movements (Simmelmann & Weigelt, 2018).

Conclusion

Two years after the first application of the eye-tracking tool Webgazer for cognitive research (Simmelmann & Weigelt, 2018), eye-tracking is still mainly reserved for in-lab research. With the rise of a global pandemic, online eye-tracking tools appealed to many researchers as the last resort for continuing their research. Online eye-tracking can enable researchers of various fields to combine the benefits of eye-tracking and online studies (Papoutsaki et al., 2016; Simmelmann & Weigelt, 2018; Yang & Krajbich, 2020). Decision-making research that is conducted on large online sample with eye-tracking tools will probably achieve greater inter-individual differences in choice preferences, decision strategies, and demographics (Amasino et al., 2019), which helps deriving interventions for supporting people at making decisions (Hertwig & Grüne-Yanoff, 2017).

We experimentally examined influence factors on the data quality of online eye-tracking studies, which will hopefully give practical guidelines for the experimental design of future studies. While asking participants to wear contact lenses instead of glasses seems like an effective intervention for improving the eye-tracking data, attempting to control head movements with a provisional chin rest could have detrimental effects on data quality. Future research should explore other participant related factors, such as webcam resolution and light (Feit et al., 2017; Paulus et al., 2017) and post-hoc data analysis methods for improving the quality. Moreover, we found partial evidence for the feasibility of measuring eye-movements during choice behavior in the online context by replicating a decision-making paradigm that was previously conducted in a lab environment (Amasino et al., 2019). Although we found some simple relations between choice behavior and eye-tracking measures, such as the last fixation, more complex eye-tracking effects could not be reproduced. Intermediate recalibration throughout the task (Yang & Krajbich, 2020) as well as gamification of the calibration tasks (Xu et al., 2015) seem promising avenues for maintaining a sufficient data quality while maintaining the participant's motivation.

Code availability

The code for the task design and the data analysis can be found on the Open Science Framework: <https://osf.io/7jrwk/>

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Appendices

Appendix A

Instructions for the Eye-Tracking Setup

a)

For a preliminary adjustment, please consider the following instructions:

1. Sit at a table and make sure that you could later rest your elbows on it.
2. Sit towards a window or lamp so that there are no shadows on your face. You might additionally turn on a desk lamp for that. Avoid having a window behind you.

Click to continue

b)

3. Check the video and stay in the highlighted rectangle so that it becomes green.
4. Try as much as possible to follow the instructions on these pictures and avoid moving your head. If you move too much, the calibration can fail and you might not be able to finish the study.
5. **If necessary, adjust your laptop, monitor, webcam, or chair.**

Sit centrally to have full visibility of face

Use your eyes to look, do not move your head

Do not move or tilt your head

Do not sit too far or too close

The image may not be too dark

Click to continue

c)

For the next two tasks, we will calibrate again. Before that, you can take a short break, loosen your posture and relax your head a little bit.

In order to make this measurement as accurate as possible, please rest your head on one of your arms, with your elbow on the desk (see image) You face may be covered a little bit but please keep your eyes visible. Get sure that you stay in the green rectangle in the video stream while doing that.

The idea is to keep your head at the same position at all time so that you **only move your eyes** when you look at the screen.

Press Space to continue

d)

For the next task, please do **not** rest your head on your arm but keep your head in a natural position. Get sure that you stay in the green rectangle in the video stream while doing that.

However, in order to make this measurement as accurate as possible, please keep your head at the same position at all time so that you **only move your eyes** when you look at the screen.

Press Space to continue

Note. Instructions for the eye-tracking setup for the sitting position, room light (a) and head positions (b). In addition, in the chin rest instruction (a), the participant is instructed to rest the head on their arm. In the control condition (b), the participant is instructed to not rest the head on the arm.

Appendix B

Selection of Trials for the Choice Task

We made some modifications to the choice task, in order to reduce the participant's biases towards either the LL- or the SS-choice options. Therefore, we selected choice-pairs with a minimum level of difficulty. Amasino et al. (2019) found that for some choice-pairs, participants always chose the LL-option, (e.g., 50 cent today vs. \$10 tomorrow). Based on the hyperbolic discounting function (equation 1 in the main text), we determined an item-specific discounting parameter k for each amount and delay combination. k is the discounting parameter, where the SS-amount a_{SS} equals the discounted value of the LL-amount a_{LL} that is delayed by time delay t_{LL} (**B1**):

$$a_{SS} = \frac{a_{LL}}{1+k \cdot t_{LL}} \quad (\text{B1})$$

Solving this equation (**B1**) for k , we obtain (**B2**):

$$k = \frac{\frac{a_{LL}}{a_{SS}} - 1}{t_{LL}} \quad (\text{B2})$$

In the original study (Amasino et al., 2019), for most of the items with $k > 0.33$, more than 95% of all participants chose the LL-option. Therefore, we selected 114 choice-pairs, where $k \leq 0.33$. With these modifications, we achieved similar frequency distributions of SS and LL amounts, reward-ratio, and time delays of our study compared to the original study.

Appendix C

Manipulation Check for the Fixation Task

To check whether participants follow our instructions and look at the stimuli in the fixation task, we analyzed the gaze saccade from the fixation cross towards the stimulus and the distribution of gaze points around the stimuli positions.

First, we plotted the gaze point offsets over time from the fixation cross ($t = -1500$ ms), to the stimulus onset ($t = 0$ ms) and the stimulus offset ($t = 5000$ ms) (**Figure A1**) (Simmelmann & Weigelt, 2018). The colored lines represent the median offset in 100ms time-bins for the respective stimulus position. Offset was largest for positions at the corner of the screen, followed by positions at the y- or x-center. The purple line does not deviate because the stimulus is at the same center position as the fixation cross. For all positions, except the center location, a saccade can be clearly identified from 0 to about 1000ms. On average, offset among the various positions decreases from $M = 43.9\%$ screen size (542 px, $SD = 1.7\%$ (16.9 px); range = 42.4% (522.4 px) to 45.7% (562.7 px)) to $M = 13.8\%$ ($M = 160.5$ px, $SD = 0.6\%$ (11.3 px); range = 13.2% (153.2 px) to 14.7% (177.1 px)). There are less gaze points a few milliseconds around the stimulus onset because of a 500ms break, where Webgazer was paused and resumed.

Moreover, as can be seen the heatmap of all gaze points after 1000ms stimulus onset (**Figure C2**), gaze was distributed around the fixation dot positions.

Figure C1*Gaze Saccades in the Fixation Task*

Note. The graph shows the deviations for each gaze point from the target stimuli for the fixation cross (-1500ms to 0) to the fixation stimuli (0ms to 5000ms). Colored lines show the median deviation for 100ms time-bins for each stimuli location.

Figure C2

Heatmap of all Gaze Points in Fixation Task

Note. Gaze point from the fixation task with $N = 210$ participants. Green areas indicate more gaze points. The heatmap was calculated with a horizontal bin size of $x = 0.2\%$ and a vertical bin size of $y = 0.1\%$ of the screen size.

Appendix D*Alternative Models for the Fixation Task*

a) Hit ratio

	Block 1							Block 2						
	<i>B</i>	<i>SE</i>	95% CI		<i>t</i>	<i>df</i>	<i>p</i>	<i>B</i>	<i>SE</i>	95% CI		<i>t</i>	<i>df</i>	<i>p</i>
			LL	UL						LL	UL			
Intercept	69.54	2.04	65.21	73.79	33.87	459.6	< .001	74.71	2.50	69.76	79.55	29.92	375.8	< .001
Trial	-1.05	0.19	- 1.45	- 0.69	- 5.49	3568.9	< .001	- 1.05	0.19	- 1.39	- 0.68	- 5.59	3568.8	< .001
x-Position ¹	-6.89	1.03	- 8.91	- 4.93	3.11	3568.6	< .001	- 6.89	1.03	- 8.86	- 5.09	- 6.72	3568.5	< .001
Frame rate	2.65	1.50	- 0.33	5.72	1.75	330.9	.078	2.60	1.48	- 0.37	5.41	1.75	327.0	.080
Chin rest ²								- 3.15	0.97	- 4.79	- 1.24	- 3.26	3570.1	.001
Glasses ³								- 8.59	3.33	-14.53	- 1.94	- 2.58	209.5	.011
Random parts														
U _{Participant}	23.12		20.62	25.66				22.73		20.18	24.86			
σ _ε	29.91		29.07	30.40				29.87		28.98	30.40			
N _{Participant}	210							210						
Observations	3779							3779						

b) Offset

	Block 1							Block 2						
	<i>B</i>	<i>SE</i>	95% CI		<i>t</i>	<i>df</i>	<i>p</i>	<i>B</i>	<i>SE</i>	95% CI		<i>t</i>	<i>df</i>	<i>p</i>
			LL	UL						LL	UL			
Intercept	13.17	0.59	11.99	14.36	22.41	422.5	< .001	11.62	0.73	10.01	13.07	15.99	348.5	< .001
Trial	0.24	0.05	0.14	0.34	4.68	3567.7	< .001	0.24	0.05	0.13	0.35	4.69	3567.3	< .001
x-Position ¹	1.91	0.28	1.34	2.47	6.73	3567.3	< .001	1.91	0.28	1.35	2.44	6.75	3567.0	< .001
y-Position	- 0.41	0.16	- 0.71	- 0.09	- 2.50	3567.3	.013	- 0.41	0.16	- 0.75	- 0.07	- 2.51	3567.0	.012
Frame rate	- 1.10	0.44	- 2.03	- 0.25	- 2.52	347.5	.012	- 1.11	0.43	- 1.97	- 0.31	- 2.56	344.9	.011
Chin rest ²								1.38	0.27	0.85	1.91	5.17	3568.7	.000
Glasses ³								2.06	0.99	0.37	4.02	2.09	208.0	.038
Random parts														
$\mu_{\text{Participant}}$	6.85		6.09	7.48				6.77		5.91	7.39			
σ_{ϵ}	8.26		8.00	8.41				8.23		8.00	8.36			
$N_{\text{Participant}}$	210							210						
Observations	3779							3779						

c) Precision

	Block 1							Block 2						
	<i>B</i>	<i>SE</i>	95% CI		<i>t</i>	<i>df</i>	<i>p</i>	<i>B</i>	<i>SE</i>	95% CI		<i>t</i>	<i>df</i>	<i>p</i>
			LL	UL						LL	UL			
Intercept	6.78	0.20	6.35	7.18	33.16	378.7	< .001	6.69	0.26	6.22	7.23	25.89	330.4	< .001
Trial	0.08	0.02	0.04	0.12	3.96	3569.1	< .001	0.08	0.02	0.04	0.12	3.96	3569.1	< .001
y-Position	- 0.56	0.07	- 0.68	- 0.44	- 8.51	3568.7	< .001	- 0.56	0.07	-0.69	-0.42	- 8.51	3568.8	< .001
Frame rate	0.20	0.16	- 0.13	0.51	1.25	318.8	.214	0.21	0.16	-0.10	0.51	1.30	318.3	.195
Chin rest ²								- 0.12	0.11	-0.34	0.10	- 1.13	3570.3	.258
Glasses ³								0.36	0.36	-0.39	1.08	1.01	209.8	.314
Random parts														
$u_{\text{Participant}}$	2.43		2.16	2.66				6.77		2.15	2.64			
σ_{ϵ}	3.30		3.22	3.37				8.23		3.22	3.38			
$N_{\text{Participant}}$	210							210						
Observations	3779							3779						

Note. Estimates of the fixed and random effects for the generalized linear mixed models where the model with the best model fit (**Table 2**) was compared against. Comparisons of the models can be found in **Table 4**. Trial-specific variables (e.g., stimulus position, chin rest) are modelled on level 1, participant-specific variables (e.g., glasses) are modeled on level 2. The random intercept $u_{\text{Participant}}$ is specified for the participant and reported as SD. σ_{ϵ} represents the standard deviation of the residuals. Df are reported as floats as a result of Welch's paired t-tests.

¹ square transformed

² 0=trials without chin rest, 1=trials with chin rest

³ 0=participants without glasses, 1=participants with glasses

Appendix E

Manipulation Check for the Choice Task

The probability for choosing the top versus the bottom option is normally distributed around $M = 50\%$ ($SD = 4\%$), which suggests that there is no effect of the choice option's spatial location on choice behavior.

The distribution of the discounting parameter $\log(k)$ was similar to the original study (Amasino et al., 2019) ($M = -5.4$, $SD = 1.7$, range = -9.5 to -2.5; **Figure E1**). Four participants showed extremely low discounting behavior ($k < .0001$ or percentage of LL-choices $> 95\%$) and were given $\log(k) = -9.5$.

Moreover, based on the participant's discounting parameter k , we estimated SVs for each choice option. (Amasino et al., 2019). The within-trial difference in SV is plotted against the probability for choosing the respective option, reaction time, and fixation counts. Like the original study (Amasino et al., 2019), we can find a logistic relationship between the relative SV and the proportion of choosing the top option (**Figure E2**). Moreover, trials with greater difference in SV were related to faster response times and fewer fixations. Note that the fixations measure in the original study (Amasino et al., 2019) was re-calculated according to the definition in this study (see the Methods section). Compared to the original study ($M = 6.02$, $SD = 1.35$), we report a lower number of fixations in this study ($M = 5.22$, $SD = 1.22$; Welch's paired t-test: $t(97.4) = 3.35$, $p = .001$ 95% CI = 0.33 to 1.29).

Figure E1

Frequency Distribution of the Discounting Parameter $\log(k)$

Note. Histogram of the log-transformed discounting parameter k . $N = 44$. The left side shows the distribution obtained from the original study (Amasino et al., 2019). The right side shows the distribution obtained from this study.

Figure E2

Relationships between the Subjective Value (SV) of the Choice Options and the Proportion of Choice, Response Time, and the Number of Fixations.

Figure E2 (continued)

Note. Choice outcomes (a), response time (c), and number of fixations (c) as a function of the difference in subjective value. Plots on the left side are calculated based on data from the original study (Amasino et al., 2019). Plots on the right side are calculated based on data from this study. Light gray lines represent individual subjects; darker lines represent group mean values; error bars represent Standard Errors of the Mean.

Appendix F

Alternative Models for the Choice Task

	Block 1						Block 2						
	<i>B</i>	<i>SE</i>	95% CI		<i>z</i>	<i>p</i>	<i>B</i>	<i>SE</i>	95% CI		<i>z</i>	<i>p</i>	
			LL	UL					LL	UL			
Intercept	1.07	0.20	0.68	1.48	5.23	< .001	1.05	0.20	0.69	1.42	5.15	< .001	1.02
Level 1 variables													
Trial	0.01	0.00	0.00	0.01	3.93	< .001	0.01	0.00	0.00	0.01	4.03	< .001	0.01
Reaction Time ¹	- 0.40	0.05	- 0.51	- 0.29	- 7.63	< .001	- 0.40	0.05	- 0.50	- 0.29	- 7.54	< .001	- 0.39
Option Index							- 0.06	0.07	- 0.21	0.08	- 0.85	.395	- 0.06
Attribute Index							0.12	0.08	- 0.03	0.29	1.46	.144	0.15
Payne Index							- 0.04	0.09	- 0.21	0.12	- 0.46	.645	- 0.01
Level 2 variables													
Option Index ²													- 0.73
Attribute Index ²													1.10
Payne Index ²													- 1.20
Random parts													
<i>u</i> _{participant}	1.20		0.91	1.49			1.19		0.91	1.48			1.05
<i>u</i> _{Option Index}													0.04
<i>u</i> _{Attribute Index}													0.20
<i>u</i> _{Payne Index}													0.03
<i>N</i> _{participant}	44						44						44
Observations	3241						3241						3241

Note. Estimates of the fixed and random effects for the generalized mixed model, where the model for Block 4 (**Table 6**) was compared against. Comparisons of all models can be found in **Table 7**. All variables, except the random intercept for participants (level 2) are modeled on level 1. The random effects *u*_{Option Index}, *u*_{Attribute Index}, and *u*_{Payne Index} are reported as SD.

¹ z-scale