Design, Implementation, and Preliminary Evaluation of a Web-based Health Risk Calculator

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Abstract
Through “health risk calculator” websites, Internet users can obtain personalized and interactive predictions about health risks. While it seems appropriate to provide laypersons with educational health information, prior research emphasizes the importance of understanding behavioral responses when communicating risk information. In order to systematically explore and analyze these relationships in the context of online health information, a new diabetes risk calculator website was developed to serve as an intervention in which the presence of personalization and interactive feedback could be manipulated for randomized experimentation. The website was integrated with pre- and post-intervention surveys in order to assess users in terms of information usage and risk perceptions. In two preliminary experiments, there was a small, unexpected negative impact of personalization on multiple measures of information usage. The implications of these results are discussed in the context of improving the presentation of online risk information for practical and experimental evaluation purposes.

1. Introduction
The effective design and dissemination of health risk information presents a difficult problem that is regularly faced by practitioners and researchers from multiple disciplines. Government, private and charitable organizations are constantly vying for consumer attention with the goal of informing health-related decision making and motivating health behavior. One leader in online health information delivery, WebMD, reports that it attracts over 40 million unique visitors to its website every month [1]. Research in health behavior and risk communication regularly consider fundamental issues about motivation, information processing, and preferences that are relevant to the development of health communications. Given the prevalence of health information on the Internet, the aforementioned research areas should be brought to bear on research in information systems design and evaluation which seeks to develop technology that improves information delivery and decision making.

The objective of the current study is to draw on theory and methods from risk communication and information systems to develop an online experimental setting for studying the effects of two common website features, personalization and interactivity, on health information usage and user risk perceptions. Recognizing that personalization and interactivity may take various forms in consumer health websites, we explore these features as they are typically instantiated in health risk calculator websites. These sites can be characterized as applications that ask users to enter current health information and then use that information to calculate personalized risk assessments for one or more health conditions. Risk may be presented using text and graphs and in various modes including percentages (e.g. 35% chance of diabetes onset in 20 years), risk relative to peers (e.g. above average risk of cancer) or other specialized scales (e.g. a risk score of 3 out of 11). Further, risk calculators often provide interactivity in the form of real-time responses to user queries about the marginal impact of changes to their health. For instance, a user could learn the impact of increased exercise on her likelihood of getting diabetes. Health risk calculators also typically incorporate general health education material to inform users about steps they can take to learn more about and mitigate their risk.

While personalized and interactive e-health services are increasingly available to the general public, little research has assessed their effectiveness, in motivating layperson users to learn about their risk and to align their perceptions with an expert model.
Communications research suggests that personalized messages are processed more systematically and may be more influential [2, 3]. However, tailored messages that are inconsistent with perceptions may lead to information avoidance and less careful information processing [4]. Further, it has been well documented in the risk literature that laypersons’ risk perceptions are complex, and behavior-relevant perceptions may be difficult to change [5, 6]. Thus, it is important to improve understanding of the behavioral impact when estimates from statistical risk models are embedded in personalized and interactive health websites.

This paper details the development of a new risk calculator website that is being used as the treatment in a series of randomized experiments using layperson Internet users as participants. The website was designed to elicit personal health information and then present users with an assessment of their pre-diabetes risk. Pre-diabetes is a diabetes pre-cursor that often leads to diabetes. Pre-diabetes and diabetes represent important public health concerns. Many people are living with these diseases but are unaware of their condition. This makes pre-diabetes risk communication an important application area to study more general research questions. The website was integrated with pre- and post-treatment surveys and functionality to randomly assign users to website versions that include or exclude personalization and interactivity. We conducted two randomized experiments that explored the impact of these website features on multiple measures of information usage and risk perceptions. This paper focus on information usage outcomes while the hypotheses and analysis pertaining to changes in risk perceptions are presented elsewhere [7].

2. Developing the risk calculator

2.1. Health risk calculator review

In September 2007, an Internet search and review of existing health risk calculator websites was conducted to inform the development of a new risk calculator that would mimic the fundamental design and functionality of risk calculator websites that are typically used by the general public. An initial Google search (keyword “risk calculator”) and subsequent search on “health risk calculator” found over 35 publicly available health risk calculators on the first three pages of results. These calculators were hosted by private, government, charitable and academic organizations1. Notably, many of the calculators appeared on the websites of well-known health information providers, such as the American Diabetes Association (ADA). This suggests that Internet users who search for more general terms (e.g., “diabetes”) or who go directly to the ADA website are likely to have the opportunity to use a health risk calculator. The review focused on calculators that assess risk of disease or chronic health conditions. Websites that addressed acute injury risks, environmental risks, exercise risks or surgical risks were excluded. While the review was not exhaustive, we believe that the websites considered formed a reasonably comprehensive sample of the risk calculator functionality that typical health information seekers are likely to encounter. The most frequently assessed risks were for diabetes, heart disease, and complications that are related to these conditions. There were also calculators that estimate cancer risk, including risk of breast and prostate cancer. As discussed above, each site applies a statistical model to user-entered data in order to produce a risk assessment. The ADA’s Diabetes PHD uses a simulation model and presents users with a curve that plots their percentage likelihood of being diagnosed with diabetes as a function of time. After reviewing these sites, it was evident that the objectives of these calculators can be summarized as: providing accurate risk information, improving users’ understanding of their personal risk, and educating users about how lifestyle changes may alter their risk. Table 1 contains a list of basic features that are common to most risk calculators. These five items formed the basis for the functional design of our experimental website, “My Diabetes Risk” (MDR).

2.2. Estimating pre-diabetes risk

The core calculation produced by MDR is an estimate of the user’s likelihood of currently having pre-diabetes. Both pre-diabetes and diabetes can be diagnosed using a Fasting Plasma Glucose (FPG) test, with a diabetes diagnosis requiring higher levels (FPG ≥126 mg/dl) than a pre-diabetes diagnosis (FPG ≥100 mg/dl). While exact rates in which people progress from pre-diabetes to diabetes have not been determined (see [8]), pre-diabetes is a strong risk factor for diabetes. The ADA also indicates that having pre-diabetes alone increases a person’s risk of heart disease. The model was estimated using the most recent four years of data from the National Health And Nutrition Examination Survey (NHANES), 2003-2006 [9]. On a subsample of its participants who have no prior diagnosis of pre-diabetes or diabetes, NHANES

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1 A sample of the websites that were reviewed:
WebMD: www.webmd.com/a-to-z-guides/interactive-tools-

American Diabetes Association (ADA): www.diabetes.org/phd
Washington University: www.yourdiseaserisk.wustl.edu
from Table 1. Introductory information describes diabetes prevalence in the United States, diagnosis criteria, guidelines for disease management and related health complications. It is explained that many people are living with undiagnosed diabetes and pre-diabetes and that these conditions may harm long-term health. The introduction also describes the website as an easy way to get information about “your personal risk for pre-diabetes and diabetes” and “to gain a more accurate idea of your risk and the knowledge you need to lower that risk.” A web form on page 1 elicits a user’s gender, age, race, height, weight, blood pressure, history of hypertension, HDL cholesterol, smoking status and activity level. These variables are input into the logistic regression model to estimate pre-diabetes likelihood. If users are unsure of their blood pressure or HDL, they are able to select “I don’t know” and an average value based on age and gender is used.

Page 2 of MDR displays the users personalized pre-diabetes risk estimate (Feature 3 in Table 1). This is presented using text, numbers and a risk graph (see Figure 1). The graph depicts risk in three forms. Risk is given as the user’s percentage likelihood of having pre-diabetes, the user’s risk as “low,” “moderate” or “high”; and the user’s risk relative to the average person’s risk given age and sex. Averages were determined using data from the NHANES data set. Page 2 also gives users the option of entering new values for their weight, blood pressure, HDL and activity level in order to see how their pre-diabetes risk estimate would change in response (Feature 4 in Table 1). Users are able to enter new values as many times as they wish, and risk estimates update when they click “Update my risk.” Figure 2 shows a screen shot of the full page 2. In addition to the personalized risk estimates and interactive risk feedback, page 2 includes a list of eight diabetes risk factors that correspond to the health variables entered by the user on page 1. For each factor, the user’s health value is printed on the screen. For example, if a user responded yes to having a close family member with diabetes, the text would read: “You do have a close family member with diabetes.” Next to each of these statements there is a corresponding hyperlink which users can click to read a general paragraph that describes the risk factor’s relationship to diabetes and gives helpful tips for managing the risk factor. This list of risk factors and

2.3. Application development

After reviewing existing risk calculators and developing a pre-diabetes estimation model, the MDR web application was developed using Java Server Pages (JSP) and a Microsoft Access database. Java code dynamically generates a user’s personalized risk assessment and controls the features presented to users based on their random assignment to a given experimental condition. The Access database collects user health information as well as click activity and timestamps to describe when and what users click on while using the application. The website consists of two pages. The first page includes Features 1 and 2

Table 1. Core health risk calculator features

<table>
<thead>
<tr>
<th></th>
<th>Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td><strong>Introductory</strong> information relevant to the disease or condition of interest and website instructions</td>
</tr>
<tr>
<td>2</td>
<td><strong>Form-based health questions</strong> which ask users to enter personal health values</td>
</tr>
<tr>
<td>3</td>
<td><strong>Personal risk estimate</strong> generated by a statistical model, often presented graphically*</td>
</tr>
<tr>
<td>4</td>
<td><strong>Interactive feedback</strong> allowing users to change their health values and update their risk estimates*</td>
</tr>
<tr>
<td>5</td>
<td><strong>Follow-up</strong> information that describes generally and/or suggests specific actions to mitigate risk</td>
</tr>
</tbody>
</table>

*Feature subsequently manipulated in randomized experiments
corresponding paragraphs represent Feature 5 (follow-up information) from Table 1 and can be seen in the bottom right of Figure 2.

3. Research question and hypotheses

Little is known about how web applications that integrate expert risk prediction models impact information usage and risk perceptions. In this study, we focus specifically on the effect of personalization and interactive functionality as they appear in health risk calculators. The general research question under investigation is:

In the context of web-based health information, how do personalized risk estimates and interactive feedback each influence information usage and subjective perceptions about personal risk of disease onset?

Ostensibly, providers of health risk calculators are interested in motivating users to attend to and carefully consider the information being presented in their websites. Research in risk communication and information systems, draw on psychological theory to evaluate different ways in which information is attended to and processed. Dual-processing models have been proposed in psychology to explain information processing and persuasion [3, 11]. According to Petty and Cacioppo’s Elaboration-Likelihood Model (ELM), central processing is characterized by higher levels of cognitive effort and careful assessment of a message (“elaboration”) whereas peripheral route processing assesses a message more quickly and less carefully. This dual processing model has been applied more specifically to information processing through the Heuristic-Systematic Model (HSM) [12]. Heuristic processing is thought to be more cue-based and results in quick judgments. Attitudes or behaviors generated by heuristic processing are expected to be less resistant to change. Systematic information processing, on the other hand, entails more detailed consideration of a message and may result in more stable attitudes and behaviors. In two risk communication studies, the heuristic-systematic model was applied to evaluate responses to risk information [13, 14]. Where HSM applications in risk communication focus more specifically on information usage as it relates to persuasion, relevant work in information systems has studied information usage and involvement with software and their relationship with technology acceptance [15]. Agarwal and Karahanna define cognitive absorption as a measure of “deep involvement” with software that is predictive of a technology’s perceived usefulness and perceived ease of use [15]. Focused immersion is one dimension of cognitive absorption and describes the extent to which “attentional resources of an individual are focused on...
As this paper attempts to integrate prior work in both risk communication and information systems, we chose to use two theoretical constructs, namely HSM and focused immersion, as information usage outcomes in evaluating a technology-enabled risk communication tool. In addition to these constructs which are measured using self-report scales, we also investigated an objective measure of the amount of information used by a risk calculator user. We termed this measure *information accessed*, and as described later, it assesses user click activity and time spent within the MDR system.

Relevance is a key factor that is discussed in the context of both message elaboration and systematic information processing. Messages that are perceived as more relevant are more likely to be elaborated on, processed systematically and lead to stable attitudes and behavior [3, 11]. An often used method for improving relevance is personalization. Personalization (or the more comprehensive matching of user information and content called *tailoring*) has been used in health communication with the goal of increasing systematic processing and thus the impact of educational material [16]. With similar underlying theoretical mechanisms as support, both personalization and interactivity have been studied in e-commerce and computer-mediated-communication (CMC). Komiak and Benbaset show the positive effect of perceived personalization on cognitive and emotional trust and thus acceptance of product recommendations [17]. In a longitudinal study of health websites, personalization was an important factor in repeat usage [18]. Real time responses, user control, connectedness, customization and playfulness have been discussed as attributes of technological interactivity [19, 20]. In a marketing study of interactive home shopping, Alba et al. define interactivity as a continuous construct capturing the extent of two-way communication in the technology [21]. In their study, response time and the extent to which communications are a function of the user’s response dictate the level of interactivity. While these studies do not make explicit theoretical connections to HSM, focused immersion, or the volume of information accessed, we propose that both personalization and interactivity may work similarly to motivate increased systematic processing, focused immersion and the amount of information accessed. It also seems plausible that these relationships may be mediated by increases in perceived relevance, though we do not explicitly test that mediation in this study.

**Hypothesis 1:** Personalized estimates of pre-diabetes likelihood and interactive feedback about modifications to that risk will each motivate more click activity, more focused immersion, and more systematic risk information processing. Heuristic information processing will be reduced by personalized risk estimates and interactive feedback.

Two variables that may moderate the hypothesized relationships between website features and information usage are a user’s prior beliefs about her pre-diabetes risk and the specific risk estimate that the website calculates. This moderation is consistent with the reasoning that higher risk estimates reflect increased relevance to the user. For example, while a personalized risk estimate may be more relevant than a non-personalized risk estimate, if the user is a priori, unconcerned about pre-diabetes or the website communicates that the user is at low risk for the condition, reduced levels of information usage may be expected.

**Hypothesis 2:** The expected relationship between personalization, interactivity and information usage will both be moderated by prior subjective risk perceptions and calculated expert risk estimates. It is expected that increased prior perceptions and increased expert estimates will be positively associated with the amount of information accessed, levels of focused immersion, and systematic information processing. A negative relationship is expected between heuristic information processing and both prior perceptions and expert estimates. Figure 4 shows a model of the hypothesized relationships.

![Figure 3. Hypothesized model of risk calculator features and information processing](image)

### 4. Experimental design

In two experiments, adults with no prior diagnosis of Type I or Type II diabetes participated in a single-session online study in a location of their choice. Participants completed the 3-part protocol that is summarized in Figure 4. MDR represented the primary intervention, and integrated questionnaires were used to assess participants both before and after they used MDR. Part 1 administered a pre-intervention questionnaire to assess each participant’s perceptions about developing diabetes in the next 20 years.
Absolute, relative, and affective risk perceptions were measured using questions similar to [22]. These measures are described in more detail in [7]. In addition, participants were asked about their diabetes risk factor knowledge [22], recent diabetes screening and health information seeking history, intentions to seek more information about diabetes, and general propensity for seeking health information [14].

Part 2 of the experiment randomized participants to one of three versions of MDR. The personalized/interactive version contained all features listed in Table 1 and its functionality matched the website described above in the Application Development section. The personalized condition was identical except that it did not feature interactive feedback. Users in this condition were not able to change the weight, blood pressure, HDL or activity level after seeing their initial risk assessment. Finally, the non-personalized (control) condition featured neither interactive feedback nor personalized risk estimates. Instead of presenting users with a risk graph and personalized estimate of pre-diabetes risk, users were shown text that read: “The average adult has a 28% chance of already having pre-diabetes.” All other features in the three conditions, including introductory information, the web form and follow-up information were identical.

Immediately after exiting the MDR website, users were directed to Part 3 of the experiment. All participants completed a post-intervention questionnaire that assessed the outcome measures described in Table 2: focused immersion, systematic information processing, heuristic information processing and information accessed. Objective outcome data including the number of risk factor links clicked and the usage of the interactive feedback features were automatically collected by MDR. Finally, in Part 3, post-intervention risk perceptions were assessed using the same risk perception measures that were given in the pre-intervention survey.

5. Data and results

In the first experiment, 100 adults over the age of

<table>
<thead>
<tr>
<th>Measure</th>
<th>Definition</th>
<th>Measurement</th>
<th>Sample item</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information accessed</td>
<td>the extent to which user explores risk factor information contained in the website</td>
<td>Count of risk factor links clicked</td>
<td>N/A</td>
</tr>
<tr>
<td>Focused immersion</td>
<td>“the experience of total engagement where other attentional demands are, in essence, ignored.” [15]</td>
<td>post intervention 7-pt disagree-agree scale</td>
<td>“While using the website, I was immersed in the task I was performing”</td>
</tr>
<tr>
<td>Systematic processing</td>
<td>“recipients exert considerable cognitive effort … actively attempt to comprehend the message’s arguments as well as to assess their validity in relation to the message’s conclusion.” [12]</td>
<td>post intervention 7-pt disagree-agree scale</td>
<td>“I thought about how what I had read in the website related to other things I know.”</td>
</tr>
<tr>
<td>Heuristic processing</td>
<td>“recipients exert comparatively little effort in judging message validity … may rely on (typically) more accessible information such as the source’s identity or other non-content cues …” [12]</td>
<td>post intervention 7-pt disagree-agree scale</td>
<td>“I skimmed through the website information.”</td>
</tr>
</tbody>
</table>
45 were recruited from the general U.S. population by a market research firm to participate in the Internet-based study. The research firm maintains a panel of participants who are compensated with points (later redeemable for merchandise) for participating in online surveys. 35 participants were assigned, by a random number generator in the Part 1 survey tool, to the non-personalized condition, 32 to the personalized, and 33 to the personalized/interactive. The average participant was 61 years old and overweight (nearly obese) according to their body mass index (BMI). Experiment invitations were sent to a mix of ethnic groups, but the respondents were overwhelmingly white. Follow-up suggested this was likely a result of selection by invited participants. The mean calculated pre-diabetes risk was 35.14% while the average pre-intervention subjective risk estimate was 27.35%. The mean post-intervention estimate was 28.25%. Of the participants assigned to the personalized/interactive condition, only two actually modified their health values and obtained updated risk estimates. The reason for minimal use of this feature is unknown, but it is consistent with the lack of interactive feature usage reported in [23]. Due to this disuse, the personalized and personalized/interactive applications represented essentially equivalent interventions. Subsequent results combine the results from these two conditions in a single condition referred to as personalized.

Participants spent an average of 4.88 minutes using MDR and clicked on 2.11 out of 8 risk factor links. Table 3 compares the mean demographics and health characteristics for the two conditions. The personalized sample reported, on average, significantly lower HDL cholesterol. It appears that a number of users may have mistakenly entered either LDL or total cholesterol levels instead of HDL. This occurred more frequently in the non-personalized intervention resulting in the significant difference in means. Subsequent results are robust to controlling for this difference. Also, despite randomization, the personalized sample self-reported as being significantly lower in their general propensity for seeking health information in their daily lives. This difference is discussed further in subsequent analyses.

Figure 5 shows mean values for each information usage measure by condition. For the self-report scales, higher values indicate increased focused immersion, increased systematic processing and increased heuristic processing, respectively. Cronbach’s alpha measures of reliability are 0.88, 0.89, and 0.63, respectively. Given its alpha value, the heuristic processing measure may be unreliable. All the differences between conditions have the opposite sign of what was predicted by hypothesis 1. Based on a two sample t-test with a Welch approximation of the degrees of freedom, users in the personalized condition clicked significantly fewer risk factor hyperlinks (t(56.1) = 2.94, p < 0.01) and reported lower systematic information processing (t(63.9) = 2.12, p = 0.04). Focused immersion was lower under personalization, and this was marginally significant (t(76.5) = 2.00 p = 0.05). There were no significant differences in heuristic information processing (t(61.1) = -0.48, p = 0.63).

Further analysis sought to control for the random difference between conditions in general health information seeking and to explore the moderators of

Table 3. Participant descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Non-Personalized (n = 35)</th>
<th>Personalized (n = 65)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>62.57</td>
<td>60.53</td>
</tr>
<tr>
<td>BMI</td>
<td>29.12</td>
<td>29.29</td>
</tr>
<tr>
<td>HDL cholesterol</td>
<td>81.43*</td>
<td>64.34</td>
</tr>
<tr>
<td>Systolic blood pressure</td>
<td>127.71</td>
<td>130.22</td>
</tr>
<tr>
<td>Diastolic blood pressure</td>
<td>75.31</td>
<td>77.06</td>
</tr>
<tr>
<td>Hypertension (yes/no)</td>
<td>51%</td>
<td>52.31%</td>
</tr>
<tr>
<td>Sex (male, yes/no)</td>
<td>37%</td>
<td>55%</td>
</tr>
<tr>
<td>Family history of diabetes</td>
<td>34%</td>
<td>32%</td>
</tr>
<tr>
<td>Regular Exercise (yes/no)</td>
<td>31%</td>
<td>25%</td>
</tr>
<tr>
<td>Smoker (yes/no)</td>
<td>29%</td>
<td>28%</td>
</tr>
<tr>
<td>Ethnicity (white, yes/no)</td>
<td>100%</td>
<td>98%</td>
</tr>
<tr>
<td>Health information seeking</td>
<td>5.76*</td>
<td>5.34</td>
</tr>
</tbody>
</table>

*Means significantly different (p < 0.05)
information usage proposed in hypothesis 2. Table 4 shows the results of a linear regression of focused immersion on the calculator’s risk estimate, a dummy variable for the personalization condition, and the interaction of these two variables. Figure 6 plots the coefficients from this regression to depict the relationship between calculated risk and focused immersion. The regression suggests that the reduction in focused immersion observed in the personalized condition may have been driven by low risk users who, upon having their risk presented to them, reported low immersion. To check the robustness of this result, a regression was then run that also controlled for the measure of baseline propensity to seek health information (because it randomly differed between conditions). In this regression, the coefficient on *Personalized* was still significant (t = -2.34, p = 0.02) and the interaction term *CalculatedRisk*\*\*\*\*Personalized* was marginally significant (t = 1.80, p = 0.07). Similar regressions were performed for the other information usage outcomes that had showed at least marginally significant negative effects of personalization in prior analysis. For systematic information processing and number of risk factor links clicked, calculated risk did not moderate the negative impact of personalization. Similar regressions also did not find any moderating effect of prior perceptions on the relationship between personalization and the information usage measures. Table 5 summarizes the tests of the study hypotheses.

A notable limitation of the first experiment was that the personalized risk graph in MDR was calibrated such that most users’ risk fell into the “moderate” risk category (represented by the yellow color in the risk graph). This could have given users the impression that their risk was not a major concern and that there was no need to attend to the information or update perceptions. This limitation was rectified in a follow-up, small sample (N=34) study of university staff members. While the sample was too small to observe statistically significant effects of the conditions, directionally similar results were observed for the three information usage measures.

### Table 4. Focused immersion on calculated risk

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Std. Err</th>
<th>t value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>5.716</td>
<td>0.368</td>
<td>15.54</td>
<td>&lt;2e-16  ***</td>
</tr>
<tr>
<td>CalculatedRisk</td>
<td>-0.010</td>
<td>0.010</td>
<td>-0.94</td>
<td>0.349</td>
</tr>
<tr>
<td>Personalized</td>
<td>-1.354</td>
<td>0.484</td>
<td>-2.80</td>
<td>0.006 **</td>
</tr>
<tr>
<td><em>CalculatedRisk</em>***Personalized</td>
<td>0.026</td>
<td>0.013</td>
<td>2.01</td>
<td>0.047 *</td>
</tr>
</tbody>
</table>

Signif.:  

| 0       | 0.001    | <0.001   | 0.01    | 0.05    | >0.1    |

Residual standard error: 1.098 on 96 df  
Multiple R-Squared: 0.088,  Adj R-squared: 0.060  
F-statistic: 3.098 on 3 and 96 DF,  p-value: 0.030

![Figure 6. Focused immersion by calculated absolute risk](image)

### Table 5. Hypothesis testing

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>H1</strong>: Personalized estimates of pre-diabetes likelihood and interactive feedback about modifications to that risk will each motivate more click activity, more focused immersion, and more systematic risk information processing. Heuristic information processing will be reduced by personalized risk estimates and interactive feedback.</td>
<td><strong>Not Supported</strong> – personalization was related to less click activity and less systematic processing. There were no significant differences in mean focused immersion or in heuristic processing.</td>
</tr>
<tr>
<td><strong>H2</strong>: The expected relationship between personalization, interactivity and information usage will both be moderated by prior subjective risk perceptions and calculated expert risk estimates. It is expected that increased prior perceptions and increased expert estimates will be positively associated with the amount of information accessed, levels of focused immersion, and systematic information processing. A negative relationship is expected between heuristic information processing and both prior perceptions and expert estimates.</td>
<td><strong>Partially Supported</strong> – the observed relationship between personalization and focused immersion was moderated by the calculated expert risk estimate (see Table 4). For the other observed effects of personalization on information usage, no moderators were found.</td>
</tr>
</tbody>
</table>
6. Discussion

After reviewing publicly accessible risk calculators and developing a pre-diabetes risk estimation model, a web-based risk calculator website was developed to serve as an intervention in randomized online experiments. Integrating theory and measurement from prior work on risk communication and information systems, a new model of the impact of personalization and interactivity on web users was developed. To test this model, we examined how users of three different risk calculator versions accessed and processed risk information. The interactive feedback manipulation was unsuccessful, so our analysis focused on personalization. There was no evidence that providing personalized risk estimates increased the extent to which study participants used risk information. Contrary to our hypothesis, there was evidence that users of the personalized condition actually processed less systematically, were less immersed and clicked fewer links to explore diabetes risk factor information. These findings are inconsistent with theory that suggests personalized messages are perceived as more relevant and thus processed more systematically. Subsequent regressions did suggest that personalization led to reduced focused immersion primarily when users were informed that their expert risk estimate was low. This suggests a somewhat sensible response that users’ attention may have waned when they were informed their risk was not too high. However, reductions in systematic processing and risk factor links clicked given personalization were not moderated by the expert risk estimate or by prior perceptions of risk. One possible explanation for the basic results is that personalized estimates offered a summary measure of risk that competed for the users’ propensity to access and carefully process the more nuanced text-based information provided by MDR. While users may have found the personal estimates more relevant, they may not have stimulated general increases in information usage. One practical implication of these results is that users of risk calculator applications may receive expert estimates of their risk, but in so doing, they may not always be motivated to read more details about the disease and how to mitigate its risk. These types of responses should be carefully considered by organizations designing online content.

The nearly complete disuse of the interactivity feature may be suggestive of users’ lack of interest in obtaining feedback about risk mitigation. However, this may have also been due to design flaws in MDR that made users unaware of this feature. Future studies will re-design MDR to ensure that the interactive feature is prominently displayed and employ post-intervention manipulation checks to determine whether participants were uninterested in the interactivity feature or simply unaware of it.

One clear limitation of this study is that the random assignment led to non-personalized version users who measured higher in health information seeking and HDL cholesterol than users of the personalized condition. These may have confounded the effects of personalization on information usage. Attempts were made to control for these statistically, and the basic results were unchanged. However, replications of these preliminary experiments are needed. A second limitation that was discussed briefly in the results section is that the personalized risk graph was calibrated such that most users’ risk fell into the “moderate” absolute risk category. Finally, although MDR was designed to mimic the basic functionality of existing risk calculators, it is not completely clear how the results from our study generalize to existing publicly available web-based risk calculators.

This study contributes to the literature on personalized web applications by extending it to consumer health information services that utilize expert models. We drew on theory and measures from risk communication and information systems to study one type of e-health service, health risk calculators. Demand for and supply of online health information is growing as are technologies to manage and analyze personal health information. Given these trends, more research is needed on how to design applications that organize and disseminate personalized health information in ways that motivate awareness, education and healthy behavior. Existing health risk calculators implement well-developed statistical models and deliver their estimates to users, but it is not clear that expert statistical estimates are the most appropriate way to inform and motivate layperson users. Future studies will refine the proposed theoretical model and experimental design to more closely examine if and when personalized risk calculators motivate users to explore disease risk information, develop more accurate risk perceptions, and change health-related behavior. These studies will also attempt to attract a larger sample of participants and employ a re-designed version of MDR. In particular, in-depth think-aloud interviews with layperson users, human-computer interaction experts and health professionals are planned to inform a risk calculator design that layperson users will perceive as simpler, more credible and generally more relevant to their needs. It is believed that efforts to improve the web intervention in these areas may generally produce cleaner tests of our hypotheses.
7. Conclusion

Online experiments with a diabetes risk calculator suggested that personalized expert model risk estimates did not generally motivate users to access more risk information, to report higher levels of immersion or to more systematically process risk information. Some, but not all, of these results appear to have been due to low risk users reducing their utilization when it became clear that their risk was low. With the increased prevalence of statistical models for predicting health problems and the ability to adapt these to publicly available tools, more research is needed to refine the design and evaluation of these tools in order to describe and predict behavioral implications when lay users access online health risk communication tools.

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9. References