Visual Analytics of Tailored Mammography Screening Interventions: Compliance and Cognitive Stage Outcomes

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Abstract— Regular mammography screening reduces breast cancer mortality, yet participation remains suboptimal in many populations. This study applies a visual analytics approach to evaluate a randomized controlled trial of tailored interventions—phone counseling, mailed materials, or both—designed to increase mammography compliance and enhance cognitive readiness for screening. Using interactive data visualizations for 958 women aged 50 and above, supported by logistic regression analyses, we explore both behavioral and cognitive outcomes. The combined phone-plus-mail intervention achieved a 39% screening compliance rate, compared with 27% in the control group, and nearly half of its participants progressed to the Action stage, versus roughly one-third in the control arm. These patterns are clearly revealed through our visualizations. Statistical modeling further corroborates these findings, with the combined intervention yielding an odds ratio of approximately 1.7 for screening compliance relative to control ($p < 0.01$). Overall, our visual analytics pipeline demonstrates how integrating interactive visualization with statistical modeling can illuminate both screening behavior and stage progression, offering actionable insights for public health strategies aimed at improving screening uptake.

Index Terms—Visual analytics, Interactive data visualization, Mammography screening, Tailored interventions, Screening compliance, Cognitive stage of readiness.

I. INTRODUCTION

Breast cancer remains the second leading cause of cancer mortality among women, with screening participation especially low among groups such as Hispanics, Native Americans, older women, and those of lower socioeconomic status [1]. Although mammography effectively reduces incidence and mortality [2], adherence is influenced by factors such as age, education, income, family history, and provider recommendations [3–9]. Tailored behavioral interventions—such as reminder letters, personalized mailings, and phone counseling—aim to address informational and motivational barriers, yet their effects on both screening uptake and cognitive readiness are not always easy to interpret using traditional table-based analyses.

To address this gap, we apply a visual analytics framework to re-examine a randomized trial of tailored mail and phone interventions. We focus on two outcomes: (1) mammography compliance within 6 months and (2) changes in cognitive stage based on the Transtheoretical Model. By integrating interactive visualizations with statistical modeling, we provide an intuitive way to compare intervention effects and reveal behavioral patterns that may be obscured in purely numeric summaries. This approach offers clearer, more actionable insights for designing strategies to improve mammography screening participation.

II. RELATED WORK

Visualization has long supported public health sensemaking by enabling overview-and-detail exploration of complex population data, from outbreak monitoring to evaluating prevention strategies [9]. In mammography research, behavioral interventions such as mailed reminders and tailored telephone counseling show modest improvements in screening uptake [1,2], yet results are typically presented through static statistical tables that limit interactive comparison across groups. Stage-based behavioral models, including the Transtheoretical Model, further characterize readiness for screening, but prior work rarely visualizes how individuals transition between cognitive stages over time [8]. This lack of visual, interaction-driven analysis constrains researchers' ability to identify heterogeneous intervention effects or intermediate behavioral shifts. Our study builds on these threads by applying visual analytics techniques to integrate statistical modeling with interactive, comparative visual representations, enabling richer sensemaking of both screening behavior and cognitive stage progression in a randomized trial setting.

III. METHODS

A. Study Design and Data

We analyzed a randomized controlled trial evaluating tailored interventions—phone counseling, mailed materials, and their combination—aimed at improving mammography screening among 958 women aged 50+ who were noncompliant with annual screening. Participants completed baseline surveys and follow-up assessments at 3, 11, and 23 months, enabling longitudinal measurement of behavioral and cognitive outcomes.

B. Outcome Measures

We evaluated two key outcomes in our visual analytics workflow: a behavioral outcome—6-month mammography compliance verified through medical records—and a cognitive outcome based on the Transtheoretical Model stages (Precontemplation, Contemplation, Action), capturing readiness for screening. To summarize overall cognitive improvement, we additionally defined an upstaging indicator reflecting whether a participant advanced to any higher stage at any follow-up during the study period.

C. Covariates and Preprocessing

Baseline predictors included age, education, income, provider recommendation, family history, and baseline stage. Missing data was handled via complete-case analysis, yielding 958 complete observations.

D. Visual Analytics Pipeline

Our visual analytics pipeline followed an overview-to-detail strategy: we first generated summary views, such as age-distribution histograms, to contextualize the cohort; we then used comparison-oriented bar charts to examine group differences in 6-month screening compliance and cognitive stage distributions, employing consistent color encodings to support perceptual alignment; finally, these integrated views enabled rapid sensemaking of intervention effects and informed the selection and refinement of subsequent statistical models, aligning with VIS design principles of clarity, comparability, and interpretability.

E. Statistical Analysis

To validate visual findings, we conducted regression modeling in parallel. Logistic regression estimated adjusted odds ratios for 6-month compliance, while multinomial logistic regression modeled cognitive stage membership at final follow-up. A separate logistic model evaluated the binary upstaging indicator. Models adjusted for all baseline covariates except baseline stage in the upstaging model. Analyses were performed in R using **stats**, **car**, **VGAM**, and related packages.

IV. Results

Table 1 and Figure 1 summarize baseline characteristics of the 958 participants. The median age was 64 years, with most women concentrated in the late 50s to early 70s. More than half reported annual income below $15,000, approximately one-third had education beyond high school, nearly 75% had received a provider recommendation for mammography, and 10% reported a family history of breast cancer. Baseline cognitive stages were similar across groups, with over 75% of participants classified in the contemplation stage, indicating a population generally receptive to behavioral interventions.

Across intervention groups, clear differences in 6-month mammography compliance were observed (Figure 2). Compliance was lowest in the Control group (27%) and progressively higher in the Phone (35%), Mail (37%), and Combined groups (39–40%). Logistic regression results (Table 2) confirmed significantly increased odds of receiving a mammogram for all three intervention arms relative to the Control group (Phone: OR = 1.56; Mail: OR = 1.67; Combined: OR = 1.71). Older age and being in the contemplation stage at baseline were also associated with higher screening likelihood. Model diagnostics, including low leverage and Cook's distance values, VIFs below 2, and a nonsignificant Hosmer–Lemeshow test ($p = 0.87$), indicated good model fit.

Cognitive outcomes at the 23-month follow-up displayed similar intervention effects (Figure 3). Only 32% of Control participants reached the Action stage, compared with 42–43% in the Phone and Mail groups and nearly 50% in the Combined group. The proportion remaining in Precontemplation was highest in the Control group (19%) and lowest in the Mail and Combined groups (11–14%). Multinomial logistic regression (Table 3) showed significantly higher odds of being in the Action stage versus Precontemplation for participants in the Mail (OR = 2.06) and Combined groups (OR = 2.24). The Phone group showed a positive but nonsignificant effect. Baseline stage remained a strong predictor of follow-up readiness. Model 2.1 demonstrated adequate fit ($p = 0.71$), though moderate multicollinearity was detected among covariates.

Upstaging patterns reinforced these cognitive findings. More than half of participants in each intervention arm experienced a positive cognitive transition at some point during the study, compared with only 39% in the Control group. Logistic regression (Table 4) showed significantly higher odds of upstaging for the Phone (OR = 1.54), Mail (OR = 1.56), and Combined groups (OR = 1.92), while no demographic covariates were significant. Model diagnostics again supported good fit (Hosmer–Lemeshow $p = 0.44$), suggesting that the interventions themselves—not participant characteristics—were the primary drivers of cognitive improvement.

Overall, both visual comparisons and statistical modeling consistently indicate that tailored interventions improved mammography screening behavior and cognitive readiness, with the combined mail-and-phone strategy producing the strongest effects. The alignment between visualization and formal modeling highlights the usefulness of visual analytics in interpreting behavioral trial outcomes and communicating intervention impact.

V. Discussion

The visual analytics approach used in this study allowed audiences to quickly understand how intervention effects differed across treatment groups, without relying solely on numerical tables or regression coefficients. The bar charts and stacked stage distributions highlighted patterns—such as the consistent performance advantage of mailed materials and the strong cognitive shifts in the combined intervention—that may not be immediately apparent in tabular summaries. These visualizations also made it easier for users to compare intervention arms side-by-side and interpret the behavioral significance of differences in screening uptake and cognitive readiness. An important insight was that simple, comparative visual encodings were sufficient to surface key patterns; users did not require complex or highly interactive displays to grasp intervention impacts. Another observation was the strong alignment between cognitive stage visuals and behavioral outcomes, suggesting that visualizing latent behavioral constructs can provide meaningful predictive insight. No major unexpected findings emerged, but the pronounced effect of mailed materials relative to phone-only interventions was more visually evident than anticipated.

IV. Future Work

Several extensions could strengthen this work. First, interactive dashboards could enable users to explore time-based transitions across all follow-up points, highlighting individual or subgroup trajectories. Second, incorporating uncertainty visualization, for example, confidence intervals or bootstrapped variability—would provide a fuller picture of effect stability. Third, future research could examine effect modification by age, socioeconomic status, or baseline readiness, potentially using stratified visualizations or multilevel modeling. Finally, collecting richer behavioral data (e.g., intention strength, communication exposure) would allow for more nuanced cognitive-stage visualizations and predictive modeling.

V. Conclusion

This study used a visual analytics framework to evaluate how tailored phone- and mail-based interventions influenced mammography screening behavior and cognitive readiness. Both visual and statistical evidence demonstrated that all interventions improved screening uptake and facilitated progress toward the Action stage, with the combined mail-and-phone intervention yielding the strongest effects. Baseline cognitive stage was also a key determinant of screening behavior. Overall, this work illustrates how visual analytics can effectively complement statistical modeling, providing intuitive insights into behavioral and cognitive changes that traditional tables alone may obscure. The findings support the use of multi-modal, tailored communication strategies to improve mammography screening participation among women who are initially noncompliant.

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APPENDIX

Table 1. Characteristics of participants by treatment group

Variable		Overall (n=958)	Control (n=266)	Phone (n=212)	Mail (n=254)	Mail & Phone (n=226)
Mammography compliance	Yes	335 (35%)	71 (27%)	78 (37%)	95 (37%)	91 (40%)
	No	623 (65%)	195 (73%)	134 (63%)	159 (63%)	135 (60%)
Follow up cognitive stage	Precontemplation	146 (15%)	48 (18%)	38 (18%)	35 (14%)	25 (11%)
	Contemplation	414 (43%)	132 (50%)	84 (40%)	110 (43%)	88 (39%)
	Action	398 (42%)	86 (32%)	90 (42%)	109 (43%)	113 (50%)
Baseline cognitive stage	Precontemplation	219 (23%)	67 (25%)	51 (24%)	60 (24%)	41 (18%)
	Contemplation	739 (77%)	199 (75%)	161 (76%)	194 (76%)	185 (82%)
Upstaging in cognition	Yes	458 (48%)	103 (39%)	105 (50%)	126 (50%)	124 (55%)
	No	500 (52%)	163 (61%)	107 (50%)	128 (50%)	102 (45%)
Age, years		64 (17)	65 (17)	64 (15)	64 (17)	62 (18)
Income < $15000	Yes	531 (55%)	156 (59%)	112 (53%)	146 (57%)	117 (52%)
	No	427 (45%)	110 (41%)	100 (47%)	108 (43%)	109 (48%)
Marital status	Yes	287 (30%)	76 (29%)	62 (29%)	80 (31%)	69 (31%)
	No	671 (70%)	190 (71%)	150 (71%)	174 (69%)	157 (69%)
Education > High School	Yes	329 (34%)	90 (34%)	71 (33%)	91 (36%)	77 (34%)
	No	629 (66%)	176 (66%)	141 (67%)	163 (64%)	149 (66%)
Doctor/nurse recommendation	Yes	719 (75%)	194 (73%)	156 (74%)	196 (77%)	173 (77%)
	No	239 (25%)	72 (27%)	56 (26%)	58 (23%)	53 (23%)
Family history of breast cancer	Yes	110 (11%)	35 (13%)	28 (13%)	24 (9%)	23 (10%)
	No	848 (89%)	231 (87%)	184 (87%)	230 (91%)	203 (90%)

Table 2. Model 1 results for 6-month mammography compliance (ref: No)

Variable		Odds ratio
Intercept		0.06 (0.02 – 0.20)
Treatment (ref: Control)	Phone	1.59 (1.06 – 2.38)
	Mail	1.67 (1.13 – 2.46)
	Mail & Phone	1.71 (1.16 – 2.54)
Age		1.01 (1.00 – 1.03)
Income < $15000 (ref: No)	Yes	0.54 (0.39 – 0.73)
Education > High School (ref: No)	Yes	1.00 (0.73 – 1.37)
Doctor/nurse recommendation (ref: No)	Yes	1.14 (0.81 – 1.60)
Baseline cognitive stage (ref: Precontemplation)	Contemplation	4.16 (2.71 – 6.38)
Family history of breast cancer (ref: No)	Yes	1.11(0.72 – 1.72)
		p-value
Hosmer and Lemeshow test		0.87

Table 3: Model 2.1 results for the follow-up cognitive stage (ref: Precontemplation)

Variable		Odds ratio: Contemplation	Odds ratio: Action
Intercept		2.78 (0.48 – 16.17)	0.63 (0.10 – 3.99)
Treatment (ref: Control)	Phone	0.75 (0.40 – 1.42)	1.24 (0.64 – 2.41)
	Mail	1.33 (0.72 – 2.49)	2.06 (1.07 – 3.94)
	Mail & Phone	1.14 (0.58 – 2.24)	2.24 (1.12 – 4.49)
Age		0.98 (0.96 – 1.00)	0.99 (0.97 – 1.01)
Income < $15000 (ref: No)	Yes	0.80 (0.46 – 1.37)	0.79 (0.46 – 1.38)
Education > High School (ref: No)	Yes	0.77 (0.45 – 1.32)	0.75 (0.43 – 1.30)
Doctor/nurse recommendation (ref: No)	Yes	0.75 (0.44 – 1.25)	0.78 (0.46 – 1.34)
Baseline cognitive stage (ref: Precontemplation)	Contemplation	29.13 (16.82 – 50.44)	49.69 (27.58 – 89.51)
		p-value	
Hosmer and Lemeshow test		0.71	

Table 4. Model 2.2 results for upstaging in cognitive stage (ref: No)

Variable		Odds ratio
Intercept		0.66 (0.25 – 1.75)
Treatment (ref: Control)	Phone	1.54 (1.07 – 2.23)
	Mail	1.56 (1.10 – 2.22)
	Mail & Phone	1.92 (1.34 – 2.75)
Age		1.00 (0.99 – 1.02)
Income < $15000 (ref: No)	Yes	0.87 (0.65 – 1.16)
Education > High School (ref: No)	Yes	0.91 (0.68 – 1.22)
Doctor/nurse recommendation (ref: No)	Yes	0.95 (0.70 – 1.28)
		p-value
Hosmer and Lemeshow test		0.44

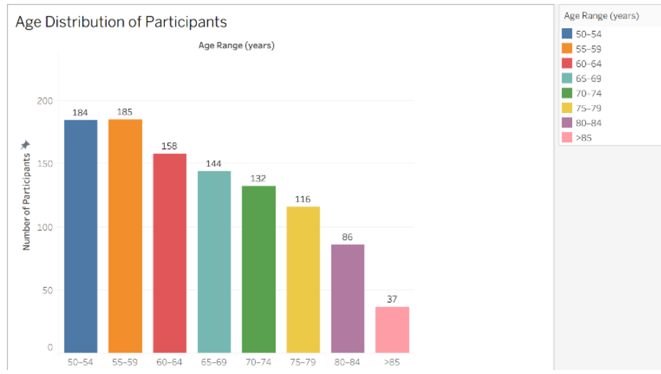

Figure 1: Age distribution of the 958 participants in the mammography screening trial (grouped in 5-year increments, from ages 50 to 85+)

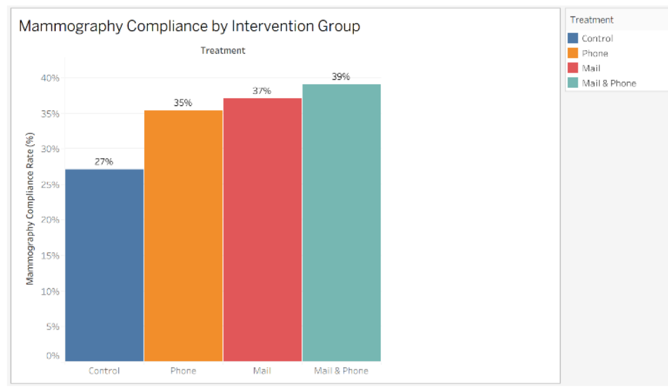

Figure 2: Mammography screening compliance rates within 6 months of enrollment, by intervention group (Control vs. Phone, Mail, and Combined interventions).

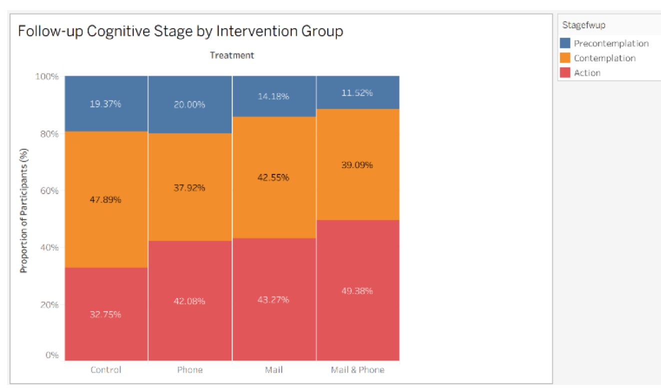

Figure 3: Follow-up cognitive stage distribution (Precontemplation, Contemplation, Action) at 23 months post-enrollment, stratified by intervention group.