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Research and Applications

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Are interactive and tailored data visualizations effective in promoting flu vaccination among the elderly? Evidence from a randomized experiment

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ABSTRACT

Objective: Although interactive data visualizations are increasingly popular for health communication, it remains to be seen what design features improve psychological and behavioral targets. This study experimentally tested how interactivity and descriptive titles may influence perceived susceptibility to the flu, intention to vaccinate, and information recall, particularly among older adults.

Materials and Methods: We created data visualization dashboards on flu vaccinations, tested in a 2 (explanatory text vs none) × 3 (interactive + tailored, static + tailored, static + nontailored) + questionnaire-only control randomized between-participant online experiment ($N = 1378$).

Results: The flu dashboards significantly increased perceived susceptibility to the flu compared to the control: static+nontailored dashboard, $b = 0.14$, $P = .049$; static-tailored, $b = 0.16$, $P = .028$; and interactive+tailored, $b = 0.15$, $P = .039$. Interactive dashboards potentially decreased recall particularly among the elderly (moderation by age: $b = -0.03$, $P = .073$). The benefits of descriptive text on recall were larger among the elderly (interaction effects: $b = 0.03$, $P = .025$).

Discussion: Interactive dashboards with complex statistics and limited textual information are widely used in health and public health but may be suboptimal for older individuals. We experimentally showed that adding explanatory text on visualizations can increase information recall particularly for older populations.

Conclusion: We did not find evidence to support the effectiveness of interactivity in data visualizations on flu vaccination intentions or on information recall. Future research should examine what types of explanatory text can best support improved health outcomes and intentions in other contexts. Practitioners should consider whether interactivity is optimal in data visualization dashboards for their populations.

Key words: human-computer interaction, influenza, public health, interactivity, data visualization, annotations

BACKGROUND AND SIGNIFICANCE

Data visualizations are visual representations used to translate large amounts of information into understandable patterns for decision making.[1] In health, they can be used to support individuals in understanding their health risks and making better health choices, but the evidence about whether, and how they influence behavior is limited.[2] In public health, data visualization dashboards are a way of presenting a large amount of information while highlighting geographic or demographic areas of concern, both for individuals and governments to act on.[3,4] Throughout the COVID-19 pandemic, for example, every US state provided a dashboard showing infection and immunization rates.[5] There is conflicting research about how different types of dashboards influence readers,[6] and though interactivity is commonly used in health, much of the interactivity research is focused on climate science and map interactivity.[7]

A dashboard is "visual display of data used to monitor conditions and/or facilitate understanding (p. xiv)," and they can contain many different elements but all have some sort of visual data such as bar charts, time-series line-graphs, or maps.[8] Two additional elements that are often included on dashboards are interactivity and explanatory text.[9]

Interactivity is a technique in data visualizations that allows people to identify information they are most interested in and make choices about what data they want to see.[10] Some research defines interactivity as simple movements, allowing users to click from website to website, use navigation buttons, or scroll through text.[11–13] Other studies look at the impact of more advanced interactivity such as the ability to zoom in and out of maps, filter, sort, and otherwise provide participants more detailed control over the types of data they see.[14–17] The evidence base for the effectiveness of interactivity is mixed. Some research finds that interactivity can increase recall of information.[18,19] In particular, interactivity increases the recall of the interactive content. Interactivity works by increasing user engagement or content comprehension, which can increase attitudes and behavioral intentions.[20,21] However, other research has found that interactivity can reduce the clarity of the main message, even reducing recall of associated, noninteractive information.[22,23] This can be particularly detrimental for dashboards, which often contain multiple pieces of competing information.

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Despite limited evidence about the improvements of recall and cognition for interactive dashboards, they are highly utilized in health communication, both for personal[2] and public health, such as in mHealth applications[24–26] or in COVID-19 dashboards.[5,27] Addressing recall of information is useful, but understanding how dashboards of health information impact health beliefs and behaviors is critical for improving population health. According to the Health Belief Model (HBM), perceived susceptibility is the belief about how likely it is to get a certain disease.[28] Increasing perceived susceptibility to a disease is a strong predictor of preventing a particular health behavior such as getting a flu shot, particularly when risk information is made salient.[28–30] Further, studies about visualizations with risk information found that they can influence perceived susceptibility.[31] While interactivity in a health data journalism story increased fear of that health issue and increased intention to engage in protective health behaviors,[32] interactivity within a HPV risk data visualization, as compared to a static data visualization, did not.[19]

The mechanisms behind how interactive visualizations may influence health beliefs are not well understood. One mechanism is that interactivity increases cognitive absorption within the material, to increase perceived relevance of the information.[14,33] Some theory suggests that interactivity increases cognitive burden, and the increased work of looking through the content is itself persuasive.[34] Another possible mechanism is that interactivity, by allowing participants to select self-relevant information, provides computer-mediated health information tailoring; participants tailor the information to what they find most relevant, such as seeing only their state instead of a map of the whole United States.[35,36] Computer-tailoring health communications is a method of taking input from the user "using data-driven rules that produce feedback automatically from a database of content elements (p. 215)."[37] Computer-tailored health communications have mainly been studied in preventing or reducing effects of chronic conditions and have been successful in improving health outcomes.[37] Other research on tailored health communications has found that personalized risk information is effective in influencing perceived susceptibility to a disease.[38] Based on this body of research showing overall effectiveness of computer-tailoring, we expect dashboards that incorporate interactivity or tailoring will improve both health susceptibility beliefs and vaccination intentions, compared with a questionnaire-only control. We also expect to see a similar improvement on these two outcomes for a dashboard with static and nontailored health information:

> H1: Participants seeing dashboards (static+nontailored, static+tailored, and interactive+tailored) will have higher perceived susceptibility to influenza compared to participants in the control condition.
>
> H2: Participants seeing dashboards (static+nontailored, static+tailored, and interactive+tailored) will have higher intention to vaccinate against influenza compared to participants in the control condition.

Most dashboards contain limited narration, and literature on creating effective graphics often focuses on minimalist design to allow readers to clearly see and understand the presented data.[39–41] A counter movement, however, supports text and visual embellishment as a way to increase memorability, having found that charts with elements like cartoons, many colors, and increased visualization complexity are more likely to be recalled or remembered later.[42,43] Additional text, in the form of contextual explanations about the main data trends, and the context of the data, are highly rated features of data visualizations.[44,45] Explanatory text that highlights the chart's most salient and important points, either in-chart, or as a title, may potentially increase dashboard effectiveness.[9] By guiding message recipients through a story, dashboards with text can be effective and accurate communication tools in health communication.[46,47] So, we propose the following hypothesis:

> H3: Dashboards with explanatory text compared to dashboards without will lead to higher recall of the key dashboard messages and attributes.

In addition to dashboard characteristics such as explanatory text and interactivity that can influence their persuasiveness and memorability, there are personal characteristics that can moderate how people react to visualizations. For instance, low numeracy and literacy skills are associated with more difficulty interpreting health risk information.[48] A systematic review of interactive data visualizations found that participants with different literacy levels have differing emotional reactions to risk information.[49] Another personal difference in how people understand dashboards, particularly with interactive dashboards, is a person's interest in new technologies and novel interfaces. Measuring the extent to which participants enjoy new technology, or is an "early adopter" can describe how people may be more confident and engaged.[50] High personal innovativeness correlates to increased use of personal health records[51] and use of other interactive web-based technologies.[52,53]

For health communication about flu and flu vaccination, age may be an important characteristic when trying to influence related health beliefs using data visualizations. One study has found that interactive versus static content provided to older adults increased recall when specifically tailored to that audience.[54] Older adults have worked on co-creation of static and interactive data visualizations of health data, identifying specific health elements[55] or data visualization formats such as bar charts[56] that are most easily understood and used. A systematic review of mobile health technologies found that providing visualizations of health information could improve usability and health outcomes for older adults, particularly when co-creating visualizations.[57] They also call out the need for additional study on how visualizations are used and understood by older adults specifically. Because of the differences in how populations of different ages may experience these dashboards, we propose the following hypothesis:

> H4: The effects of explanatory text on information recall will be moderated by age.

OBJECTIVES

Influenza is a highly contagious disease that can pose a serious health risk, particularly for adults over age 65.[58] The influenza vaccine is effective at preventing hospitalization and death particularly among older adults,[59] yet studies show that only around 40–60% of older adults in the United States receive a flu vaccine each year.[60] Following the HBM, but without empirical evidence, public health professionals use data visualizations to increase perceived susceptibility to the flu and increase flu vaccination rates.[61,62] This study aims to examine how dashboard tailoring, interactivity and text can improve 3 outcomes related to flu vaccination: vaccine intentions, perceived susceptibility to the flu, and information recall.

MATERIALS AND METHODS

Experimental design and procedure

We completed a between-participants 2 (explanatory text or no explanatory text) × 3 (static + nontailored, static + tailored, or interactive + tailored) online randomized experiment, where participants were randomized into 1 of 7 conditions, 6 in which participants saw a data dashboard looking at flu vaccination rates, and a questionnaire-only control condition in which participants saw no dashboard. The study was reviewed and approved by the Institutional Review Board of the corresponding author's institution. Participants were first asked questions measuring covariates about age group, gender, rurality, and race, history of flu vaccination, and vaccine hesitancy. After randomization, participants saw the dashboard intervention and answered questions about vaccine beliefs, recall, manipulation checks, and flu attitude. The stimuli, data, and analysis script are available at the Open Science Framework website: https://osf.io/5w37k/.

Dashboard prototyping

We obtained multiple types of flu data to create the prototype data visualization dashboard, including number of flu deaths and rate of flu vaccinations by US county, both commonly used convey a population's susceptibility to, severity of disease.[63,64] Flu death data by county came from the Centers for Disease Control and Prevention,[65] and county-level vaccination data came from the Behavioral Risk Factor Surveillance System.[66] Using Tableau Desktop Version 2022.3,[67] we created a dashboard prototype, which is used in the initial stages of human-centered design to verify that participants can obtain needed information from the dashboard, identify major issues in the design, and learn new insights.[68] Revised versions after incorporating feedback from the focus group (detailed below) were then embedded into the survey tool.

Focus group and stimuli

A small focus group of individuals over age 55 ($n = 4$) convened to provide feedback on the initial prototype. Participants were recruited through paper flyers, Facebook posts onto a community group, and an email to a neighborhood listserv. We used a semistructured interview guide asking participants about their experiences looking at medical, health, or public health information, including in dashboards, such as for the COVID-19 pandemic data (Supplementary Appendix SA). Participants then accessed the website with the prototype and provided feedback about their user experience and their thoughts on the content, with a think-aloud protocol.[69] We also piloted the recall and recognition questions in the focus group.

After gathering usability feedback from the focus group in which participants stated the importance of "[Vaccination rates] instead of the death, [which] you can't do anything about," we simplified the dashboard to show influenza vaccination rates by county for Medicaid recipients. This change led to focusing the hypotheses on perceived susceptibility to the flu. Participants also found the dashboard text both informative and at times confusing, and overall spent a great deal of time reading and thinking about the explanatory text on the dashboards, which supported moving forward with the study manipulation of explanatory text on the dashboards.

The dashboard stimuli used the most common data visualization elements including maps and bar charts.[70] Each of the 3 dashboard types (static+nontailored, static-tailored, and interactive+tailored, Figure 1) were developed to be as similar as possible while maintaining the manipulation. The static +nontailored dashboard provided a single map of the United States with the national flu vaccination rate. The static+tailored condition requested participants' home state and county, and then provided a dashboard showing that county's flu vaccination rate as compared to the United States and the state rate, a personalization identified in past research.[36] The interactive+tailored condition (Figure 2) first showed participants a map of the United States which they could hover over to get state-specific vaccination rate. Participants were encouraged to click on their state and shown a gif to demonstrate. Clicking on the US map in the interactive+tailored condition filtered to show just that state with county flu vaccination levels using hover text. The explanatory text condition showed either no additional text beyond basic titles such as "Influenza Vaccination Rates" or "Flu Vaccination Rate in Wisconsin," or included explanatory text with the main dashboard takeaway on the dashboard, such as "Delaware and other states in the Northeast have the highest flu vaccination rates, while North Dakota and other states in the Western US have the lowest," and "Alabama ranks 46 with a low vaccination rate of 42% of adults vaccinated" (Figure 3).

Participants

We recruited 1,384 participants living in the United States to complete the online experiment delivered through Qualtrics. The sample was recruited using a survey contractor called Lucid that maintains a large and diverse national online panel, with a minimum 50% quota of participants over 55, screened for English fluency. Six participants were removed because of technical trouble for a total of 1,378. Exact age could not be obtained due to IRB data privacy concerns, but the largest proportion of the population was between 40–44 (9.5%), 65–69 (10.4%), and 70–74 (9.5%), and 50.6% identified as female ($N = 697$). Individuals identifying their race as Black made up 20.5%, 64.9% identified as White, 6.1% as Asian or Hawaiian, 3.6% as multiple races and 2.6% as American Indian. Additional demographic characteristics are listed in Table 1 by dashboard condition. Most participants completed the survey on a mobile device (65.9%) or laptop (33.8%). The dashboards were mobile optimized.

Measures

Means, standard deviations, ranges, correlations, and Cronbach's α for all measured variables are listed in Table 2.

Covariates

We included covariates to improve estimation efficiency for treatment effects. *Vaccine hesitancy* was measured by a 10-question scale (from 1 to 10) measuring the complex feelings of delaying or refusing vaccines, including constructs about

Figure 1. Example flu vaccination dashboard stimuli from each of the six conditions into which participants were randomized.

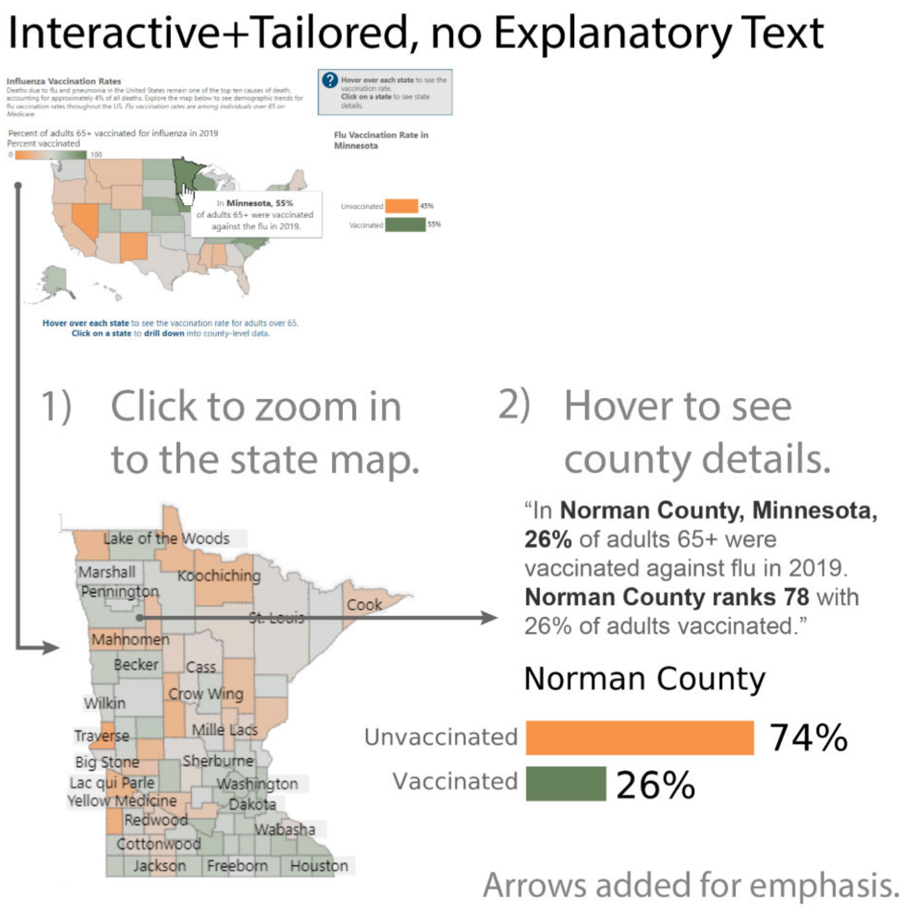

Figure 2. Workflow for the interactive+tailored, no explanatory- text condition in which participants first saw a map of the United States and could click on their state for detailed information about flu vaccines.

behavior, efficacy, safety, and general trust.[71] Higher scores indicate greater vaccine hesitancy. The *Personal Innovativeness Scale* uses 4 questions on a scale from 1 (*not at all like me*) to 4 (*very much like me*) to measure a participant's interest in using new software, such as "I like to experiment with new software."[72] The *Ageism* scale is a 5-question scale from

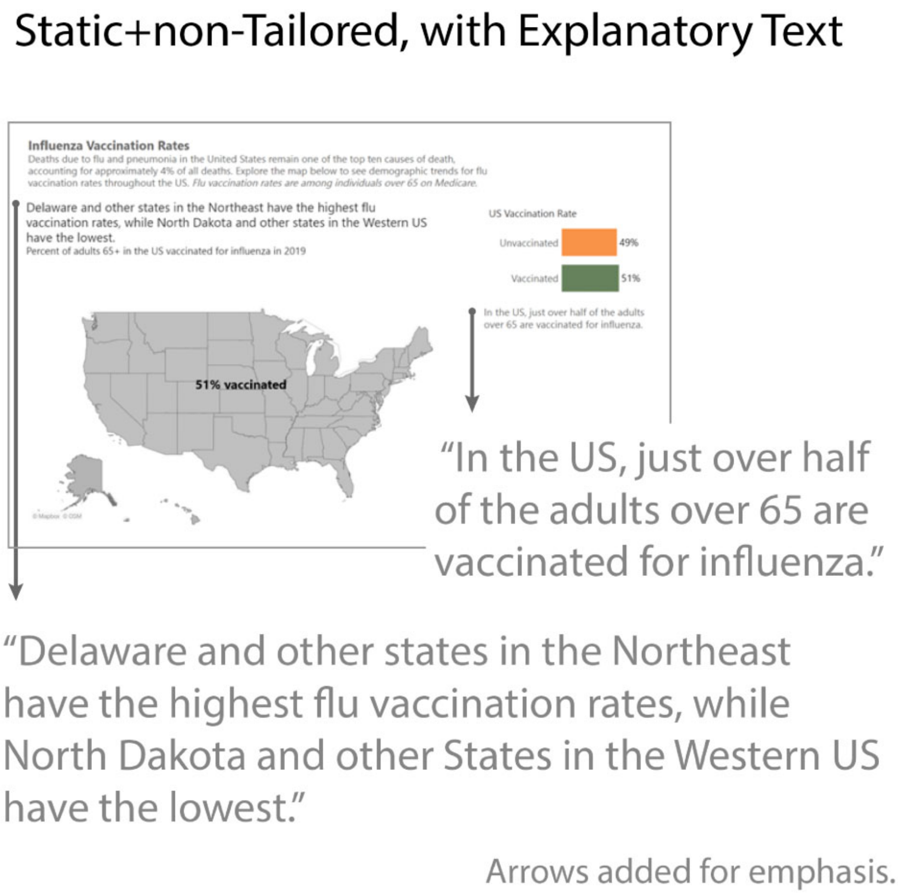

Figure 3. Close-up of the text included on the flu vaccination dashboards in the explanatory text condition.

1 (*strongly disagree*) to 7 (*strongly agree*) asking participants to rate how much their age influences others' perceptions of them, adapted to include questions about physical and mental health.[73,74] Ageism can effect self-reported health measures such as susceptibility to disease, and participants were asked 5 questions such as "Some people feel that I'm physically weak because of my age."[75] *Rurality* may influence both map literacy and health care beliefs. Participants were categorized as "rural" if they answered "What type of place do you live in?" as *Small town* or *Rural*. Ability to read and understand statistics is a foundational part of understanding data visualizations, so following existing protocols, participants answered 5 questions to rate their *numeracy levels*.[76] After dropping one question which the majority of the participants answered incorrectly, the numeracy scale reliability was moderate.

Outcomes

Measures of susceptibility to flu is a common outcome in health communications, particularly for vaccine-preventable diseases.[28] After viewing the stimuli, participants were asked "It is likely that I will get the flu," "I am at risk of getting the flu," and "It is possible that I will get the flu" with responses on a 5-point scale from *1 = strongly disagree* to *5 = strongly agree*.[77] *Vaccine intentions* were assessed with a single-item, "How likely are you to get a flu vaccination next season?" and answered on a 5-point scale. *Recall* was assessed with twelve questions about the dashboards that participants saw, such as the types of visualizations, and the type of information, to which they responded *yes* or *no* (Supplementary Appendix SB). Based on research on signal detection,[78] we normalized the number of correct responses after adjusting for false positives and incorrect misses, to calculate the metric d', a measure of an individual's ability to correctly recall information free of response biases. This was calculated with the *dprime* package in the statistical programming language *R*.[79]

Statistical analyses

All statistical analyses were done using the statistical programming language *R* (version 4.2.2). We used the *estimatr* package to calculate robust standard errors on all linear regression models with dummies representing between-condition contrasts. In addition to using survey covariates in the linear regression models, we included county vaccination rate as an additional covariate in all regression models, which was the percent of Medicaid recipients in the respondents county who were vaccinated against the flu.[66] All tests were 2-tailed.

RESULTS

Manipulation check

To check manipulation success about dashboard interactivity, participants in all conditions were asked if they interacted with the dashboard. Participants in the interactive+tailored condition were significantly more likely to report interacting with the dashboard, $F(1, 1150) = 283.80$, $P < .001$. To test

Table 1. Demographic characteristics of survey participants by condition ($N = 1378$)

		No explanatory text			Explanatory text			
	Control ($n = 222$)	Static+nontailored ($n = 192$)	Static+tailored ($n = 200$)	Interactive+tailored ($n = 191$)	Static+nontailored ($n = 199$)	Static+tailored ($n = 190$)	Interactive+tailored ($n = 184$)	Overall ($n = 1378$)
Age								
Under 55	115 (51.8%)	117 (60.9%)	108 (54.0%)	107 (56.0%)	95 (47.7%)	110 (57.9%)	97 (52.7%)	749 (54.4%)
55 and Over	107 (48.2%)	75 (39.1%)	92 (46.0%)	84 (44.0%)	104 (52.3%)	80 (42.1%)	87 (47.3%)	629 (45.6%)
Gender								
Man	104 (46.8%)	89 (46.4%)	96 (48.0%)	103 (53.9%)	99 (49.7%)	89 (46.8%)	90 (48.9%)	670 (48.6%)
Woman	116 (52.3%)	102 (53.1%)	103 (51.5%)	87 (45.5%)	99 (49.7%)	98 (51.6%)	92 (50.0%)	697 (50.6%)
Self-described	2 (0.9%)	1 (0.5%)	1 (0.5%)	1 (0.5%)	1 (0.5%)	3 (1.6%)	2 (1.1%)	11 (0.8%)
Rurality								
Rural	56 (25.2%)	48 (25.0%)	67 (33.5%)	47 (24.6%)	57 (28.6%)	50 (26.3%)	47 (25.5%)	372 (27.0%)
Urban	166 (74.8%)	144 (75.0%)	133 (66.5%)	144 (75.4%)	142 (71.4%)	140 (73.7%)	137 (74.5%)	1006 (73.0%)
Race								
White	148 (66.7%)	121 (63.0%)	134 (67.0%)	121 (63.4%)	128 (64.3%)	118 (62.1%)	124 (67.4%)	894 (64.9%)
Black	39 (17.6%)	43 (22.4%)	43 (21.5%)	44 (23.0%)	37 (18.6%)	42 (22.1%)	34 (18.5%)	282 (20.5%)
Multiple or Self-described	35 (15.8%)	28 (14.6%)	23 (11.5%)	26 (13.6%)	34 (17.1%)	30 (15.8%)	26 (14.1%)	202 (14.7%)
Vaccine Hesitancy								
Mean (SD)	6.47 (0.84)	6.42 (0.73)	6.40 (0.83)	6.54 (0.84)	6.34 (0.84)	6.43 (0.80)	6.55 (0.80)	6.45 (0.81)
Ageism								
Mean (SD)	3.75 (1.46)	3.72 (1.51)	4.02 (1.44)	3.96 (1.47)	3.81 (1.46)	3.88 (1.48)	3.96 (1.34)	3.87 (1.45)
Numeracy								
Mean (SD)	2.37 (1.30)	2.42 (1.33)	2.35 (1.30)	2.47 (1.26)	2.52 (1.29)	2.40 (1.26)	2.49 (1.26)	2.43 (1.29)
Personal Innovativeness								
Mean (SD)	2.30 (0.80)	2.40 (0.83)	2.26 (0.76)	2.42 (0.75)	2.30 (0.79)	2.45 (0.71)	2.34 (0.81)	2.35 (0.78)
County Vaccination Rate								
Mean (SD)	48.3 (7.00)	46.9 (7.30)	47.2 (7.68)	48.2 (6.85)	47.1 (7.38)	46.7 (7.60)	47.1 (6.48)	47.4 (7.21)

Table 2. Summary of correlations, means, and standard deviations for key variables and outcomes ($N = 1378$)

		M	SD	Min–Max	1	2	3	4	5	6
1	Intention to vaccinate	3.61	1.52	1–5						
2	Susceptibility	3.25	0.85	1–5	.23*	α=.74				
3	Vaccine hesitancy	6.45	0.81	1–5	−.57*	−.17*	α=.89			
4	Ageism	3.87	1.45	1–7	.17*	.23*	−.04	α=.88		
5	Numeracy	2.43	1.28	0–4	−.03	−.03	−.16*	−.17*	α=.57	
6	Personal innovativeness	2.34	0.78	1–4	.08*	.10*	−.02	.03	−.20*	α=.77
7	County vaccination rate	47.37%	7.21	19–63	.02	.00	.01	−.02	.08*	−.04

Note: Cronbach's α is listed along the diagonal where applicable.
* Statistically significant at $P < .05$.

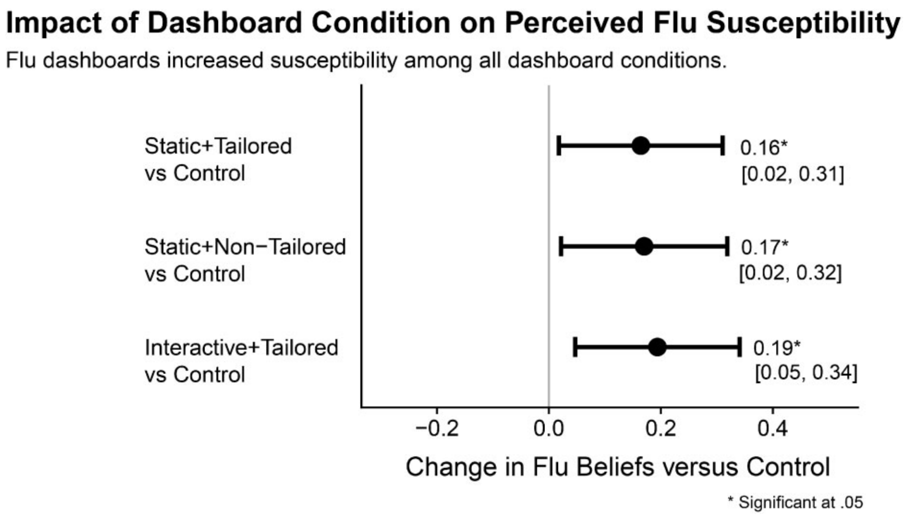

Figure 4. Results showing that all three dashboard conditions (static+tailored, static+non-tailored, interactive+tailored) increased perceived flu susceptibility.

the tailoring manipulation, participants were asked 3 questions about whether they were able to find tailored and personally relevant information from the dashboard. Participants who were randomized to a tailored dashboard condition were more likely to say that they saw a tailored dashboard, $F(1, 1147) = 71.34$, $P < .001$. Experimental manipulation on interactivity and tailoring were thus deemed successful.

Effects of dashboard interactivity and tailoring

We first tested potential interactions between the 2 experimental factors (explanatory text condition and dashboard conditions) on perceived susceptibility, intention for vaccination, and recall, after controlling for covariates, and found no significant interaction effects. Then, we moved on to test main effects for each factor respectively for each outcome.

To answer H1, we regressed perceived susceptibility to the flu on the 3 dashboard conditions. We then ran a multiple-regression model in which we regressed perceived susceptibility on dashboard condition dummies, controlling for age, gender, rurality, race, existing vaccine hesitancy, ageism, numeracy, personal innovativeness, and county vaccination rate. Three dashboard conditions all improved perceived susceptibility, when compared with the questionnaire-only control condition (see Figure 4): static+nontailored dashboard, $b = 0.14$, $P = .049$; static+tailored, $b = 0.16$, $P = .028$; and interactive+tailored, $b = 0.15$, $P = .039$ (Table 3). Results were consistent with an unadjusted model without covariates. In terms of covariates, the analyses revealed that age ($b = -0.04$, $P < .001$) and vaccine hesitancy ($b = -0.20$, $P < .001$) were significantly associated with reduced perceived susceptibility. We found no significant difference of susceptibility between the static+nontailored dashboard compared to the static+tailored, $P = .614$, or interactive+tailored dashboards, $P = .919$.

We regressed participants' reported intention to vaccinate against the flu in the coming year (H2) and found no significant effects of dashboard conditions on intention, $P = .762$.

Lastly, we compared the 3 dashboard conditions against each other and age as a moderator. We regressed information recall on dashboard conditions, age, and their interaction, adjusting for covariates. We found that age did not significantly moderate the difference in the static + nontailored versus the interactive + tailored comparison, $b = 0.03$, $P = .073$ (see Figure 5), nor for the static+tailored version versus the interactive+tailored dashboard comparison, $b = 0.02$, $P = .290$.

Effects of adding explanatory text

To test H3 and H4, we estimated a multiple regression model in which we regressed recall, susceptibility, and intention to vaccinate against the flu on the text condition dummy and age (continuous, mean-centered), their interaction, and the covariates (Table 4). There was no significant main effect of the explanatory text condition on recall $b = -0.01$, $P = .90$, thus the data did not support H3. In support of H4, the interaction between text and age was statistically significant such

Table 3. Main effects of dashboard conditions compared to questionnaire-only control for perceived susceptibility, and intention to vaccinate against flu, adjusted for covariates

	Perceived susceptibility			Intention to vaccinate		
	Estimate	[95% CI]	*P* value	Estimate	[95% CI]	*P* value
Intercept	**2.82**	**[2.34, 3.29]**	**<.001**	**5.7**	**[5.02, 6.40]**	**<.001**
Static+nontailored vs control	**0.14**	**[0.00, 0.29]**	**0.049**	−0.11	[−0.32, 0.09]	0.285
Static+tailored vs control	**0.16**	**[0.02, 0.30]**	**0.028**	−0.13	[−0.34, 0.08]	0.238
Interactive+tailored vs control	**0.15**	**[0.01, 0.30]**	**0.039**	−0.07	[−0.28, 0.14]	0.503
Covariates						
Age (continuous)	**−0.04**	**[−0.05, −0.02]**	**<.001**	0.00	[−0.03, 0.02]	0.823
Gender—Woman	0.01	[−0.08, 0.10]	0.805	−0.08	[−0.22, 0.06]	0.263
Rural	0.01	[−0.03, 0.04]	0.682	0.05	[−0.11, 0.22]	0.530
Race—Black	−0.15	[−0.28, −0.01]	0.032	**−0.20**	**[−0.38, −0.01]**	**0.035**
Race—Other	−0.09	[−0.22, 0.04]	0.173	0.10	[−0.10, 0.30]	0.313
Vaccine hesitancy	**−0.20**	**[−0.25, −0.14]**	**<.001**	**−1.10**	**[−1.18, −1.02]**	**<.001**
Ageism	**0.14**	**[0.10, 0.17]**	**<.001**	**0.14**	**[0.09, 0.18]**	**<.001**
Numeracy	0.01	[−0.03, 0.05]	0.594	**−0.13**	**[−0.19, −0.08]**	**<.001**
Personal innovativeness	0.04	[−0.02, 0.11]	0.192	0.07	[−0.03, 0.18]	0.188
County vaccination rate	0.00	[0.00, 0.01]	0.332	**0.01**	**[0.00, 0.02]**	**0.048**

Bolded values are statistically significant at $P < .05$.

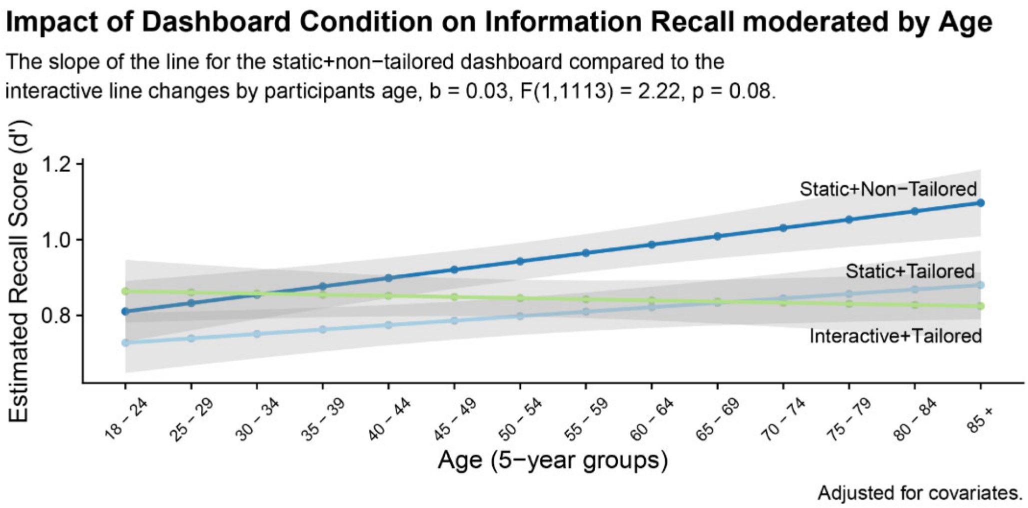

Figure 5. Results showing the interaction between dashboard condition (static+tailored, static+non-tailored, interactive+tailored) and age on information recall.

that for every 5-year increase in age, the effect of explanatory text on improving recall increased by 0.03, $P = .025$ (see Figure 6). There was a significant effect of age but not text condition on susceptibility to flu, and no significant effect of either text condition nor age on intention to vaccinate (Table 4).

DISCUSSION

We found that all 3 dashboard types (static+nontailored, static+tailored, and interactive+tailored) increased perceived susceptibility to the flu compared to the control, however that did not translate into increased intention to vaccinate against the flu in the coming season. Risk information such as percent of people vaccinated against the flu and the potential herd immunity that imbues may not be strong enough to influence flu beliefs. We found no significant effects of interactivity on information recall. When comparing interactive+tailored dashboards with the static versions, we did not find evidence to support the interactive designs' relative advantages, neither in the overall sample nor among the elder participants. While some studies have found positive results for computer-mediated health communication,[80] this study found no benefits of interactive dashboards. This aligns with an early study of interactivity on health risk which concluded that "interactivity, however visually appealing, can both add to respondent burden and distract people from understanding relevant statistical information (p. 1)."[81] There were significant correlations on outcome by race and age, such that individuals who identified as younger or Black were less likely to report an intention to vaccinate against the flu. These correlational results on race have been found elsewhere, as Black Americans often have past negative experiences that lead to medical mistrust and vaccine hesitancy.[82–85]

Studying the impact of interactivity in dashboards is still nascent, however, and there are methodological constraints such as controlling the experience between dashboards, or how the participants engage with the stimuli. We did not control how much time participants spent on the dashboards, nor

Table 4. Impact of interaction between language condition and age on information recall, perceived flu susceptibility, and vaccination intention, adjusted for covariates

	Recall			Susceptibility			Vaccination intention		
	Estimate	[95% CI]	*P* value	Estimate	[95% CI]	*P* value	Estimate	[95% CI]	*P* value
Intercept	**0.48**	**[0.06, 0.90]**	**0.026**	**2.87**	**[2.39, 3.35]**	**<.001**	**5.68**	**[4.95, 6.41]**	**<.001**
Explanatory text vs no text	0.00	[−0.08, 0.08]	0.919	0.04	[−0.05, 0.13]	0.427	0.10	[−0.04, 0.24]	0.17
Age (continuous)	**0.02**	**[0.01, 0.04]**	**0.012**	**−0.04**	**[−0.07, −0.02]**	**<.001**	−0.01	[−0.04, 0.03]	0.72
Language type×age	**0.03**	**[−0.05, 0.00]**	**0.025**	0.00	[−0.02, 0.03]	0.770	0.00	[−0.04, 0.04]	0.91
Covariates									
Gender—Woman	0.02	[−0.08, 0.11]	0.725	0.03	[−0.07, 0.13]	0.562	−0.04	[−0.2, 0.11]	0.59
Rural	−0.08	[−0.17, 0.01]	0.071	−0.06	[−0.16, 0.04]	0.211	0.14	[−0.04, 0.32]	0.13
Race—Black	**−0.14**	**[−0.26, −0.03]**	**0.016**	−0.13	[−0.27, 0.01]	0.066	**−0.20**	**[−0.39, −0.01]**	**0.04**
Race—Other	−0.07	[−0.20, 0.06]	0.299	−0.03	[−0.17, 0.11]	0.652	0.14	[−0.08, 0.35]	0.22
Vaccine hesitancy	−0.02	[−0.07, 0.03]	0.357	**−0.21**	**[−0.27, −0.15]**	**<.001**	**−1.11**	**[−1.2, −1.03]**	**<.001**
Ageism	**−0.03**	**[−0.06, 0.00]**	**0.030**	**0.15**	**[0.11, 0.18]**	**<.001**	**0.13**	**[0.08, 0.18]**	**<.001**
Numeracy	**0.14**	**[0.11, 0.17]**	**<.001**	0.01	[−0.03, 0.05]	0.475	**−0.13**	**[−0.19, −0.07]**	**<.001**
Personal innovativeness	−0.02	[−0.08, 0.03]	0.425	0.04	[−0.03, 0.11]	0.290	0.07	[−0.05, 0.19]	0.25
County vaccination rate	0.00	[0.00, 0.01]	0.134	0.00	[0.00, 0.01]	0.219	0.01	[0.00, 0.02]	0.10

Bolded values are statistically significant at $P < .05$.

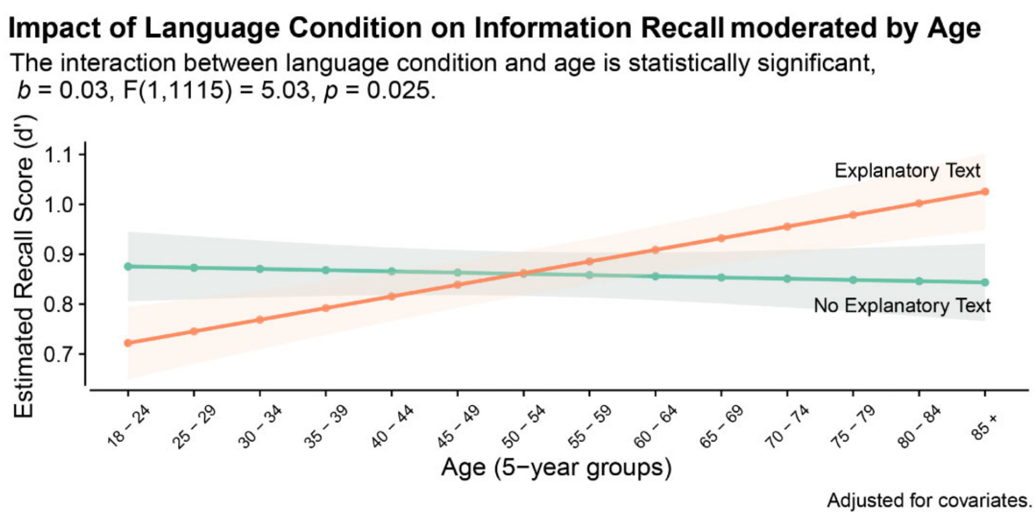

Figure 6. Results showing the significant interaction between the explanatory text condition (explanatory text vs none) on recall.

how much or how little participants in the interactive condition truly engaged with the dashboard. Therefore, our results represent an intention to treat analysis, possibly underestimating the true effects of interactive design should participants be forced to engage. We believe these results are still informative and high in external validity, as in real life the public typically are not offered incentives to fully engage with a health data visualization dashboard. Furthermore, there were minor differences in phrasing between conditions. Although we cannot rule out the possibility that this could be a confounder, such minor differences are unlikely to substantially alter our key results. Future studies can benefit from using a more reproducible, programmed tool for developing dashboards instead of a user-interface.[86] Finally, health communication, though critically important, may not be as fun or engaging as other types of data that may be more persuasive in interactive forms.

We also found that there are benefits to using explanatory language on dashboards for improving recall compared to no text, which differed by age such that older adults reported higher recall when in the explanatory text condition. The benefits of including explanatory text match existing literature about some of the benefits of annotations on data visualizations.[44,69]

CONCLUSION

This study attempted to identify the impact of seeing interactive, tailored data visualizations on susceptibility beliefs, flu intentions, and recall. We found that the data visualization dashboards improved perceived susceptibility compared to the control, and that dashboards with explanatory text led to more information recall, particularly for older adults who are most at risk. Showing older adults risk information in the form of a dashboard with explanatory text may lead to increased perceived risk among this population, a key method to decrease flu morbidity and mortality.[7] This study showed that visualizations about flu vaccinations did not decrease participants' intentions to vaccinate against the flu, which in and of itself is an important finding given the prevalence of visualizations in public health, and the frequency with which health messaging backfires.[87,88]

Despite the popularity of using interactive dashboards, our experimental data did not show the superiority of interactivity as a design feature. In contrast, for the elderly population, interactive dashboards not only did not outperform static versions of data visualizations but appeared to perform worse in terms of information recall. Adding explanatory text is a more promising strategy to improve information recall. These results call for careful randomized tests of design features such as hover text and click-to-filter in data visualization dashboards to optimize the effective delivery of health information to vulnerable populations. Further research is also needed to explore how text on dashboards, not just in single data visualizations, can influence health behaviors. Finally, data visualization is common in mHealth applications,[89] and these results also indicate additional research on dashboard features within mHealth applications for self-monitoring is needed, to identify their persuasive potential for improving health.

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AUTHOR CONTRIBUTIONS

LMC and SY designed the study, including the data collection instruments. LMC created the study stimuli, conducted the focus group, and analyzed the data with SY. LMC drafted the manuscript, and SY reviewed the manuscript and revised it for critical content.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Journal of the American Medical Informatics Association* online.

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CONFLICT OF INTEREST STATEMENT

The authors have no competing interests to report.

DATA AVAILABILITY

The data underlying this article are available in OSF at https://osf.io/5w37k/, doi: 10.17605/OSF.IO/5W37K.

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