

Investigating Status Quo Effects in Visualization-Aided Choice

Basak Oral , Wouter Ubbink, Evanthia Dimara , and Angelos Chatzimpampas 

Abstract—Status quo effects refer to an increased likelihood of selecting a default option over available alternatives. Although widely documented in behavioral research, their role in visualization-supported decision making remains unclear. We examine default adherence in probabilistic medical treatment decisions while systematically varying visualization format (quantile dotplots, density plots, probability bars, hypothetical outcome plots), default quality (good, average, or poor expected value), time pressure, and gain-loss framing. In a mixed-factorial experiment ($N = 123$), visualization was manipulated between participants and the remaining factors within participants. Default adherence was analyzed using mixed-effects logistic regression; decision accuracy (normalized expected value of the selected option) and response time were analyzed as complementary outcomes. Default adherence increased with default quality. Visualization format showed a marginal main effect on default adherence, though the observed differences appeared to be driven by specific visualization-default quality interactions under time pressure. Gain-loss framing showed no reliable association with default selection. Overall, our results suggest that choice-architecture factors such as defaults and time pressure can shape decision behavior in ways distinct from probabilistic decision accuracy. Supplementary material: https://osf.io/349jh/overview?view_only=89adaaaee52b4b4eb567dc5f05ffe058

Index Terms—Visualization, decision making, decision support systems, cognitive biases, status quo, defaults, empirical studies.

1 INTRODUCTION

Many visualization-aided workflows surface guidance that can privilege one option, for example by presenting recommended action plans [14] or by ranking candidate charts [32]. In behavioral research, the tendency to favor a default option is commonly described as *status quo bias* [19, 31]. Status quo effects have been observed in consequential domains, including vaccination decisions [30], pension plan allocations [31], and environmental policy [26]. Defaults also appear explicitly in user interfaces, for example as recommended selections in clinical order sets [24, 28]. Together, these examples illustrate how interfaces can privilege one option through recommendation, guidance, or attention-steering cues, motivating default adherence as a behavioral measure alongside how well users assess the displayed information.

Visualization and HCI research increasingly treats cognitive biases as measurable distortions of judgment and decision making that can be induced, detected, and eventually mitigated through interface design and information framing [2, 4, 13, 18, 35, 36]. Empirical studies in visualization and visual analytics have reported several such distortions under controlled interface manipulations. Anchoring and priming have been observed when early views, reference points, or training cues steer subsequent judgments, interaction patterns, or confidence [7, 33, 37]. Work on progressive visualization shows that partial, incrementally revealed results can induce systematic shifts in users' beliefs and actions, including anchoring-like effects and other bias patterns tied to when and how evidence is disclosed [29]. In visual communication, framing and belief-consistent processing have been documented, including political framing effects that persist across exposures [3] and confirmation-biased interpretation of "data facts" or visual evidence [8, 23]. Other studies show that visualization design choices can steer social interpretation, for example by encouraging stereotyped judgments when variability is hidden [20]. Finally, visualization research has adapted classic multi-option choice paradigms to detect choice-set effects such as the attraction and phantom effects, where adding a dominated decoy or an unavailable "phantom" alternative can shift selection among the remaining options [11, 12, 27].

Status quo bias has not been studied in visualization research, yet our prior work [25] suggests that default-like tendencies may arise in visualization-mediated choice. That study contrasted probabilistic judgments ("What is the best option?") and decisions ("What do you choose?") in repeated five-option tasks across scenarios and visual encodings. The option set included an inferior do-nothing alternative that participants selected at non-trivial rates. However, the study was not designed to isolate default mechanisms: the do-nothing option was not framed as the "default" option, and its quality relative to the remaining options was not systematically varied. As a result, it remained unclear whether these selections point to a broader default-like tendency or instead reflect task-specific interpretations of what it means to choose the "best" option.

Designing a visualization experiment that examines status quo effects is not straightforward, as multiple mechanisms and paradigms have been proposed to explain why people retain defaults [19]. One account is loss aversion: switching from the current option can be experienced as giving something up, so the perceived loss outweighs comparable gains [34]. Another is omission bias: harms caused by action can be judged more harshly than equivalent harms caused by inaction, making the default feel safer to keep [30]. Defaults may also persist because changing course invites anticipated regret, emotional conflict, or cognitive effort when trade-offs are difficult [1]. Action-bias accounts suggest that departures from the current option often require improvements from change to be clearly perceptible [26], while formal models suggest that greater choice complexity can amplify status quo tendencies [39]. Decision time has also been suggested as a contributing factor, but findings are mixed as to whether time pressure amplifies default reliance or reduces do-nothing tendencies [10, 17, 21, 38].

The present study investigates status quo effects in a visualization-mediated multi-option choice task. Building on the mechanisms and moderating factors outlined above, we experimentally manipulate the visualization encoding used to present option outcomes, the relative standing of the default option, the presence of time constraints, and gain-loss framing. Because these factors may interact, we use a factorial design to assess their association with default adherence.

Accordingly, we ask:

RQ: How is default adherence in multi-option choice associated with visualization encoding, default quality, time pressure, and gain-loss framing?

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2 PARTICIPANTS

We recruited 128 participants via Prolific¹ (age ≥ 18 , English fluency, and a 95% acceptance rate; no exclusions based on statistical or visualization training). Participants were paid £2; the median completion time was 13 minutes 30 seconds. Demographics are reported for all 128 recruited participants. Age: 18–30 (68), 31–40 (32), 41–50 (19), 51–60 (7), 60+ (2). Gender: male (74), female (51), non-binary (3). Education: Associate Degree (2), Bachelor’s Degree (70), College Degree (8), High School or equivalent (24), Master’s Degree (20), PhD or Doctorate (3), and Professional Degree (1). Initial visualization assignment was balanced: density (32), bars (32), HOPs (32), dotplots (32). Berlin Numeracy Test: $M = 3.13$, $SD = 1.22$. Five participants had at least one timed trial in which a timeout was recorded as the selected option and were excluded from the analysis, leaving $N = 123$. After exclusion, the analyzed visualization counts were density (31), probability bars (31), dotplots (31), and HOPs (30).

A post-hoc sensitivity analysis (G*Power v3.1), approximating the design as a mixed ANOVA with four between conditions and repeated-measures factors, indicated that with $N = 123$ the study had power $> .80$ at $\alpha = .05$ to detect small-to-medium main effects and two-way interactions ($f = .076-.223$, $\eta_p^2 \approx .006-.047$); this estimate is conservative given the use of mixed-effects regression for primary analyses. Data were collected anonymously (GDPR-compliant) with informed consent.

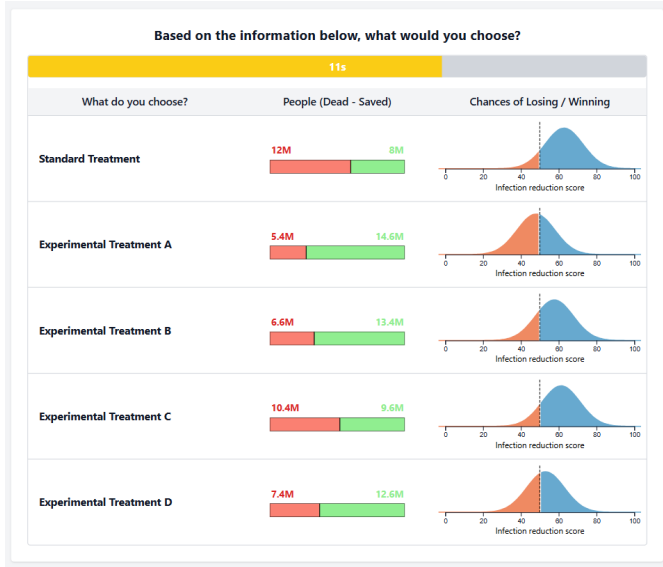


Fig. 1: Decision task interface under time pressure. Participants selected one of five treatment options. One row was framed as the standard default option; participants could keep it or switch to an experimental treatment. Each row combined projected lives lost/saved with the distribution over infection reduction scores. The best option was the one with the highest expected value, not necessarily the default option. In untimed trials, the same interface was used without the countdown bar.

3 EXPERIMENTAL DESIGN

The study employed a mixed factorial design with visualization format as a between factor (quantile dotplots, density plots, probability bars, Hypothetical Outcome Plots (HOPs)) and three within factors: time pressure (15 s limit vs. no limit), outcome framing (gain vs. loss wording), and default quality (good, average, poor). Default quality was operationalized by manipulating the expected value of the default option relative to the remaining four alternatives. The within factors

¹The Ethics and Privacy Quick Scan of the Utrecht University Research Institute of Information and Computing Sciences classified this research as low-risk, and therefore a full ethics review was not required.

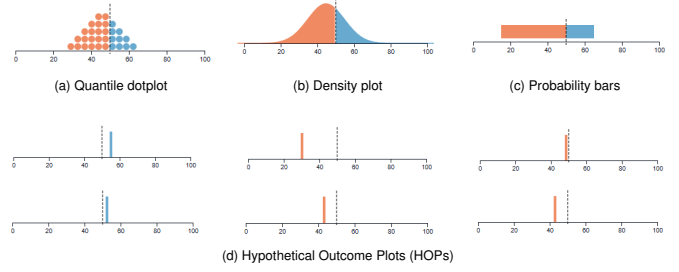


Fig. 2: Visualizations used in the experiment. The four formats represent different ways of showing distributions over infection reduction scores: (a) sampled quantiles, (b) continuous distribution summaries, (c) compact probability summaries, and (d) animated outcome samples.

were fully crossed, yielding a $2 \times 2 \times 3$ structure. Each participant completed 12 randomized five-alternative forced-choice trials covering all within-condition combinations. This design allows default adherence (selection of the default option) to be analyzed independently from decision accuracy (selection of the highest expected-value option).

3.1 Task and Stimuli

The task was framed as choosing a medical treatment during an infectious disease outbreak. On each trial, participants selected exactly one of five treatment options arranged in rows (Fig. 1) with the goal of saving as many lives as possible. One row was framed as the standard default option.

Each option combined two pieces of information. The loss–save bar indicated the magnitude of the outcome (projected lives lost in red and lives saved in green), while the probability visualization indicated the likelihood of better versus worse infection-reduction outcomes. To choose the best treatment, participants had to consider both: the option with the largest green segment was not necessarily best if its probability of favorable outcomes was lower. We defined the best option as the one with the highest expected outcome (expected lives saved), which was not necessarily the default.

As shown in Fig. 1, each row displayed (1) the treatment label (Standard or Experimental A–D), (2) the horizontal loss–save bar (People Dead–Saved), and (3) a probability visualization of the outcome distribution over infection-reduction scores (Chances of Losing–Winning). The loss–save bar and the probability visualization were shown side-by-side for each option. As shown in Fig. 2, we used four common visualization formats [16, 18, 22, 25] to depict the probability distribution: quantile dotplots (30 sampled quantiles as stacked markers), density plots (kernel density estimates with fixed axes), probability bars (proportional summary bars), and Hypothetical Outcome Plots (HOPs; animated sampled outcomes). Visualization format was assigned between participants and remained constant throughout the experiment.

This task and the visual encodings build on Oral et al. [25], the closest prior visualization study to our setup. As in Oral et al. [25], selecting the best option required integrating outcome magnitude from the loss–save bar with likelihood from the probability visualization by weighing larger saved/lost outcomes by how likely they were. Thus, we retained the same multi-option choice structure and comparable encodings, but indicated an explicit default-framed option and manipulated its expected-value quality. This allowed us to test whether the default-like selections observed in [25] persist when the status quo is operationalized as a default-framed option. Unlike [25], the present study used a medical context rather than a sports scenario, aligning the task with prior status quo research on consequential decision making [1, 31, 39].

In timed trials, a 15 s countdown bar appeared at the top of the interface (Fig. 1); if no selection was made before expiration, the trial was recorded as a timeout. Untimed trials used the same interface without the countdown bar.

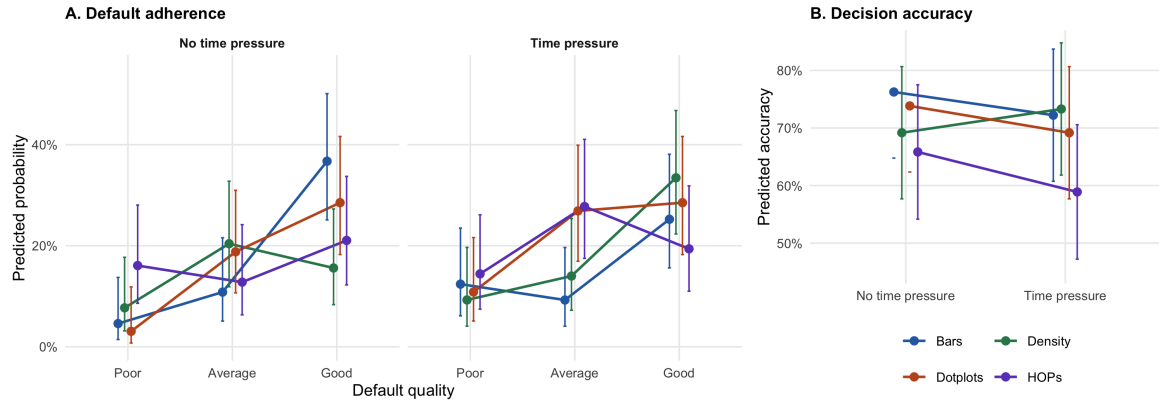


Fig. 3: Model-predicted probability and accuracy. Default adherence is averaged over framing; decision accuracy is averaged over framing and default quality. Error bars show 95% Wald CIs; full outputs are in the supplementary material.

3.2 Pilot

A pilot study ($N = 6$) evaluated task difficulty, visualization interpretation, and timing. It indicated that the task was challenging but tractable: default selection averaged 19.4%, and best-option selection averaged 38.9%. We refined the tutorial to clarify how to combine probability and outcome information, and adjusted the countdown timer to avoid tab-visibility timing errors.

3.3 Procedure

The study was conducted online using a custom-built experimental platform (React/TypeScript frontend with D3.js visualizations and an Express.js backend). After providing informed consent, participants completed: (1) a nine-page interactive tutorial tailored to their assigned visualization format, explaining distribution interpretation, framing, and default selection, following the same protocol as Oral et al. [25] (with the addition of a dedicated tutorial for HOPs; see supplementary material for screenshots); (2) 12 randomized decision trials; and (3) a numeracy test, an open-ended strategy question with the prompt “Did you use any particular strategy to complete the tasks?”, and demographic questions (see Sec. 2). Trial parameters, responses, and timestamps were recorded anonymously.

3.4 Measures

The dependent variable was default adherence, defined as a binary indicator of selecting the default-framed option. Decision accuracy was defined as the normalized expected value of the chosen option, $Accuracy = \frac{|EV_{chosen} - EV_{worst}|}{|EV_{best} - EV_{worst}|}$, where 1 denotes selecting the highest and 0 the lowest expected-value option. Response time was measured from trial onset to selection (15 s cap in timed trials); numeracy was assessed with the Berlin Numeracy Test [9].

3.5 Data Analysis

Analyses were conducted in R (v4.6.0) using `lme4`, `lmerTest`, and `emmeans`. Default adherence was modeled using generalized linear mixed-effects models (GLMMs with a logit link), while decision accuracy and response time were analyzed using linear mixed-effects models (LMMs). Response time was log-transformed because response times are typically positively skewed, with a long right tail, and was subsequently standardized. Fixed effects included visualization format (reference level: probability bars), default quality (reference level: poor), time pressure (reference level: untimed), framing, and their interactions. The full GLMM with all interactions showed separation-related instability because one condition cell had no default selections (dotplot $\times$ poor default $\times$ untimed $\times$ negative framing condition) and negligible framing effects, so we refitted a revised GLMM excluding framing interactions but retaining framing as a main effect. Models included random intercepts for participants. Fig. 3 summarizes model predicted outcomes; full coefficient tables, omnibus tests, and follow-up contrasts

are in the supplementary material. We used omnibus fixed-effect tests to identify reliable model terms, coefficient tables to describe direction and magnitude relative to the reference condition, and post-hoc contrasts to compare individual conditions. Coefficient-level and omnibus p -values are unadjusted; Bonferroni correction was applied only to post-hoc contrasts.

We also tested whether visualization effects were moderated by numeracy, age group, and education. Education was collapsed into Eurostat ISCED-based Medium and High attainment groups [15]; no participant fell into the Low group. Qualitative strategy responses were coded inductively into non-mutually-exclusive themes [5].

4 RESULTS

4.1 Default Adherence

As summarized in Fig. 3, model-predicted default adherence was generally low for poor defaults, whereas higher adherence appeared only in selected visualization-by-quality-by-time-pressure conditions. Omnibus tests for the revised default-adherence GLMM showed significant effects for default quality ($\chi^2(2) = 20.38$, $p < .001$), a significant visualization $\times$ default quality interaction ($\chi^2(6) = 17.66$, $p = .007$), and a significant visualization $\times$ default quality $\times$ time pressure interaction ($\chi^2(6) = 13.73$, $p = .033$), plus a marginal visualization effect ($p = .061$). Time pressure ($p = .131$) and framing ($p = .162$) were not reliable main effects. Post-hoc contrasts showed that default adherence increased as default quality improved. Additionally, in the average-default, time-pressure condition, default adherence was marginally higher in HOPs (Bar/HOP, $OR = 0.26$, $p = .074$) and dotplots (Bar/Dotplot, $OR = 0.28$, $p = .092$) compared to probability bars. Pairwise contrasts following the marginal main effect of visualization condition were not significant.

4.2 Decision Accuracy

For decision accuracy, only time pressure was reliable in omnibus tests ($\chi^2(1) = 4.32$, $p = .038$); visualization format, default quality, framing, and all interactions were not reliable. The post-hoc contrast for time pressure was marginal, indicating slightly higher accuracy without time pressure than with time pressure (no time pressure – time pressure estimate = 0.029, $p = .071$).

4.3 Time, Decision Accuracy, and Default Adherence

Analyses were restricted to untimed trials. With log-transformed response time, longer deliberation predicted higher accuracy ($\beta = 0.038$, $p = .004$), but response time was not associated with default adherence ($\beta = 0.045$, $p = .657$).

4.4 Individual Differences

Exploratory individual-difference models did not provide reliable evidence that numeracy, age group, or education predicted decision accu-

racy or default adherence, nor that these variables moderated visualization effects.

5 QUALITATIVE ANALYSIS

We coded open-ended responses (see Sec. 3.3) from 123 participants into non-mutually-exclusive strategies. The most common were integrated risk-benefit or expected-value reasoning ($n = 67$), outcome prioritization ($n = 58$), probability-focused comparison ($n = 52$), and visual heuristics ($n = 40$). Elimination or shortlisting appeared in 9 responses, and 20 participants reported no specific strategy. Only two participants explicitly mentioned the standard/default option: one described the standard treatment as an initial comparison point before checking the visual distributions and lives saved/lost bars for better alternatives, and one noted that sometimes doing nothing or keeping the same treatment could be better than choosing an experimental option with a high chance of failure. Four participants explicitly mentioned timed decisions, or time pressure; these responses described relying on colors or visual patterns for quick cost-benefit assessment, panicking in timed trials, or feeling pressured before being ready. Because strategies were elicited once after all tasks rather than separately for timed and untimed trials, these comments should be interpreted as anecdotal participant-reported evidence of possible time-pressure-related effects, not as systematic evidence of within-participant strategy shifts. Overall, participants often combined probability reading with outcome magnitude, typically through approximate visual comparison rather than formal calculation.

6 DISCUSSION

This study examined default adherence in probabilistic decisions as a function of default quality, time pressure, outcome framing, and visualization format. The clearest evidence concerned the main effect of default quality: post-hoc contrasts showed higher default adherence as default quality improved. In addition, visualization conditions differed in default adherence only under specific combinations of default quality and time pressure. Decision accuracy showed a different pattern: the analysis showed only a significant main effect of time pressure, with accuracy slightly lower under time pressure, whereas visualization format was not reliable overall.

Status quo-related effects have been linked to decision time, but prior work does not converge on a single directional expectation. Some studies report that time pressure reduces “doing nothing” responses, for example by decreasing choice deferral [10]. Others report the opposite pattern, where shorter decision times increase reliance on a default cue, including socially induced defaults [21] and action defaults [38]. Evidence from prosocial choice manipulations likewise does not yield a single monotonic prediction [17]. In our visualization-mediated probabilistic choice task, time pressure interacted with default quality and visualization format. This extends Oral et al. [25], who used the same uncertainty encodings without time pressure and found decisions comparatively resistant to status quo bias; our results suggest time pressure can elevate default adherence in specific visualization-by-default-quality conditions, even though poor defaults remained unlikely to be chosen.

The strategy reports mainly described how participants sought accurate choices and were largely silent on default adherence. Many participants described integrated risk-benefit reasoning, outcome prioritization, probability comparison, visual heuristics, or elimination strategies, consistent with seeking high expected-value options without formal calculation. Only two participants mentioned the standard/default option, treating it as an initial comparison point or a reasonable choice when alternatives carried high failure risk. That default adherence nonetheless varied with default quality and time pressure suggests the default influenced choices without being part of participants’ reported strategies. Time-pressure comments were also limited: four participants mentioned timed decisions, panic, or pressure, reporting quick reliance on colors, patterns, or salient cues. These hint at time-pressure-driven visual simplification but cannot establish systematic timed-vs-untimed shifts, since the strategy question was asked once.

Probability bars yielded numerically the highest decision accuracy, with quantile dotplots and density plots performing similarly but lower, and HOPs performing lowest; however, the visualization effect and all related interactions were not significant (all $p \geq .554$, Cohen’s $w \leq .05$), so these differences are descriptive only. This contrasts with prior work: Castro et al. [6] found that distributional formats (quantile dotplots, density plots) supported more accurate judgments than summary formats. Notably, our numerically best format, probability bars, is a summary format—precisely the class Castro et al. found inferior to distributional displays. Unlike their interval summaries, however, bars encode the decision-relevant probability directly, which may neutralize the extraction advantage that dotplots and densities otherwise provide. The numerically lowest accuracy for HOPs fits a similar account: HOPs distribute probability information across animated frames, and Kale et al. [22] found that HOPs yielded the least sensitivity to effect size, with only a few viewers adopting the frame-counting strategy required to read probabilities from them. Our descriptive order thus follows the effort required to extract the probability: bars display it directly, dotplots and densities require visual aggregation at a glance, and HOPs—although they encode outcome frequencies directly—spread this information across animated frames, demanding sustained observation over time. This pattern, however, was not statistically reliable.

6.1 Design Implications

These results suggest three practical implications for visualization-aided decision support. First, defaults should be treated as active design choices rather than neutral starting points. Second, improving probabilistic accuracy may not be sufficient to reduce default adherence, because accuracy and adherence can follow different patterns. Third, claims about one uncertainty visualization format outperforming another should be tied closely to the task, training, and decision context. More broadly, because decision making involves integrating probabilities with outcome consequences and committing to a course of action [25], support for probabilistic evaluation does not necessarily determine how users act on a plausible default option.

6.2 Limitations and Future Work

Several limitations qualify these findings. First, our manipulation captures a minimal status quo/default framing rather than a full real-world status quo. Participants had no prior ownership, long-term commitment, or institutional relationship with the default option. The results should therefore be interpreted as default adherence in visualization-aided choice, not as a complete model of clinical status quo bias. Second, the medical scenario was simplified: participants chose among five static treatment options with limited context, whereas real clinical decisions often involve richer information, professional expertise, interaction, and repeated deliberation. Third, the 15-second time limit was designed to impose cognitive pressure, but it should not be treated as representative of all medical decision settings. Fourth, the formats differed in temporal demands. HOPs required observing an animation, so the 15-second limit may have constrained their interpretation more than the static encodings. Thus, the numerically lower model-estimated accuracy for HOPs should be interpreted cautiously rather than as evidence of an inherent disadvantage of this format. Future work should test stronger default cues, richer decision contexts, interactive visualizations, and more realistic time constraints.

7 CONCLUSION

We investigated default adherence in visualization-aided probabilistic choice by varying visualization format, default quality, time pressure, and gain-loss framing. The results suggest that default adherence and probabilistic decision accuracy are partly separable: default adherence was shaped by default quality and condition-specific interactions with visualization and time pressure, whereas decision accuracy showed only limited evidence centered on time pressure. These findings indicate that visualized probabilistic decision tasks should consider not only how well users read probabilities, but also how defaults, task constraints, and time pressure can influence choices.

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