The Impact of Web-Based Risk Calculators on Health Risk
Perceptions and Information Processing

Christopher A. Harle

H. John Heinz III School of Public Policy & Management
Carnegie Mellon University, Pittsburgh, PA

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Committee:
Julie Downs, PhD (co-chair)
Daniel Nagin, PhD
Rema Padman, PhD (co-chair)

Abstract
Every day, millions of Americans use the Internet to obtain health information. To satisfy this demand, organizations deliver a variety of content that promotes awareness and education and informs health-related decision making. Given advances in web technology, new statistical models of disease, and the shift towards shared patient decision making, these e-health services are increasingly complex. Through applications such as personal health records and “health risk calculators” Internet users can obtain personalized and interactive feedback about their current health state, model-based predictions about their future health, and tailored education about healthy behavior. While providing the public with more content to inform health-related decisions is an appropriate goal, research in health psychology and behavioral decision making suggest the importance of clearly understanding the perceptual and behavioral responses when laypersons are presented with statistical results and personalized risk information. Little research has studied how web-based personalized and interactive health applications actually impact the beliefs and behavior of users. In two separate experiments, we measured the effect of a type 2 diabetes “risk calculator” website on user information processing and subjective risk perceptions about diabetes. In the first experiment, 100 middle-aged and elderly adults were randomized to one of three conditions in order to determine how personalized risk estimates and interactive risk feedback influenced information usage and beliefs about future diabetes onset. Results showed that personalization and interactive features did not lead to increases in information utilization as expected. Instead, we show in some cases personalization actually reduced the amount of information accessed and the extent to which users attended to and carefully considered health risk content. The experiment did show that personalization was related to modest increases in the accuracy of absolute diabetes risk estimates but did not motivate significant changes in relative or affective risk perceptions. A second study of 34 university staff members was qualitatively suggestive of similar results. Future work is needed to further understand the behavioral implications when complex statistical models are integrated with publicly available health information websites. This may aid the design of health information applications and ensure that providers of these tools are effectively motivating improved awareness and education about health risks.
1 Introduction

According to a 2006 Pew report, 8 in 10 Internet users have searched for health information online (Fox 2006). The same report suggests that daily use of the Internet for health information is comparable to daily use of the Internet for paying bills and searching for addresses and phone numbers. In this crowded outlet for health information, government organizations, insurers, private firms and charitable organizations are vying for consumer attention in order to improve health awareness and related decision making. The leader in online health information delivery, WebMD, reports that it attracts over 40 million unique visitors per month (Freudenheim 2007). The increased provision of online health information is partially a reflection of the pervasiveness of the Internet and maturation of web technologies. Also, the movement in health care towards shared patient decision making has pushed the tasks of health information seeking and management towards the consumer. Government pressure for improved management and integration of personal health information has led to increases in electronic medical records. Technology giants Microsoft and Google are currently developing web-based personal health record services which allow consumers to more effectively store and manage their personal health information. A beta version of Microsoft’s HealthVault is already available for public use\(^1\). This website serves not just as a record of health information. It also integrates with applications that use personal health data to better inform patients about their health state and allow them to make informed health-related decisions. Combined, these trends have thrust the Internet and information systems generally into a critical role of supporting consumer-oriented access to, organization, and usage of personal health information.

Personalization is a critical feature of web-based consumer health information. User information can be entered manually or through connections to technology that collects and stores data. Once collected, data can be processed and organized to provide calculations, graphs and text-based messages that are tailored to an individual’s health status. A second feature often found in e-health services is interactivity. In this paper, we focus on interactivity that allows users to obtain feedback about how behavior modifications will impact their long-term disease risk. For example, statistical models embedded in web applications can be used to help users understand how changes to their current weight or exercise levels will affect their risk of conditions such as

\(^1\) http://www.healthvault.com/
heart disease and diabetes. Recognizing that personalization and interactive feedback may be implemented in multiple ways in consumer health websites, this study explores the impact of these two features in the context of a particular type of application, web-based risk calculators. On WebMD.com alone, there are more than a dozen calculator tools that predict measures such as stroke risk, stress levels, and fertility. These calculators enter personal health data into statistical models, calculate corresponding risk levels for one or more conditions, and give feedback to users about their personal risk. Risk assessments are communicated using various modes including graphs, percentages, risk relative to other people and other specialized scales. The typical calculator couples the risk assessment with additional information to inform the user about next steps they can take to learn about and mitigate their risk. Two of the most accessible (via search engine) risk calculators are from the American Heart Association (AHA) and American Diabetes Association (ADA) respectively. Each asks users for information including height, weight, blood pressure and then returns risk estimates. The AHA High Blood Pressure Health Risk Calculator provides relative risk estimates of heart attack, stroke and other conditions. The ADA calculator, Diabetes PHD, uses the Archimedes simulation model (Schlessinger and Eddy 2002) to estimate future likelihood of diabetes, heart attack, stroke and other diabetes-related complications. Each of these tools also provides an interface that give users interactive feedback about the impact of hypothetical health improvements on their estimated risk levels. Data we acquired from the ADA showed that over an 82 day period in 2006, approximately 13,000 risk assessments were performed by Diabetes PHD.

While health risk calculators and other personalized, interactive e-services are increasingly available for use by the general public, their effectiveness, in motivating users to learn about their risk and to align their subjective risk perceptions with an expert model, is unclear. Diabetes PHD and other calculators utilize well-known, research-validated statistical models to produce risk estimates. These models include Archimedes for diabetes and related complications (Eddy and Schlessinger 2003), the Framingham model for heart disease (Anderson, Wilson et al. 1991), and the Gail model for breast cancer (Gail, Brinton et al. 1989). These methods are not perfect forecasters of the future, but they have been rigorously developed and tested by medical researchers. In comparison, the web applications in which these models are embedded have not been rigorously tested to determine how user beliefs and behavior respond to the risk information presented by these calculators. Presumably, the organizations that host these calculators intend
that personalization and interactive feedback will motivate users to engage with and systematically process the informational content in order to improve the accuracy of their beliefs and the quality of future decisions. Communications research does suggest that personalized messages are processed more systematically (Kreuter, Bull et al. 1999; Petty and Cacioppo 1986). However, tailored messages that are inconsistent with perceptions may lead to information avoidance and heuristic information processing (Radcliffe and Klein 2002). Psychological, biases including framing effects, numeracy problems and over-optimism may influence how people utilize personalized health, are persuaded to change their beliefs and improve their health-related decisions. Given these effects, it is important to develop a better understanding of the behavioral impact when estimates from expert statistical models are embedded in consumer health information applications. There has been a disproportionate amount of research on the development of statistical models for risk prediction as compared to research on the design and development of behaviorally informed applications for communicating the results of these models to laypersons. Without better knowledge of the latter, it is unlikely that the potential benefits of these risk models can be fully realized in the context of consumer health applications. Prior research in decision making and risk communication have the potential to inform the design of risk calculators and other consumer health information applications which leverage personal health data and statistical models to improve consumer-centric health decision making.

This paper addresses the effects of personalization and interactivity on information usage and risk perceptions when these features are embedded in a web-based diabetes health risk calculator. Our Google searches (keywords: “risk calculator” and “health risk calculator”) and review of the top results found over 35 publicly available risk calculators on websites of reputable private, government, charitable and academic organizations². The most frequently estimated risks are for diabetes, heart disease, and related conditions. There are also calculators that estimate cancer

²WebMD: http://www.webmd.com/a-to-z-guides/interactive-tools
ADA: http://www.diabetes.org/phd/default.jsp
Washington University: http://www.yourdiseaserisk.wustl.edu/
risk, including that for breast and prostate cancer. Research has noted that many people are living with diabetes or pre-diabetes, but are unaware of their condition (Cowie, Rust et al. 2006). These fact and the costliness of unmanaged diabetes make diabetes risk calculators an important application area for studying web-based consumer health applications. In reviewing existing risk calculators, it was evident that objectives of these tools can be summarized as: providing the most accurate risk information, improving user understanding of risk, and educating user about how health changes will modify their risk. In most calculators, risk estimates are not provided in isolation. Predictions are presented with descriptions of the health condition of interest and advice for reducing risk. We assume that organizations intend for their risk calculators to stimulate users to read and engage with the health advice that is typically provided in conjunction with the expert risk estimate.

Given our stated objectives and assumptions, we designed an experimental diabetes risk calculator called *My Diabetes Risk*. The primary function of this calculator is to educate non-experts about diabetes and undiagnosed pre-diabetes. After asking a user to provide multiple health measures, the calculator estimates his probability of currently having pre-diabetes. In two experiments, non-diabetic participants were recruited and randomly assigned to different versions of *My Diabetes Risk*. In the different versions, we manipulated the presence of personalized estimates and interactive feedback and then measured the propensity of users to engage with the website and thoughtfully process its content. We also measured changes in users’ subjective perceptions about their personal risk of getting diabetes. The educational information contained in our experimental website included explanations of various diabetes risk factors and strategies for mitigating the impact of these factors. 20-year subjective diabetes risk perceptions were elicited both before and after participants visited *My Diabetes Risk* in order to measure changes in perceptions due to the calculator. Perceptions were elicited using three modes of risk including absolute risk of diabetes onset, relative risk of diabetes onset and affective risk using perceived worry about and perceived control over diabetes risk. Levels of engagement and information processing were measured in terms of *focused immersion* and systematic/heuristic information processing. Objective data on time spent using the calculator and the number of informational links that the user clicked were also collected to provide an objective measure of the amount of information accessed. An overview of the experiment is depicted in Figure 1.
2 Prior Literature

2.1 Personalization, Interactivity and Information Processing

Dual-processing models have been proposed in psychology to help explain attitudes, persuasion and information processing (Eagly and Chaiken 1993; Petty and Cacioppo 1986). According to Petty and Cacioppo’s Elaboration-Likelihood Model (ELM), central route processing is characterized by higher levels of cognitive effort and careful assessment of a message (“elaboration”) whereas peripheral route processing may assess a message more quickly and less carefully. This dual processing model has been applied more specifically to information processing by the Heuristic-Systematic Model (HSM) (Eagly and Chaiken 1993). 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 entails more detailed consideration of a message and may result in more stable attitudes and behaviors. While each processing mode may influence the extent to which perceptions are updated, the stability and durability of attitudes, they are not necessarily mutually exclusive. A given message may be processed using both systematic and heuristic processing.
The heuristic-systematic model of information processing has been applied in multiple studies to explain risk communication and information processing (Griffin, Neuwirth et al. 2002; Johnson 2005; Trumbo 1999). These studies have developed and estimate models of risk information processing (Johnson 2005; Kahlor, Dunwoody et al. 2003; Trumbo 1999). The models focus on factors including self-efficacy, motivation and information insufficiency and their relationship with heuristic and systematic processing. The relationship between processing and risk judgments is also considered. It has also been proposed that information processing may influence behavior and fit between attitudes and behavior (Griffin, Dunwoody et al. 1999).

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 form stable attitudes and behavior (Eagly and Chaiken 1993; Petty and Cacioppo 1986). An often used method for improving method relevance is through personalization. Personalization or tailoring has been in health communication with the goal of more systematic processing and thus better understanding of educational material (Kreuter and Wray 2003; Petty and Cacioppo 1996).

With the same underlying theoretical mechanisms as support, personalization and also interactivity have received significant attention in information systems and computer-mediated-communication (CMC). Practically, personalization can be implemented in many ways within web technologies. Conceptually, one definition of personalization in information systems is the identification of user preferences, the matching of those preferences with a product or service, and subsequent evaluation of that matching (Murthi and Sarkar 2003). Much of the information systems research on web-based personalization and customization has focused on the use of these features for e-commerce. Komiak and Benbaset show the positive effect of perceived personalization on acceptance of product recommendations (2006). In this study, they provide evidence that personalization increases intentions by increasing both cognitive and emotional trust in the recommendation agent. The acceptance of personalized ring tone recommendations depended on the timing, with the decision making process, in which the recommendation was presented (Tam and Ho 2005). Kramer et al. discuss personalized technologies as an “evolving set of tools” that may improve the user experience, but are not always useful (2000). They caution designers not fall into the trap of the “coolest” features that may not add value to the end
user. In a longitudinal study of informational health website usage, personalization, were important factors in repeat usage (Sillence, Briggs et al. 2007).

Similar to personalization, the construct of interactivity within web technologies is broadly defined by some studies. Real time responses, user control, connectedness, customization and playfulness have been discussed as attributes of interactivity (Dholakia, Zhao et al. 2000; Kramer, Noronha et al. 2000). Palmer et al. suggest interactivity is one of five critical factors in well designed websites (Palmer 2002). 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 (Alba, Lynch et al. 1997). In their study, response time and the extent to which communications are a function of the user’s response dictate the level of interactivity. They describe early electronic marketplaces which were limited in interactivity as compared to brick-and-mortar stores where sales associates provider high interactivity. While these studies do not always make a theoretical connection to dual-processing models, it may be that interactive feedback increases the relevance web-based content and increases the likelihood of systematic information processing.

Perhaps related to constructs describing levels of information processing, this study considers another measure of information usage, focused immersion. Agarwal and Karahanna defined cognitive absorption as a measure deep involvement with software that is predictive of a technology’s perceived usefulness and perceived ease of use (2000). One dimension of cognitive absorption is focused immersion. This dimension describes the extent to which “attentional resources of an individual are focused on the particular task.” The authors posit that all five dimensions of cognitive absorption, including focused immersion will lead to increased perceived usefulness and perceived ease of use of a technology. In the present study, we chose to use the single dimension of focused immersion as it best describes the assumed goals that a health information provider has for risk calculator users, focused attention to the content.

The health informatics literature contains one study of particular relevance to our work. Emmons et al, developed and studied a computer-based colon cancer risk communication tool (2004). The authors examine how accuracy of risk perceptions for colon cancer change after using a personalized estimation tool. Users who received personalized risk estimates were more
likely to have accurate post-intervention perceptions. However, additional results from this study found improved correlations between expert and perceived risk after using their tool were no better for subjects who had been given personalized risk estimates than for those that received no risk estimate (Weinstein, Atwood et al. 2004). These results suggest the need for further experimentation to better understand if and how web-based informational interventions impact subjective risk perceptions. The previous paper also highlights the need to explore risk calculators in the context of other diseases. Emmons et al. showed pre-intervention colon cancer risk perceptions were approximately 10-15 times higher than the risks estimated by the expert model. This may be due to the fact that actual colon cancer risks are very small for the typical person. The authors also hypothesize that users may have simply mistrusted the expert tool’s risk estimate which led to significant anchoring on their prior risk beliefs. As discussed above, issues of trust and credibility have been shown to important in designing informational web content.

2.2 Risk Communication and Medical Decision Making

While few studies in information systems have looked at the impact of expert-informed risk communication on laypersons, a significant amount of more fundamental work has been conducted in decision making and psychology. Paul Slovic identified the multidimensional nature of perceptions (Slovic 1987). In this paper, he categorizes perceptions about many hazards on two dimensions, knowledge of the risk and dread. Later work expanded on the importance of affective responses to personal health risks and other hazards (Loewenstein, Weber et al. 2001; Slovic, Finucane et al. 20024) Each of these highlight the relevance of different emotions in predicting behavior in response to risks. In the present study, risk perceptions were elicited not only using probability assessments but also in terms of risk relative to other people and in terms of affect. In a study relating perceptions about flu risk and compliance with flu vaccinations, Weinstein et al. showed that different modes of risk elicitation were correlated but had significantly different power in predicting vaccination behavior (Weinstein, Kwitel et al. 2007). Klein suggests relative risk assessments are strongly related to behavioral outcomes (Klein 1997). These studies underline the importance of understanding that risk perceptions and subsequent behavior are complex and not always a product of consistent internal preferences and decisions based on objective probability weighted outcomes. Decisions to learn more about
health risks and engage in health protective behavior are subject to biases and inconsistencies including susceptibility to social comparison and emotions. In studying and designing web-based health information services, a more comprehensive measurement and understanding of these complexities may provide useful insights and improve the effectiveness of these tools.

There is a significant amount of research on how expert sources should design interventions to communicate health risk messages and improve non-expert decision making (Frosch and Kaplan 1999; O'Connor, Wennberg et al. 2007; Rothman and Kiviniemi 1999). These studies do not necessarily focus on web-based tools or the translation of statistical models for layperson usage, but they are informative for the present study of this application. Fischhoff et al. propose the mental models approach for learning about non-expert risk perceptions in order to design effective risk communications (Morgan, Fischhoff et al. 2002). This approach recognizes the inherent complexities of layperson-expert communication and puts forth an explicit prescription for designing communications that overcome this barrier. Work in medical decision making and the use of decision aids has begun to look closely at the design of interventions to help patients make informed medical decisions. These aids incorporate expert information and educate patients about the tradeoffs in difficult medical decisions. The objective of decision aids is generally to help patients make the best decisions, however suggest determining and measuring the “best” decision is difficult (Nelson, Han et al. 2007). Decision aid studies have highlighted the influence of psychological biases including framing and anchoring (Armstrong, Schwartz et al. 2002; Edwards, Thomas et al. 2006). The effect of numeracy on decisions has also been extensively studied (Ancker and Kaufman 2007; Peters, Vastfjall et al. 2006).

### 2.3 Diabetes Risk

The present study focuses on diabetes risk perceptions in particular. Diabetes is an important area of study because it affects a disproportionately large number of people and is disproportionately costly to manage. In early stages, diabetes is asymptomatic, and public health studies have shown that many people are living with undiagnosed diabetes. This puts them at higher risk for many complications including heart attack and stroke. Attention is also paid to pre-diabetes. Pre-diabetes occurs when blood glucose levels are elevated but not to the level required for a diabetes diagnosis (American Diabetes Association 2007). Pre-diabetes is of concern because it often leads to diabetes (Nelson, Han et al. 2007). Pre-diabetes alone may also
increase risk of heart disease (American Diabetes Association 2007). The risk calculator designed for use in the present study estimates a user's probability of currently having pre-diabetes given multiple factors including height, weight, age, and activity level. Given the importance of identifying pre-diabetes due to its own health hazard and its relationship with diabetes, this is an important application area for studying web-based risk calculators. A few studies have begun to shed light on laypersons’ beliefs about their risk of diabetes onset. There is evidence of a lack of lay knowledge about diabetes and its risk factors relative to experts. Studies suggest that many diabetes risk factors not associated with increased risk perception, and there is evidence of optimism bias (Adriaanse, Snoek et al. 2003; Fisher, Walker et al. 2002). Walker et al. show that diabetes is perceived as serious but less dreaded and fatal than heart disease, AIDS, stroke, and cancer (2007).

3 Research Questions

Little is known about how specific features common in web-based health risk calculators impact user information processing and risk perceptions. In the present study, we focus on the use of web-based personalization in the form of personal diabetes risk estimates computed by a statistical model and presented in an informational health website. We also examine interactive feedback about personalized risk. For our study, we define interactivity as functionality that allows real-time adjustments to health values so that users can learn how changes to their current health situation affect their estimated pre-diabetes risk. The general research question under investigation is: In the context of web-based health information, how do personalized and interactive feedback each influence information usage and subjective perceptions about personal risk of disease onset?

3.1 Impact on Information Usage

Presumably, providers of health risk calculators are interested in motivating users to engage with their web applications and to think critically about the message being delivered. Figure 2 shows our proposed model of the relationships between website features and information usage. We define information usage using four outcome measures. The first is an objective measure: the number of informational hyperlinks that the user clicked while using My Diabetes Risk. We expected this measure to provide a useful complement to three self-report scales which also
measured different constructs relevant to information usage. The three subjective measures of information usage were focused immersion, systematic information processing, and heuristic information processing. Studies in information systems and computer-mediated-communication (CMC) suggest that personalization and interactivity are key features in usage and acceptance (Komiak and Benbasat 2006; Palmer 2002). Based on these, we hypothesized the following:

**Hypothesis 1:** In a website aimed at improving pre-diabetes and diabetes risk awareness, personalized estimates of pre-diabetes likelihood and interactive feedback about modifications to that risk will each motivate users to read more information, become more immersed, and systematically process risk information. Heuristic information processing will be reduced when users are provided with personalized risk estimates and interactive feedback.

We also expected that prior perceptions and the particular risk estimate that is provided will moderate the impact of personalization and interactivity on information usage. Some work in health psychology has shown that information that causes fear or is inconsistent with prior beliefs may lead to information avoidance (Radcliffe and Klein 2002). However, consistent with information processing theory, high expert risk estimates may be perceived as more relevant and motivate increased information usage. We proposed the final hypothesis regarding information usage.

**Hypothesis 2:** The expected positive influence of personalization and interactive feedback on information usage will both be moderated by prior risk perceptions and expert risk estimates. It is expected that increased prior perceptions of risk and increased expert risk 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 these features and heuristic information processing.
3.2 Impact on Post-Usage Risk Perceptions

The second objective was to examine if and how websites containing personalization and interactive feedback lead to changes in users’ subjective perceptions about getting diabetes. Ostensibly, an application that provides personalized risk estimates and interactive feedback will provide users with specific expert reference point on which they can base new and more accurate perceptions. Modest evidence for this effect was found in the Emmons et al. study of colon cancer risk communication (2004). An expert model that not only provides a single point estimate of disease risk, but allows users to explore how changes in their current health would affect their risk estimates may add relevance by giving users an additional opportunity to obtain expert feedback that explains their personal risk and the factors that play into it. This type of feedback may also improve understanding and acceptance of the expert information. As mentioned previously, health information providers that publish risk calculators indicate that their primary goal is to provide users with accurate risk information. Implicit in this goal is that users internalize that risk information and maintain accurate perceptions about their susceptibility to the given disease or other health hazard. Figure 3 shows our proposed model of
risk perception updating. The primary outcome of interest is the extent to which users change their prior risk perceptions after using a risk calculator intervention. This was explored using three measures of risk perception (absolute, relative, and affective). The next hypothesis is:

**Hypothesis 3:** In a website aimed at improving pre-diabetes and diabetes risk awareness, personalized estimates of pre-diabetes likelihood and interactive feedback about how to reduce personal risk will lead to increased updating of prior risk perceptions and an increased concordance between expert predictions and user beliefs about diabetes likelihood.

Finally, similar to the hypotheses about information usage, we expected the impact of personalization and interactivity would be moderated by prior beliefs and the specific expert risk estimate provided by the calculator. While we expected that personalization and interactive feedback would provide additional information, consistent with anchoring and adjustment, prior beliefs about risk may serve as a salient reference point on which post-intervention perceptions are at least partially based (Kahneman, Slovic et al. 1982). In addition, as discussed above, health risk information that induces fear may be avoided and not accepted (Loewenstein, Weber et al. 2001).

**Hypothesis 4:** The expected positive influence of personalization and interactive feedback on changes in risk perceptions will be moderated by prior risk perceptions and expert risk estimates. It is expected that users who initially underestimated their diabetes risk will be less likely to revise their perceptions than users who initially overestimate their risk.

We explored these questions in two randomized experiments.
4 Experiment 1

4.1 Experimental Design

100 adults over the age of 45 were recruited from the general U.S. population by a market research firm to participate in an Internet-based study. The research firm maintains a panel of participants who are compensated with points for participating in surveys. These participation points are then redeemable for merchandise. Only adults with no prior diagnosis of Type I or Type II diabetes were invited to participate. In a single online session in a location of their choice (such as their home or office), participants completed a 3-part experiment.

Part 1 administered a questionnaire to assess their perceived risk of developing diabetes and other relevant baseline measures. Absolute, relative terms, and affective perceptions terms using similar to the questions used in (Walker, Mertz et al. 2007) Two questions measured absolute risk perceptions, both asking for participants’ perceived likelihood of getting diabetes in the next twenty years. The first used a 7-point categorical scale anchored by “Almost zero” and “Almost
certain.” The second absolute risk question asked participants to choose their perceived risk level on a scale of 0 to 100 using 5-point intervals. One question elicited risk perceptions relative to other people of the same age and gender. This question used a 7-point scale anchored by “Well below average” and “Well above average.” Two measures of affective risk were elicited using a slightly modified version of the affective risk questions used in (Walker, Mertz et al. 2007). The first was a two item measure of worry about diabetes. The second contained four item measuring the extent to which participants feel that they can control their risk of future diabetes onset. In addition to these primary questions, participants were asked about their diabetes risk factor knowledge (Walker, Mertz et al. 2007), history of diabetes related screenings, diagnoses, and discussions with health professionals, frequency with which they seek health related information (either online or otherwise), intentions to seek more information about diabetes in the near future and their education level. A six-question scale previously used by (Kahlor, Dunwoody et al. 2003) assessed participants’ baseline propensity for seeking health information,

Part 2 of the experiment randomized participants to one of the three versions of our experimental risk calculator called *My Diabetes Risk*. These website versions were designed to mimic the common functionality found in web-based health risk calculators that are currently made available by research, charitable and other health organizations. The application’s main features include:

1. **Background** information explaining diabetes and pre-diabetes
2. **Form-based Questions** which ask users to enter personal health values
3. **Personal Risk Estimation** generated by a statistical prediction model
4. **Interactive Feedback** allowing users to change their values and update their risk estimates
5. **“Read More” Links** to provide further information and advice about diabetes risk factors such as obesity and family history.

The first page of each condition included features 1 and 2, *Background* and *Health Questions*. Background included basic descriptions of disease prevalence in the United States, diagnosis criteria, guidelines for disease management and related health complications. It was also explained that many people are living with undiagnosed diabetes and pre-diabetes and that these
conditions may harm long-term health. In addition, the first page described the goals and functionality of the *My Diabetes Risk* website. This was provided in two paragraphs. The first described the site 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.*” The second paragraph explained that the website needed to ask the participant multiple questions about his health. A web form elicited the user’s gender, age, race, height, weight, blood pressure, history of hypertension, HDL cholesterol, smoking status and activity level. If the participant was unsure of their blood pressure or HDL, they were able to select “I don’t know” and an average value based on age range and gender was used instead. All questions were required in order to continue.

Page 2 of *My Diabetes Risk* varied based on experimental condition as described below:

**A. Non-Personalized Version:** This control condition provided users with primarily non-personalized text information about diabetes and its multiple risk factors (feature 5 only). The condition contained text in the upper left corner reading: “*The average adult has a 28% chance of already having pre-diabetes.*” It also contained a reminder of the that pre-diabetes is a precursor to diabetes and nearly all individuals that develop diabetes first have pre-diabetes. Users also saw a list of eight diabetes risk factors and encouraged them to click “Read More” links next to each factor. Each link popped up a small window with a short paragraph describing the specific diabetes risk factor and tips for mitigating that risk. Each read more link was preceded by a sentence the reminded the user of their value on that particular risk factor based on their responses on the first page of the website. A screen shot of the control version is shown in Figure 4 below.

**B. Personalized Version:** The control condition was meant to serve as a minimal information source that provided little personalized feedback and no interactive capabilities to the user. In contrast, the personalized condition contained pre-diabetes risk estimates in the form of absolute percentage estimates and relative risk estimates. These were presented using text, numbers and a risk graph. The graph contained a percentage scale marking the estimated probability that the participant currently has pre-diabetes (see Figure 5). These risk estimates were generated using a logistic regression model that predicts undiagnosed pre-diabetes. In addition, the graph depicted pre-diabetes risk relative to other adults of the same sex and in the same age range using markers
for the average person that could be compared to the user’s risk estimate marker. The regression model was estimated by the investigators using data on undiagnosed pre-diabetes contained in the National Health and Nutrition Examination Survey ((CDC) 2005-2006). The development of the model is discussed in more detail below.

Figure 4. My Diabetes Risk – Non-Personalized condition

Figure 5. Risk Graph for Personalized and Personalized/Interactive versions
C. Personalized/Interactive Version: The personalized/interactive website condition included the same percentage and relative risk estimates but also gave the users the ability to enter 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. In this condition, users were able to enter new values as many times as they wished and the textual, numeric and graph-based estimates were updated when they clicked “Update my risk.” Figure 6 shows a screen shot of the personalized/interactive condition in My Diabetes Risk.

![Image of My Diabetes Risk interface]

Figure 6. My Diabetes Risk interface containing both Personalized and Interactive feedback features.

Notice that in each of the three conditions users were provided with estimates of pre-diabetes risk. The minimal information condition provided the average adult’s risk of currently having pre-diabetes. The personalized and personalized/interactive conditions entered the user’s information into a logistic regression model that predicted their individual probability of currently having pre-diabetes. Throughout the website, textual information was given about both
pre-diabetes and diabetes, and it was explained that pre-diabetes can be thought of as a precursor to diabetes. By not giving users a direct estimate of their 20 year diabetes risk, we aimed to provide them with a related value that they could later use to inform a revised subjective estimate of their 20 year diabetes risk. We believed this would help avoid the problem of users simply recalling the exact risk that was provided by the calculator and actually report their personal perceived risk estimates. A detailed discussion of how the estimates in *My Diabetes Risk* were generated and how they can be interpreted is provided in the Appendix.

Part 3 of the experiment followed usage of the *My Diabetes Risk*, website. All participants completed a follow-up survey that assessed focused immersion, systematic information processing and heuristic information processing. Objective system data including time spent using the calculator, the number of risk factor links clicked and the usage of interactive feedback was automatically collected by the web application. These provided multiple metrics for understanding how users engaged with the risk calculator and processed the diabetes risk information. Finally, changes in risk perceptions were be assessed using the same absolute, relative and affective risk perception measures that described in the baseline survey.

5 Data and Results

5.1 Data

35 participants were randomly assigned to the *Non-Personalized* application, 32 to the *Personalized*, and 33 to the *Personalized/Interactive*. The average participant was 61 years old and overweight (nearly obese) according to their BMI. Experiment invitations were sent to a mix of ethnic groups, but the respondents were overwhelmingly white. The reason for this disparity is unclear. Of the participants assigned to the personalized/interactive risk calculator, only two actually modified their risk 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 (Weinstein, Atwood et al. 2004). Due to this disuse, the personalized and personalized/interactive applications represented essentially equivalent interventions. Subsequent analyses combine the results from these two conditions into a single condition referred to as *personalized*, and we only discuss the influence of personalization. In terms of information
usage, participants spent an average of 4.88 minutes using *My Diabetes Risk* and clicked on 2.11 out of 8 risk factor links.

Table 1 compares the mean demographics and health characteristics for the two groups after collapsing the two conditions. Notable is that the personalized sample reported significantly lower HDL cholesterol and the risk calculator estimated that this condition was at higher risk (marginally significant). 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. Also, the personalized sample self-reported as being significantly lower in baseline health information seeking. These differences between the conditions are considered below when interpreting results.

Table 1:  
**Experiment 1 – Participant descriptive statistics by condition**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Basic (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>History of 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 (yes/no)</td>
<td>34%</td>
<td>32%</td>
</tr>
<tr>
<td>Exercise 3+ days / week (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 (1: low – 7: high)</td>
<td>5.76*</td>
<td>5.34</td>
</tr>
<tr>
<td>Education (1: &lt;High School – 8: Professional)</td>
<td>Modes: &quot;high school&quot; &amp; &quot;some college&quot;</td>
<td>Mode: &quot;high school&quot;</td>
</tr>
</tbody>
</table>

*Means significantly different (p < 0.05)*

Table 2 shows mean risk estimates given by the participants and the risk calculator respectively for each condition. A significant proportion of participants reported perceived risk below the
calculated risk, and a significant proportion reported perceived risks above the calculated risk.

### Table 2: Experiment 1 - Absolute risk perceptions by condition

<table>
<thead>
<tr>
<th>Variable</th>
<th>Non-Personalized (n = 35)</th>
<th>Personalized (n = 65)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-intervention perceived diabetes risk %</td>
<td>27.71 (26.88)</td>
<td>27.15 (21.90)</td>
</tr>
<tr>
<td>Calculator pre-diabetes risk %</td>
<td>30.69 (18.20)</td>
<td>37.54 (18.21)</td>
</tr>
<tr>
<td>Post-intervention perceived diabetes risk %</td>
<td>28.00 (26.68)</td>
<td>28.39 (22.13)</td>
</tr>
</tbody>
</table>

*Standard deviations in parentheses*

### 5.2 Information Usage

Figure 7 shows mean values for each information utilization measure in each condition. For the three self-report scales, higher values indicate increased focused immersion, increased systematic information processing and increased heuristic information processing respectively. Cronbach’s alpha measures of reliability are 0.88, 0.89, and 0.63 respectively. Alpha for heuristic information processing is low and potentially unreliable, so we view this result with caution. The differences between conditions all have the opposite sign of what was predicted by our hypotheses. Users in the personalized condition clicked significantly fewer risk factor hyperlinks ($t(56.1) = 2.94, p = 0.005$) 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 differences in baseline health information seeking and explore the potential moderation of information usage by the expert estimates and prior beliefs about diabetes risk. Table shows the results of a linear regression of immersion on the calculator’s risk estimate, a dummy variable for personalization, and the interaction of these two variables. Figure 8 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, reduced their attention.

Figure 7. Experiment 1 - Information usage measures by condition (*error bars are standard errors*)

Figure 8. Experiment 1 - Focused Immersion by Calculated Absolute Risk
Table 3:

Experiment 1 - Focused Immersion and Calculated Risk

|                          | Estimate | Std. Error | t value | Pr(>|t|) |
|--------------------------|----------|------------|---------|----------|
| (Intercept)              | 5.716    | 0.368      | 15.542  | < 2e-16  *** |
| CalculatedRisk           | -0.010   | 0.010      | -0.941  | 0.349    |
| Personalized             | -1.354   | 0.484      | -2.800  | 0.006 **  |
| CalculatedRisk*Personalized | 0.026   | 0.013      | 2.012   | 0.047 *   |

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 1

Residual standard error: 1.098 on 96 degrees of freedom
Multiple R-Squared: 0.08827, Adjusted R-squared: 0.05977
F-statistic: 3.098 on 3 and 96 DF, p-value: 0.03042

In other words, results indicate that when low risk users were informed that they are low risk they became less immersed. To check the robustness of this result, a similar regression was run that also controlled for our measure of baseline information seeking. 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). A similar regression was run that replaced calculated absolute risk with the calculated relative risk and also controlled for baseline information seeking propensity. The coefficient on Personalized was significant (t = -2.26, p = 0.03), and its interaction with Calculated Relative Risk was marginally significant (t = 1.80, p = 0.08). Similar regression analyses were performed for the other information usage outcomes to understand the influence of the particular risk estimate given by the calculator. For systematic information processing and number of risk factor links clicked, calculated risk did not moderate the negative impact of personalization. A regression analysis for heuristic information processing suggested a significant interaction between personalization and the difference between prior estimate and calculator estimate. This difference can be thought of as a measure of accuracy of prior beliefs, with negative values indicating under-estimation and positive values over-estimation of personal risk. This is depicted in Figure 9 and Table 4.
Hypothesis 1 was not supported. There was no evidence that personalization increased the extent to which users accessed risk information, were immersed in the website or systematically processed the information being provided. The negative relationship with heuristic processing...
was also not found. In fact, results suggested that in some cases personalization reduced information usage. Further analysis suggested that differences in calculated risk levels helped explain this unexpected finding. This supports a moderating effect of calculated risk though not the specific moderation proposed in Hypothesis 2.

5.3 Absolute Risk Perceptions

Figure shows the differences in risk perception updating observed between the experimental conditions. The first two bars answers the descriptive question: “By how much did users change their diabetes risk estimate after using My Diabetes Risk?” The mean of the absolute value of updating was marginally significantly higher in the personalized condition than in the non-personalized condition (t = 1.84, p = 0.07). The second set of bars answers a normative question: “By how much did users revise their diabetes risk estimates towards the expert calculator estimate?” As discussed previously, accepting updates towards the expert value as the normative response assumes that the calculator’s pre-diabetes estimate is at least a close approximation of twenty-year diabetes risk. Under this assumption, as predicted by Hypothesis 3, mean updating towards the expert estimate was significantly larger in the personalized condition than in the non-personalized condition (t = 1.99, p = 0.05). Further analysis showed that 33.8% of personalized users updated their prior estimate in the post-intervention survey and 17.1% of non-personalized users updated their estimates. This difference in proportions was marginally significant ($\chi^2 = 3.15, p = 0.08$). These results support Hypothesis 3, though the positive relationship between personalization and absolute risk estimate revisions may be practically modest in size.

Hypothesis 4 proposed that users who underestimated their risk may be less prone to revise their estimates after learning about their expert estimated risk. After separating personalized users into those whose prior estimates were well below the calculated value and those whose prior estimates were well above the calculated value, no significant differences in updating were. Results for these analyses are presented in Appendix Table A.
5.4 Relative Risk Perceptions

Similar to the results for absolute risk perceptions, we measured the differences between the experimental conditions in terms of changes in estimates of risk relative to other people of the same age and sex. The signs of the differences are all suggestive of increased updating activity among users of the two personalized conditions, but these differences are not significant. These results are given in Appendix Table B.

5.5 Affective Risk Perceptions

Participants were assessed both before and after using My Diabetes Risk using multiple affective measures. Summary results are presented in Appendix Table C. Users responded being slightly more worried about diabetes in the post-intervention survey, but the increase is not significant. There were no significant differences between conditions in changes to the affective measures.
6 Experiment 2

6.1 Experimental Design
A second experiment was conducted to help clarify the results found in Experiment 1. The one major design change made was that the coloring of the risk graph presented in the personalized and personalized/interactive versions was changed. The graph had three sections. The lower section was colored blue and indicated low risk, the middle section orange for moderate risk, and the upper section red for high risk. However, in Experiment 1, the moderate risk section covered the area between 9% and 74% meaning that nearly all of the users fell into this category. If participants in Experiment 1 were more likely to respond to the risk range in which they fell (as opposed to their specific risk percentage), then this could help explain why updating levels were modest. In Experiment 2, the low risk category ranged from 0 – 20%, the moderate from 20% to 50%, and high risk from 50% to 100%. For Experiment 2, adult participants over the age of 40 were recruited through announcements to University staff email distribution lists. The age requirement was lowered from 45 to 40 with the goal of attracting more participants. We did not expected that this particular change would significantly influence the results. Participants were compensated with a $10 gift card for their participation.

7 Data and Results

7.1 Data
34 adult participants participated in Experiment 2. 12 were assigned to the Non-Personalized information condition, 11 to the Personalized condition, and 11 to the PersonalizedInteractive condition. The average participant was 51 years old and categorized as overweight with a BMI of 27. The sample was 18% male, and 41% of the users reported a family history of diabetes. Similar to Experiment 1, nearly all of those assigned to the personalized/interactive condition failed to use the interactive feedback capabilities. Given this, we again combined this group with the personalized condition in our data analysis. The average participant reported a perceived 20 year diabetes risk of 29.56% while the risk calculator estimated an average pre-diabetes risk of 21.77%. After using the intervention website, average perceived risk was 27.06%. Tables 5 and 6 compare the mean demographics, health characteristics and risk estimates of the two groups.
after collapsing the two conditions. No significant differences were found between conditions on these measures.

### Table 5:

**Experiment 2 - Mean demographics by condition**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Non-Personalized (n = 12)</th>
<th>Personalized (n = 22)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>50.17</td>
<td>51.18</td>
</tr>
<tr>
<td>BMI</td>
<td>26.4</td>
<td>28.08</td>
</tr>
<tr>
<td>HDL cholesterol</td>
<td>61.42</td>
<td>63.04</td>
</tr>
<tr>
<td>Systolic blood pressure</td>
<td>124.08</td>
<td>119.50</td>
</tr>
<tr>
<td>Diastolic blood pressure</td>
<td>75.58</td>
<td>76.64</td>
</tr>
<tr>
<td>History of hypertension (yes/no)</td>
<td>25.00%</td>
<td>27.27%</td>
</tr>
<tr>
<td>Sex (male, yes/no)</td>
<td>33.33%</td>
<td>9.09%</td>
</tr>
<tr>
<td>Family history of diabetes (yes/no)</td>
<td>50.00%</td>
<td>36.36%</td>
</tr>
<tr>
<td>Exercise 3+ days / week (yes/no)</td>
<td>41.67%</td>
<td>22.73%</td>
</tr>
<tr>
<td>Smoker (yes/no)</td>
<td>0%</td>
<td>9.09%</td>
</tr>
<tr>
<td>Ethnicity (white, yes/no)</td>
<td>100%</td>
<td>95.45%</td>
</tr>
<tr>
<td>Health information seeking (scale 1,low - 7,high)</td>
<td>5.57</td>
<td>5.83</td>
</tr>
<tr>
<td>Education (1, &lt;High School - 8, Professional)</td>
<td>Mode: “some College”</td>
<td>Mode: “some College”</td>
</tr>
</tbody>
</table>

### 7.2 Information Usage

There were no significant differences between conditions on any of the information usage measures. However, we see that the unexpected trends which were observed in Experiment 1 were also evident in Experiment 2 (see Appendix Table D). In terms of risk factor links clicked, focused immersion, and systematic information processing, the means values in the non-personalized condition suggest more information in the absence of personalization. Also, in the personalized condition, the mean measure of heuristic processing is larger than in the non-personalized condition.
Table 6: Experiment 2 – Absolute risk perceptions by condition

<table>
<thead>
<tr>
<th>Variable</th>
<th>Non-Personalized (n = 12)</th>
<th>Personalized (n = 22)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-intervention perceived diabetes risk %</td>
<td>26.25 (15.83)</td>
<td>31.36 (18.46)</td>
</tr>
<tr>
<td>Calculator pre-diabetes risk %</td>
<td>22.91 (11.33)</td>
<td>21.15 (9.46)</td>
</tr>
<tr>
<td>Post-intervention perceived diabetes risk %</td>
<td>27.08 (17.25)</td>
<td>27.05 (21.64)</td>
</tr>
</tbody>
</table>

Standard deviations in parentheses

7.3 Risk Perception Updating

Again, in this small sample study, there were no significant differences between conditions in terms of revisions to risk perceptions on any of the three modes of measurement. However, the observed differences between conditions are suggestive of increased updating towards the calculator estimate in the personalized condition. See Appendix Tables E – G.

8 Discussion

This study examined how users of a specific class of web-based health applications utilized risk information and revised their perceived risk of diabetes after using the application. We experimentally manipulated the presence of personalized risk estimates and interactive feedback about changes to those risk estimates through a statistical model. 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 users focused on the website content or systematically processed the information contained in the site. Contrary to our hypothesis, there was evidence that users of the non-personalized condition were actually more immersed in the website, more systematically processed the risk information and explored diabetes risk factor links. These findings are inconsistent with theory that suggests personalized messages are perceived as more relevant and thus processed more systematically. Regression analysis suggested that personalization led to reduced immersion and increased heuristic processing when users were informed that their true risk was low in absolute terms and
low relative to their prior beliefs respectively. Reductions in systematic processing and risk factor lacks accessed under personalization could have been due to the fact that personalized estimates offered a summary measure of risk that competed for the users’ attention. While users may have found the personal estimates more relevant, these estimates may not have stimulated increased attention or systematic processing of the content generally. Practical implications of these findings are that users of risk calculator applications may learn expert estimate of their risk, but in so doing, they may not always be more motivated to read more details about the disease and how to mitigate its risk. The nearly complete disuse of the interactivity future is also suggestive of a generally low propensity for obtaining quantitative, expert feedback about risk mitigation.

In terms of perceptual updating, users of the personalized risk calculator did show some adjustment of their absolute risk perceptions towards the calculated value. However, these adjustments were moderate in magnitude and post-intervention perceptions were much more correlated with pre-intervention perceptions than they were with expert calculator estimates. While not a formal test, this is suggestive of a strong anchoring effect of prior perceptions. Results for changes in relative risk perceptions and affective risk perceptions were weaker. While relative risk perceptions in the personalized condition updated towards the calculated relative risk estimate, the magnitude of updating was not significantly larger than in the non-personalized condition. One possibility is that relative risk beliefs are better formed and thus more difficult to change than absolute risk estimates. Affective measures of worry about diabetes and control over diabetes risk showed little or no response to either risk calculator condition. Since research has suggested that relative risk perceptions (Klein 1997) and affective perceptions may be more predictive of behavior (Slovic, Finucane et al. 2004) than absolute perceptions, our results do not strongly support the potential for web-based risk calculators to motivate risk mitigating behavior. It is encouraging to see absolute risk estimates changing in response to expert risk estimates, but the moderate magnitude and lack of significant change in relative and affective risk measures suggests that stronger informational interventions may be needed in order for users to more accurately align their risk estimates with an expert model and truly revise their beliefs about personal disease risk.
An alternate explanation for most of our findings is that users may have deemed the calculator’s pre-diabetes risk estimate to be reasonably consistent with (e.g. “close enough to”) their prior perceptions, and therefore did not engage or update extensively. In the Weinstein et al. study, absolute colon cancer risk estimates averaged more than ten times the expert prediction (2004). These large discrepancies may have provided users more impetus to update their beliefs than did the smaller differences in our study of diabetes risk perceptions. However, we found no evidence of more substantial revisions in perceptions for users whose prior beliefs about diabetes were largely different from the expert calculator. Other potential explanations are that health messages that are inconsistent with beliefs or perceived as non-credible may be less persuasive and lead to information avoidance (Radcliffe and Klein 2002). Numeracy difficulties may have also limited understanding of risk estimates. Collection of a larger data sample and new experimental designs and data analyses that disentangle these factors may produce more definitive results. Finally, although we designed our experimental risk calculator to mimic the basic functionality of existing risk calculators, it is unclear how the results from our tool generalize to current use of available web-based risk calculators.

We should also discuss three specific limitations that may have weakened the observed effect of the risk calculators. The risk estimates presented by *My Diabetes Risk* pertained to current pre-diabetes risk while the measured perceptions focused on twenty-year diabetes risk. Instructions were included to explain that there is a strong relationship between these risks, but it is unclear how participants perceived the relationship. At one extreme, they may have assumed these two risks were equivalent. Alternatively, participants may have viewed these risks as unrelated and thus failed to update their perceptions. A second limitation is that the random assignment led to non-personalized version users who measured higher in baseline health information seeking than users of the personalized condition. This may have weakened the observed effects of personalization on user engagement, information processing and perceptual updating. Attempts were made to control for this statistically. Finally, in Experiment 1, the personalized risk graph was calibrated such that most users’ risk fell into the “moderate” absolute risk category. 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
Experiment 2, and qualitatively similar results were still observed. However, the small sample size in Experiment 2 makes it difficult to make strong conclusions from this data.

This study contributes to the literature on personalized web applications by extending it to health information services. We drew on theory from psychology and behavioral decision making 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, increased study of how to best design applications that organize and disseminate personalized health information in ways that motivate awareness, education and healthy behavior is important. Existing health risk calculators implement well-developed statistical models and deliver their estimates to laypersons, but it is not clear that expert statistical estimates are the most appropriate way to inform and motivate laypersons. We are currently planning future experiments that refine our design and more closely examine if and when personalized risk calculators motivate users to explore disease risk information and develop more accurate risk perceptions. Work is also needed to explore why users in our study and past studies have resisted the opportunity to obtain interactive feedback about risk mitigation. Future studies are needed to better define how web-based health information can be personalized not only to the user’s health characteristics but also to the user’s knowledge, preferences for information design, and to effectively counter well known biases in the usage of information and health risk perceptions.

9 Conclusion

Online experiments with a diabetes risk calculator found that personalized diabetes risk estimates had a modest impact in altering absolute risk perceptions. However, post-intervention perceptions were more strongly related to pre-intervention perception than the expert estimate. Relative and affective risk perceptions were not influenced more by the personalized calculator than the non-personalized version. These experiments also suggested that expert model risk estimates did not generally motivate users to explore more risk information or to report higher levels of attention and careful processing of risk information. Some of this may 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 understand the behavioral implications when laypersons use web-based risk communication tools.

10 Appendix

10.1 Estimating Risk

Here, we discuss the details of how pre-diabetes risk was estimated in our experimental risk calculator and how it should related to diabetes risk. Recall that pre-diabetes and diabetes are diagnosed using the same scale (e.g. fasting plasma glucose). Diabetes diagnosis just requires a higher measurement on this scale. The relationship between absolute (percentage) risk of currently having pre-diabetes and developing diabetes within the next 20 years is less clear. The medical literature has not produced consistent evidence on the percentage of pre-diabetics who progress to diabetes (Nichols, Hillier et al. 2007). Further, the studies that have been conducted have not measured rates of progression beyond 10 years. For most of our analyses, we assume that risk of currently having pre-diabetes risk is a close approximation of 20 year diabetes risk. The information provided by the risk calculator was also designed to convey this assumption to the user, though it was not explicitly stated. A safer assumption is that our models estimates of pre-diabetes risk provide an upper bound on 20 year diabetes risk. In other words, actual 20 year diabetes risk may be somewhat lower than the pre-diabetes risks predicted by our model. This possibility is discussed later in the context of our analysis. In terms of risk relative to other people of the same age and sex, we assume that risk of pre-diabetes and 20 year diabetes risk are the same. This is intuitively reasonable and consistent with the literature on the relationship between diabetes and pre-diabetes. For example, it is reasonable to assume that a person with an above average risk of currently having pre-diabetes also has an above average risk of developing diabetes in the next 20 years.

Alternate approaches that would have avoided the above inconsistency would have been to present users with a model that predicted 20 year diabetes risk directly or to instead measure pre-diabetes perceptions in the pre- and post-intervention surveys. We chose not to pursue the first approach for two reasons. First, no model for predicting 20 year diabetes risk was readily available and feasible for implementing in our experimental application. Second, worried that this would encourage users to simply recall the exact risk that was presented to them rather than
report their beliefs about diabetes risk based on the information they had received in the risk calculator. By presenting users with pre-diabetes risk and explaining that this risk is similar but not identical to 20 year diabetes risk, users were more likely to report their perceptions rather than use simple recall. The second alternative would have suffered the same potential problem of participants using simple recall in responding to the perception elicitation in the post-intervention survey. Further, this alternative would have required users to be somewhat familiar with pre-diabetes at the start of the experiment and able to provide risk estimates of the disease. Given that pre-diabetes is likely to be less familiar to most lay individuals than diabetes, we were concerned that prior risk perceptions would have been even more difficult for participants to provide reliably.

The risk estimation model we did incorporate into *My Diabetes Risk* was developed using the most recent four years of data from the NHANES (2003-2006). On a subset of survey participants, NHANES measures the risk factor information used by *My Diabetes Risk*. The participants in this subsample also take a Fasting Plasma Glucose (FPG) test to detect undiagnosed pre-diabetes (FPG ≥ 100 mg/dl) and diabetes (FPG ≥ 126). We coded observations with FPG ≥ 100 as pre-diabetic and then estimated a logistic regression model on this variable using the same covariates described above as being elicited by *My Diabetes Risk*. We validated the plausibility of this model by comparing the sign and magnitude of the coefficients to the expected relationships suggested by the medical literature on diabetes. For example, we verified that the regression coefficient on BMI reflected the strong positive relationship between BMI and pre-diabetes risk. The regression model was not validated in terms of actual predictive accuracy, and we make no claims of its robustness in terms of predictive accuracy. However, it was estimated using a large sample of reputable data on a representative adult population. Further, our goal in this study was not to develop a statistical model for future implementation in a publicly available risk calculator. Existing diabetes prediction models, such as Archimedes have been subject to extensive validation and are more appropriate for practical instantiations (Eddy and Schlessinger 2003). Instead, we focused on developing a plausible model whose estimates would be accurate enough that lay users would find them as acceptable as any other statistical prediction model that they might encounter. Given this assumed plausibility, our primary objective was then to explore the behavioral implications when the outputs of these types of models are presented to non-expert users.
10.2 Additional Results

### Appendix Table A:
**Experiment 1 - Normative Revisions in Absolute Risk Perceptions**

<table>
<thead>
<tr>
<th></th>
<th>Non-Personalized (n=35)</th>
<th>Personalized (n=65)</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>High (≥10%) Overestimaters</td>
<td>1.43</td>
<td>4.50</td>
<td>-3.07</td>
</tr>
<tr>
<td>Low (&lt;10%) Overestimaters</td>
<td>-2.50</td>
<td>1.67</td>
<td>-4.17</td>
</tr>
<tr>
<td>All Overestimaters</td>
<td>-0.67</td>
<td>3.16</td>
<td>-3.83</td>
</tr>
<tr>
<td>High (≥10%) Underestimaters</td>
<td>2.08</td>
<td>3.47</td>
<td>-1.39</td>
</tr>
<tr>
<td>Low (&lt;10%) Underestimaters</td>
<td>-1.50</td>
<td>3.13</td>
<td>-4.63</td>
</tr>
<tr>
<td>All Underestimaters</td>
<td>0.00</td>
<td>3.04</td>
<td>-3.04</td>
</tr>
</tbody>
</table>

Positive cell values indicate revisions towards the calculator estimate

* p < 0.1, ** p < .05, *** p < .01

### Appendix Table B:
**Experiment 1 - Relative risk perception updating**

<table>
<thead>
<tr>
<th></th>
<th>Non-Personalized (n=35)</th>
<th>Personalized (n=65)</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of users updating</td>
<td>51.4%</td>
<td>67.7%</td>
<td>-16.3%</td>
</tr>
<tr>
<td>% of users updating towards calculator†</td>
<td>40.00% (n=15)</td>
<td>64.71% (n=34)</td>
<td>-24.71%</td>
</tr>
<tr>
<td>Mean absolute value of update</td>
<td>0.74</td>
<td>1.05</td>
<td>-.31</td>
</tr>
<tr>
<td>Mean update towards calculator†</td>
<td>0.67 (n=15)</td>
<td>1.00 (n=34)</td>
<td>-.33</td>
</tr>
</tbody>
</table>

* p < 0.1, ** p < .05, *** p < .01

† For updating towards calculator, only users who were inaccurate at baseline were considered
### Appendix Table C:
Experiment 1 - Affective Risk Perception Updating

<table>
<thead>
<tr>
<th></th>
<th>Non-Personalized (n=35)</th>
<th>Personalized (n=65)</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Update on “I worry about diabetes”</td>
<td>0.06</td>
<td>0.34</td>
<td>-0.28</td>
</tr>
<tr>
<td>Update on “Worrying about diabetes is upsetting to me”</td>
<td>-0.029</td>
<td>0.14</td>
<td>-0.17</td>
</tr>
<tr>
<td>Update on perceived control over diabetes risk</td>
<td>-0.10</td>
<td>0.05</td>
<td>-0.15</td>
</tr>
</tbody>
</table>

* p < 0.1, ** p < .05, *** p < .01

### Appendix Table D:
Experiment 2 – Information Usage

<table>
<thead>
<tr>
<th></th>
<th>Non-Personalized (n=12)</th>
<th>Personalized (n=22)</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean # links clicked</td>
<td>4.00</td>
<td>2.95</td>
<td>1.05</td>
</tr>
<tr>
<td>Mean Focused Immersion (α = .92)</td>
<td>5.72</td>
<td>5.23</td>
<td>0.46</td>
</tr>
<tr>
<td>Mean Systematic Proc. (α = .87)</td>
<td>5.60</td>
<td>5.37</td>
<td>0.23</td>
</tr>
<tr>
<td>Mean Heuristic Proc. (α = .71)</td>
<td>2.97</td>
<td>3.17</td>
<td>-0.20</td>
</tr>
</tbody>
</table>

* p < 0.1, ** p < .05, *** p < .01
### Appendix Table E:
**Experiment 2 - Absolute risk perception updating**

<table>
<thead>
<tr>
<th></th>
<th>Non-Personalized (n=12)</th>
<th>Personalized (n=22)</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of users updating</td>
<td>75%</td>
<td>77.27%</td>
<td>-2.27%</td>
</tr>
<tr>
<td>% of users updating</td>
<td>33.33%</td>
<td>59.09%</td>
<td>-25.76%</td>
</tr>
<tr>
<td>towards calculator</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean absolute value of</td>
<td>8.33</td>
<td>8.86</td>
<td>-0.53</td>
</tr>
<tr>
<td>update</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean update towards</td>
<td>2.50</td>
<td>4.32</td>
<td>-1.82</td>
</tr>
<tr>
<td>calculator</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*In Rows 3-4, positive cell values indicate revisions towards the calculator estimate*

### Appendix Table F:
**Experiment 2 - Relative risk perception updating**

<table>
<thead>
<tr>
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<th>Non-Personalized (n=12)</th>
<th>Personalized (n=22)</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of users updating</td>
<td>83.33%</td>
<td>86.36%</td>
<td>-3.03%</td>
</tr>
<tr>
<td>% of users updating</td>
<td>75%</td>
<td>83.33%</td>
<td>-8.33%</td>
</tr>
<tr>
<td>towards calculator†</td>
<td>(n=4)</td>
<td>(n=6)</td>
<td></td>
</tr>
<tr>
<td>Mean absolute value of</td>
<td>1.08</td>
<td>1.27</td>
<td>-0.19</td>
</tr>
<tr>
<td>update</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean update</td>
<td>1.00</td>
<td>1.67</td>
<td>-0.33</td>
</tr>
<tr>
<td>towards calculator†</td>
<td>(n=4)</td>
<td>(n=6)</td>
<td></td>
</tr>
</tbody>
</table>

*p < 0.1, ** p < .05, *** p < .01

† For updating towards calculator, only users who were inaccurate at baseline were considered*
Appendix Table G:
Experiment 2 - Affective Risk Perception Updating

<table>
<thead>
<tr>
<th></th>
<th>Non-Personalized (n=12)</th>
<th>Personalized (n=22)</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Update on “I worry about diabetes”</td>
<td>0.05</td>
<td>0.44</td>
<td>-0.39</td>
</tr>
<tr>
<td>Update on “Worrying about diabetes is upsetting to me”</td>
<td>-0.03</td>
<td>0.14</td>
<td>-0.17</td>
</tr>
<tr>
<td>Update on perceived control over diabetes risk</td>
<td>-0.1</td>
<td>0.05</td>
<td>-0.15</td>
</tr>
</tbody>
</table>

11 References

(CDC)."National Center for Health Statistics (NCHS), National Health and Nutrition Examination Survey Data.," U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, Hyattsville, MD, 2005-2006.


Fox, S. "Online Health Search 2006," Pew Internet & American Life Project, Washington, D.C.


