Protocol #: 20-1866 NCT05376241
Project Title: Understanding Affective Processing of Scientific Evidence to Promote Informed Choice for Breast Cancer Screening
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Ipsos study analysis plan March 10, 2022

Study Information

Hypotheses

SPECIFIC AIM 1: Predictors of REDS PRIMARY HYPOTHESES: H1: Perceived discordance with prior knowledge will predict REDS. We developed an assessment of the degree to which the DA information conflicts with prior knowledge. We predict that when the DA information conflicts with an individuals' prior knowledge about BCS, they will express more disbelief, reactance, self-exemption, and source derogation. H2: Perceived threat and screening efficacy will predict REDS. We derive our predictions from the Extended Parallel Process Model (EPPM) which is an extension of the fear appeal model. The EPPM proposes that people are most likely to reject information when they feel threatened AND feel they cannot do anything to address the threat (i.e. a high threat, low efficacy message). We predict that women who perceive high affective cancer risk AND have high preexisting expectations for screening will express the strongest reactance, self-exemption, disbelief and source derogation (because they experience the DA as a high threat, low efficacy message). We will test this hypothesis by examining pre-test screening expectations (perceived screening benefit minus perceived harm), and pre-test affective cancer risk perceptions, as predictors of "REDS" outcomes. H3: Perceived threat and screening efficacy will predict information rejection after controlling for discordance with prior knowledge. Putting predictors from H1 and H2 together in a model, discordance with prior knowledge will no longer be a significant predictor of REDS whereas affective cancer risk and preexisting expectations of screening will continue to be significant predictors. SECONDARY HYPOTHESES: SH1: Other significant predictors of REDS responses will include: 1. stronger injunctive norms (i.e. people think I should screen), 2. Medical maximizing (vs. minimizing), 3. Prior screening use (yes/no), 4. Have friends or family diagnosed with breast cancer (vs. not), 5. Lower pre-test trust in the healthcare system, 6. Viewing screening as a protected value (i.e. moral imperative). We predict that all of these variables will show significant bivariate correlations with REDS responses but we do not have specific hypotheses about which will be significant in a model including all predictors. SH2: Relative to White women, Black women will express more self-exemption (feeling that the information does not apply to them) but not necessarily more disbelief, reactance or source derogation. Our rationale for using race as a predictor is that, due to longstanding health disparities related to insufficient care among minority women, and a historic lack of inclusion of BIPOC individuals in clinical trials, Black women will be more likely than White women to believe that the information does not apply to them. SH3: Factors that will not significantly predict REDS will include: 1. Insurance status, 2. Structural barriers, 3. Pre-test knowledge. SPECIFIC AIM 2: Predictors of screening intentions H4: There will be an association between objective cancer risk and screening intentions such that women at higher cancer risk will be more likely to intend to screen before 50 (vs. wait to screen or not screen at all). H4a: There will also be an interaction such that women with lower REDS responses will show a stronger correlation between objective cancer risk and screening intentions, and women with higher REDS will show smaller or null correlations between objective risk and intentions. H5: There will be an association between post-DA knowledge and

screening intentions such that women with lower post-DA knowledge will be more likely to intend to screen before 50. H5a: There will also be an interaction with REDS such that women with lower REDS responses will have a stronger correlation between knowledge and intentions, and women with stronger REDS will show smaller or null correlation between knowledge and screening intentions. Other secondary hypotheses related to the effect of the DA and the nature of REDS: SH4: Trust in the healthcare system will decrease from pre- to post-DA. This effect will be stronger for women with greater REDS responses. SH5: Screening knowledge will improve from pre- to post-DA. REDS responses will be associated with less knowledge increase from pre to post-DA, and will be associated with less total knowledge post-DA. SH6: Perceived screening benefits will decrease from pre- to post-DA; perceived screening harms will increase. REDS responses will be associated with less change from pre- to post-DA. SH7: REDS are predicted to reflect a more emotion-laden set of reactions, whereas perceived discordance with prior knowledge is conceptualized as a more cognitive reaction. Therefore, REDS will be associated with emotional responses to the DA (anger, anxiety), whereas perceived discordance with prior knowledge will not be associated with emotional responses to the DA (after adjusting for REDS).

Design Plan

Study type

Observational Study - Data is collected from study subjects that are not randomly assigned to a treatment. This includes surveys, “natural experiments,” and regression discontinuity designs.

Blinding

- No blinding is involved in this study.

Is there any additional blinding in this study?

No additional blinding.

Study design

Cross-sectional survey

No files selected

Randomization

No randomization was performed (observational study).

Sampling Plan

Existing Data

Registration prior to analysis of the data

Explanation of existing data

There is no previously existing data. Weekly summary reports will be generated as data is collected to check for data collection issues and to identify eligible individuals for qualitative studies. No inferential statistics will be computed with these data.

Data collection procedures

Participants will be recruited through Ipsos.

No files selected
Sample size

Our expected sample size is 500 participants.
Sample size rationale

The study was powered to detect an interaction between objective cancer risk and REDS on receipt of screening (Aim 2). We estimated power by simulation based on 2000 data sets using R statistical software. We use a logistic regression model for the outcome of screening (yes/no) with fixed effects for REDS (high/low) and objective cancer risk (continuous) and their interaction. Assuming that there is a probability of 50% of high REDS (treated as a binary variable), a sample size of 500, and that 10% of variability is explained by other factors in the model (confounders), we would be able to detect a difference in the log odds of -0.3 with 90% power (alpha=0.05). Thus, if the odds of the outcome is 1 in the low REDS group, for every unit increase in cancer risk we can detect an odds of 0.74 (=exp(0-0.3)) in the high REDS group (i.e., an odds ratio of 1.35). Additionally for the outcomes in Aim 1, with a sample size of N=500 we will be able to estimate the prevalence of REDS with a margin of error of 2.8-3.0% depending on the actual prevalence 30-70%. The sample size of 500 will also allow us to detect an increment of 1.2% in variability explained in the linear regression models assuming other factors explain 20% of the variability with 80% power (alpha=0.05).
Stopping rule

We have contracted with Ipsos to collect 500 participants.

Variables
Manipulated variables

Not applicable (observational study)

No files selected
Measured variables

Reaction to screening benefits: Reactance (4 items), Self-exemption (4 items), Disbelief (4 items) Reactions to overdiagnosis: Reactance (4 items), Self-exemption (4 items), Disbelief (4 items) Reactions to false positives: Reactance (4 items), Self-exemption (4 items), Disbelief (4 items) Bayesian updating (4 items) – asked three times for the three domains (benefits, overdiagnosis, false positives) Source trust/derogation in reaction to DA as a whole – 4 items Each of the items indicated above are Likert scale questions Screening intentions: categorical outcome (screen before 50, wait to screen until 50, never intend to screen) Screening knowledge (Hersch et al 2015) – add up number of questions or proportion correct (pre-DA and post-DA)

No files selected
Indices

We will compute Cronbach's alpha reliability for the REDS items to justify collapsing them into a single measure (mean of all items). We will compute correlations among the REDS scores (10 scores: source derogation to decision aid (DA) as a whole; reactance, self-exemption, and disbelief for benefit, overdiagnosis, false-positives). If responses across the three domains are highly correlated (r>0.50), and the Cronbach's alpha among the individual items is also high

(alpha>0.70) then we will further reduce the data by collapsing across the domains to obtain a mean score. This would result in a single score for each REDS construct (4 total scores). Otherwise, if responses are moderately correlated we will use multivariate analyses to test hypotheses, and if responses has low correlation we will test hypotheses below separately for reactions to benefits, overdiagnosis, and false-positives.

No files selected

Analysis Plan

Statistical models

H1. Perceived discordance with prior knowledge will predict REDS. • Dependent variable: Overall score averaged across REDS domains [Continuous] • Independent variable: Bayesian updating (4 items) averaged [Continuous] • Hypothesis: Higher (more negative) scores on conflicts with prior knowledge (Bayesian updating) will be correlated with higher (more negative) scores for other domains • Hypothesis: Higher correlation for the benefits domain than the other two domains (overdiagnosis and false positives) • Analysis: Compute bivariate correlation between these two scores within each informational domain; No plans to adjust for covariates in this analysis. Fit linear regression model (correlation) for association between Bayesian updating and REDS. H2. Perceived threat and screening efficacy will predict REDS • Dependent variable: Overall REDS [Continuous] • Independent variable: Pre-test perceived threat (average of 3 affective risk questions; should have high reliability) [Continuous] • Independent variable: Pre-test screening efficacy (questions on how beneficial and harmful is screening) = (perceived benefit – perceived harm) [Continuous] • Hypothesis: Women who perceive high affective cancer risk AND have high preexisting expectations for screening will express strongest (most negative) REDS • Analysis: Linear regression model for overall REDS with interaction term between perceived threat and efficacy (interaction effect indicates that the effect of perceived threat on REDS is modified by screening efficacy) • Interpretation/Visualization: Will make at least one of the variables binary H3. Perceived threat and screening efficacy will predict information rejection after controlling for discordance with prior knowledge (Bayesian updating). • Dependent variable: Overall REDS [Continuous] • Independent variable: Perceived threat (average of 3 affective risk questions) [Continuous] • Independent variable: Screening efficacy (perceived benefit – perceived harm) [Continuous] • Independent variable: Bayesian updating (4 item) [Continuous] • Hypothesis: Contribution of Bayesian updating will be less than the emotional factors • Analysis: In regression model for H2, adjust for Bayesian updating and assess interaction effect and effect of Bayesian updating. Compare to models H1 and H2 and assess whether fit (total variance explained; R-squared) is improved (change in variance when you add the second set of predictors). Perform analysis for each of the domains and see if results are consistent across the domains. SH1: Other significant predictors of REDS • Predictors: 1. stronger injunctive norms (i.e. people think I should screen), 2. Medical maximizing (vs. minimizing), 3. Prior screening use (yes/no), 4. Have friends or family diagnosed with breast cancer (vs. not), 5. Lower pre-test trust in the healthcare system, 6. Viewing screening as a protected value (i.e. moral imperative), 7. Structural barriers, 8. Pre-test knowledge • Analysis: Perform bivariate analyses to assess for the association between the predictors and the REDS. We will also add these variables to the H3 models, to test the unique

predictive ability of all of these items adjusting for others. Model will be inspected for multicollinearity and scales will be removed or collapsed as indicated by VIFs. SH2: Relative to White women, Black women will express more self-exemption (feeling that the information does not apply to them) but not necessarily more disbelief, reactance or source derogation. Our rationale for using race as a predictor is that, due to longstanding health disparities related to insufficient care among minority women, and a historic lack of inclusion of BIPOC individuals in clinical trials, Black women will be more likely than White women to believe that the information does not apply to them. • Analysis: Will use t-tests to assess for the differences in mean scores for the individual REDS components between White and Black women SH3: Factors that will significantly predict REDS will include: 1. Insurance status, 2. Structural barriers, 3. Pre-test knowledge • Analysis: Perform bivariate analyses for the association with REDS • Include in multivariable models for H1-H3 H4: There will be an association between objective cancer risk and screening intentions such that women at higher cancer risk will be more likely to intend to screen before 50 (vs. wait to screen or not screen at all). H4a: There will also be an interaction such that women with lower REDS responses will show a stronger correlation between objective cancer risk and screening intentions, and women with higher REDS will show smaller or null correlations between objective risk and intentions. • Dependent variable: Screening intentions [Binary/categorical] • Independent variables: Objective cancer risk [Continuous]; Overall REDS [Continuous] • Analysis: In a logistic regression model, we will test the effect of objective cancer risk, REDS total score, and their interaction on screening intentions. We will perform analysis for each of the domains (benefits, harms, overdiagnosis) and see if results are consistent across the domains, in which case we will use an overall model to describe the relationships. H5: There will be an association between post-DA knowledge and screening intentions such that women with lower post-DA knowledge will be more likely to intend to screen before 50. H5a: There will also be an interaction with REDS such that women with lower REDS responses will have a stronger correlation between knowledge and intentions, and women with stronger REDS will show smaller or null correlation between knowledge and screening intentions. • Dependent variable: Screening intentions (binary/categorical) • Independent variable: post-DA knowledge (continuous); Overall REDS (continuous) • Analysis: In a logistic regression model, we will test the effect of post-DA knowledge, REDS total score, and their interaction on screening intentions. We will perform analysis for each of the domains (benefits, harms, overdiagnosis) and see if results are consistent across the domains, in which case we will use an overall model to describe the relationships. SH4: Trust in the healthcare system will decrease from pre- to post-DA. This effect will be stronger for women with greater REDS responses. • Analysis: Assuming high reliability (alpha>0.70), a mean score for healthcare system trust will be computed across the relevant questions. Paired t-tests will be used to examine mean difference in trust pre-DA versus post-DA. A difference score will be computed for health care system trust: post-DA minus pre-DA, such that negative scores indicate decreased trust, and positive scores indicate increased trust from pre to post DA (zero = no change). From a linear regression model for the outcome of change in trust, we will test the effect of REDS overall and domain scores. SH5: Screening knowledge will improve from pre- to post-DA. REDS responses will be associated with less knowledge increase from pre to post-DA, and will be associated with less total knowledge post-DA. • Analysis: A total knowledge score will be computed. Paired t-tests will be used to examine mean difference in knowledge pre-DA versus post-DA. A difference score will be computed for knowledge: post-DA minus pre-DA,

such that negative scores indicate decreased knowledge, and positive scores indicate increased knowledge from pre to post DA (zero = no change). From a linear regression model for the outcome of change in knowledge, we will test the effect of REDS overall and domain scores. We will also assess the association between post-test knowledge and REDS scores. SH6: Perceived screening benefits will decrease from pre- to post-DA; perceived screening harms will increase. REDS responses will be associated with less change from pre- to post-DA. • Analysis: Paired t-tests will be used to examine mean difference in perceived screening benefits and harms pre-DA versus post-DA. A difference score will be computed for perceived benefits and harms: post-DA minus pre-DA, such that negative scores indicate decreased perceived benefit/harm, and positive scores indicate increased perceived benefit/harm from pre to post DA (zero = no change). From a linear regression model for the outcome of change in perceived benefits/harm, we will test the effect of REDS overall and domain scores. SH7: REDS are predicted to reflect a more emotion-laden set of reactions, whereas perceived discordance with prior knowledge is conceptualized as a more cognitive reaction. Therefore, REDS will be associated with emotional responses to the DA (anger, anxiety), whereas perceived discordance with prior knowledge will not be associated with emotional responses to the DA (after adjusting for REDS). • Dependent variables: Emotional responses (anger, anxiety) • Independent variables: overall REDS score [Continuous]; Bayesian updating [Continuous] • Analysis: In separate linear regression models for each of the emotional response items, we will test the effect of REDS score and discordance (Bayesian updating)

No files selected

Transformations

The REDS components and Bayesian updating scores will be computed by averaging across the Likert scale questions. The overall REDS score will be averaged across the REDS domains. Additional averaging across the settings of screening benefits, overdiagnosis, and false positives will be performed if there is strong correlation. Perceived threat will be an average of the three affective risk questions. Pre-test screening efficacy will be computed as (Perceived benefit - Perceived harm).

Inference criteria

We will use the standard $p<0.05$ criteria for assessing statistical significance. We will adjust for multiple comparisons when testing the same hypotheses across the multiple domains of screening benefits, overdiagnosis, and false positives.

Data exclusion

We will exclude data from individuals that fail both attention check questions. We will additionally assess for straight lining (i.e., providing the same response) for all of the REDS questions and will perform sensitivity analyses excluding these individuals.

Missing data

Respondents were required to provide a response to key questions and thus we do not expect there to be missing data for these variables.

Exploratory analysis

No response

Other

Other