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The influence of memory for and affective response to health messages on self-care behavioral intentions

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ABSTRACT

Clinical test results are often presented in digital health solutions (e.g., patient portals, mobile phone apps) with limited context to help patients understand implications of this numeric information. Guided by a framework that integrates cognitive and health behavior theories, we identified processes involved in understanding and responding to health messages as a basis for designing more effective digital health solutions that include clinical test results. This framework emphasizes the importance of presenting numeric information in ways that support memory, decision making, and action. In previous studies we measured memory for and affective response to messages about cholesterol and diabetes screening test results, perceived risk associated with these test results, as well as attitudes toward and intention to perform behaviors that address these risks (e.g., adherence to exercise recommendations). The focus of the present paper is to analyze direct and indirect relationships among these health decision making and behavioral variables through multivariate path analyses. Consistent with previous findings, we found that memory for messages was only indirectly related to behavioral attitudes and intentions. Affective responses to risk-related information, on the other hand, directly related to these variables, perhaps because behavioral attitudes and intentions are often based on information organized around affective/evaluative dimensions. These results suggest appropriate affective response may not only directly support risk perception, but attitudes toward behavior addressing this risk. We discuss implications for human factors and ergonomics researchers and practitioners to the design, implementation and evaluation of digital health solutions.

Introduction

Clinical test results are often presented in patient portals to Electronic Health Record (EHR) systems as a table of numbers with limited context to help patients understand implications of this information for health (Morrow et al., 2017; Morrow et al., 2019; Zikmund-Fisher et al., 2017). Similarly, while the number of digital health solutions continue to flourish and the transforming effects of digital technologies in healthcare have never been more evident, many barriers remain to ensure that patients can accept, understand and engage with these digital health solutions in productive ways (Anderson & Perrin, 2017; Cummins & Schuller, 2020; Löckenhoff, 2018; Morey et al., 2019; Perski & Short, 2021). As a consequence, patients, particularly older adults with limited literacy and numeracy abilities, often struggle to understand and use their test results to make appropriate decisions and self-manage their illness. Helping users to understand and act on their clinical test results is critical to the success of many digital health solutions. For example, it is estimated that 47% of older adults (ages 65 or above) have high cholesterol and 27% have diabetes. Furthermore, 80% of older adults have at least one chronic condition and 68% have two or more chronic conditions (National Council of Aging, 2021). Human factors and ergonomics researchers find that users often struggle to understand health information presented in digital health solutions (i.e., difficulty understanding graphical information in: health displays:

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McLaughin & Pak, 2020; mobile health apps: Azevedo et al., 2022; Morey et al., 2019; Portenhauser et al., 2021; Trinh et al., 2023; patient portals: Azevedo & Morrow, 2018; Morrow et al., 2019; Nahm & Son, 2020; Tao, Yuan, & Qu, 2018; Turchioe et al., 2019; see also: Liu et al., 2022; Schueller, 2021).

The goal of our paper is to evaluate and refine a framework that integrates health literacy, fuzzy trace memory, text comprehension, and health behavior theories. This framework not only underpins the predictions tested in the present study, it may guide development of innovative human factors and ergonomics approaches to presenting information in portals and other digital health solutions in ways that support patient decision-making about self-care.

As described below, this framework incorporates insights from behavior change theories that self-care behaviors such as following medication, diet, or exercise recommendations depend on attitudes toward, and intentions to perform these behaviors, which in turn reflect risk perception and decision making (e.g., Brewer et al., 2007; Webb & Sheeran, 2006). Reflecting health literacy theories of comprehension and memory (e.g., Chin et al., 2017), the framework posits that these more 'action-proximal' processes depend on understanding and remembering illness and treatment concepts that drive risk perception, which in turn are shaped by broader cognitive (processing capacity; knowledge) and affective patient resources (see Fig. 1).

Fuzzy Trace Theory (FTT) provides an approach to analyze the relation between the processes underlying comprehension of and memory for numeric health information on the one hand, and decision-making and behavioral processes on the other (Reyna, 2008; Reyna, 2021; Reyna & Lloyd, 2006; Reyna, Nelson, Han, & Dieckmann, 2009; Wilhelms et al., 2015). Comprehension of health information involves simultaneous encoding of verbatim and gist information. The verbatim trace is a surface-level memory representation of the information (literal numbers and facts). In addition, making decisions about health information requires creating gist representations of the bottom-line health implications of the information. Gist representations are organized around qualitative, often affective and evaluative, dimensions. Gist reasoning combines new information with previous knowledge to generate meaning that is personally relevant (Chapman & Mudar, 2013). For instance, gist representations of cholesterol test results may capture ordinal risk values (e.g., lower/borderline/higher) for heart disease. People tend to operate on the fuzziest or least precise representation to accomplish a task, with categorical or ordinal gist often preferred for understanding implications of test results for risk (Peters et al., 2009; Reyna, 2008; Reyna, 2021).

Understanding linguistic health information involves cognitive processes such as recognizing words and integrating the concepts associated with these words into idea units (e.g., Chin et al., 2011; Chin et al., 2017). Understanding numeric information (e.g., cholesterol test scores) requires similar processes (Peters, 2012; Reyna et al., 2009; Reyna, 2021) such as encoding numeric values (verbatim representation) and mapping them to categorical or ordinal risk categories (gist representation; Morrow et al., 2017; Morrow et al., 2019). These processes depend on cognitive patient resources. For example, comprehension requires processing capacity (e.g., working memory) and knowledge (Chin et al., 2017). These processes also depend on affect, that is, positive or negative feelings often associated with bodily experiences, which helps organize gist representations of risk for illness (Reyna, 2008; Reyna, 2021; see also: Peters et al., 2009; Slovic et al., 2002; Slovic et al., 2004). While cognition and affectare interrelated and can influence each other, they can serve distinct roles in influencing health behaviors (Peters et al., 2009). Furthermore, affective resources may be especially important for older adults because aging is accompanied by increasing focus on affect and emotion related to health information (Blanchard-Fields, 2007; Carstensen, 2006; Carstensen & Hershfield, 2021; Scheibe & Carstensen, 2010).

Comprehension and memory for information such as clinical test scores in turn influence perception of the risk associated with the information (see right side of Fig. 1). Risk perception is also shaped by other factors such as beliefs about illness (e.g., How susceptible and vulnerable to the illness am I?; Ajzen & Fishbein, 1977; Ajzen & Madden, 1986; Brewer et al., 2007). Risk perception shapes attitudes toward behaviors that may mitigate perceived risk (e.g., getting vaccinations, take medications as prescribed; Brewer et al., 2007; Loewenstein et al., 2001). These attitudes are also influenced by factors such as beliefs about whether these actions are likely to influence illness (Brewer et al., 2007; Webb & Sheeran, 2006, see also: Crano & Prislin, 2008). For example, patients may understand that their cholesterol scores indicate high risk, but they might not think that exercise reduces this risk. Finally, behavioral attitudes predict intentions to act, which in turn predict performance of the behaviors (for review, see: Webb & Sheeran, 2006).

In short, the framework depicted in Fig. 1 suggests memory for health information influences health decisions and behaviors, which underlines the importance of presenting digital health-based information in ways that support memory. However, the health communication literature suggests that improving memory for information is not enough to impact behavior, and that knowledge often has, at best, indirect effects on decision making and behavior. For example, warning labels (e.g., targeting smoking cessation) can have a 'diminishing cascade of effects' on the sequence of processes that link communication to action, with larger effects on attention, comprehension, and memory than on

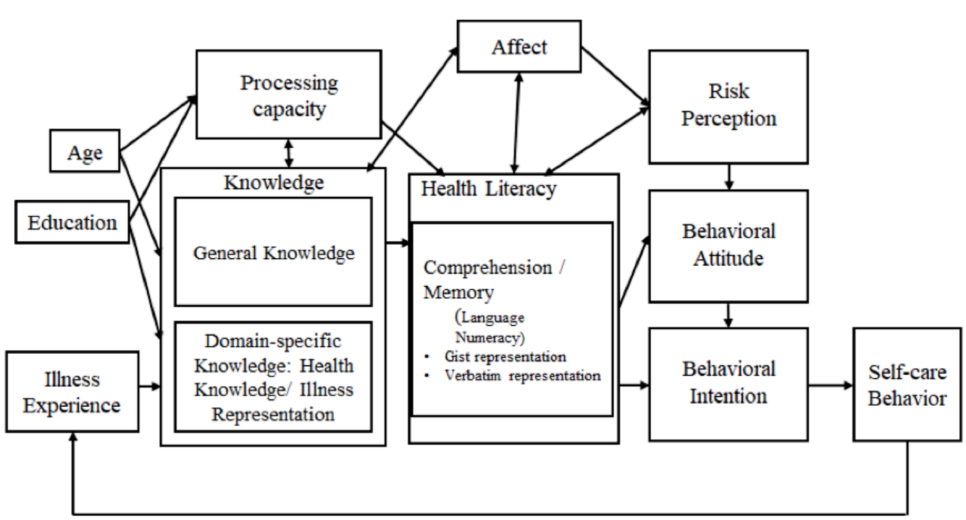

Fig. 1. Framework guiding the design and evaluation of portal messages (Morrow et al., 2017; Morrow et al., 2019).

risk perception, behavioral intentions and actions (for review, see: Purmehdi et al., 2017).

Affective response to health information, on the other hand, may play a broader role in influencing health behavior, reflecting the idea that affect serves multiple functions in decision making (Peters, Lipkus, & Diefenbach, 2006). Because affect can serve as a 'spotlight' that directs attention to key information (Emery et al., 2014; Peters et al., 2006), and also helps organize gist memory (Reyna, 2008), it may influence behavior through its impact on memory for clinical test results. Equally important, affect can serve as information that guides evaluation of risk associated with decision options (Clark & Isen, 1982; Loewenstein et al., 2001; Peters et al., 2011, 2006; Schwarz, 1990; Slovic & Peters, 2006; Slovic et al., 2007), so affective responses to test results may influence behavior through risk perception and behavioral attitude. Judgements of risks and benefits are assumed to be derived by reference to an overall affective evaluation of the stimulus item.

Finally, and most broadly, affect can function as a motivator, directly linking stimuli to affective categories that instigate behavior (Peters et al. 2006; Slovic et al., 2002; Slovic et al., 2004). In some cases, affective responses to risky situations even diverge from memory for those risks. As mentioned by Slovic et al. (2007), the affect heuristic has much in common with the model of "risk as feelings" proposed by Loewestein et al., (2001), that shows that emotional responses to risky situations, including feelings such as worry, fear, dread, or anxiety, often diverge from cognitive evaluations and have a different and sometimes greater impact on risk-taking behavior than do cognitive evaluations. When such divergence occurs, affective responses have been shown to drive behavior (Loewenstein et al., 2001). In this way, affective response to test results messages may have more direct effects than memory for the content of the messages does on behavior, circumventing the diminishing cascade of effects from communication to behavior.

In previous studies, we investigated older adults' cognitive and affective responses to risk-related health information in the context of studies in which messages about cholesterol and diabetes screening test results (as part of hypothetical patient scenarios), which were implemented in a simulated patient portal, were presented to older adults. Guided by our framework (see Fig. 1), we measured memory for and affective response to these health messages, perceived risk associated with the test results in the messages, as well as attitudes toward and intentions to perform behaviors that would address these risks (e.g., adherence to diet and exercise recommendations). The focus of the previously published results was to investigate whether message formats designed to enhance the context of numeric test scores improved memory for and response to the messages compared to the standard message format (i.e., a table of numbers; Morrow et al., 2019). We investigated verbally enhanced formats (labeling the risk category associated with the scores), graphically enhanced formats (embedding the scores in number lines with color coding of line segments corresponding to lower, borderline, and higher levels of risk), and video-enhanced formats (the same number lines accompanied by video of a provider providing commentary about the risk implications associated with the scores) (see Fig. 6 in Appendix A). As expected, enhanced formats generally improved gist but not verbatim memory for the scores. However, while affective, risk perception, and behavioral attitude and intention responses generally reflected the level of risk associated with the test scores; there was little evidence that the type of format moderated these effects (see Morrow et al., 2019; also see Azevedo et al., 2017). The finding that format benefits were greatest for message memory compared to other measures closer to behavior is generally consistent with the 'diminishing effects' model of health communication (Donnelly et al., 2018; Evans et al., 2015; Noar et al., 2016a, 2016b, 2017; Purmehdi et al., 2017).

Guided by the framework in Fig. 1, the goal of the present paper is to directly analyze relationships among the variables from our earlier studies (Azevedo et al., 2017; Morrow et al., 2019, see also Azevedo et al., 2015), in order to further evaluate this framework. This approach may serve as a benchmark for evaluating and improving digital health solutions. We explored both direct and indirect relationships among these variables by conducting multivariate path analyses (McDonald & Ho, 2002; Rosseel, 2012; Sanchez, 2013; Schreiber et al., 2006). We evaluated the following predictions:

1) Affective response should relate to gist memory for the test result messages (Reyna et al., 2008; Reyna, 2021; Reyna & Brainerd, 1995)
2) Gist memory and affective response should relate to perception of risk associated with the messages (Figner et al., 2009; Brewer et al., 2007; Peters et al., 2009; Slovic et al., 2007).
3) Risk perception should relate to behavioral attitudes (Ajzen & Madden, 1986; Brewer et al., 2007; Schwarzer et al., 2008) and behavioral intentions (Webb & Sheeran, 2006).
4) While gist memory should influence behavioral intentions only indirectly (Donnelly et al., 2018; Evans et al., 2015; Noar et al., 2016a, 2016b, 2017; Purmehdi et al., 2017), affective response should have a broader influence, with direct as well as indirect effects on intentions (Loewenstein et al., 2001; Peters et al., 2006; Slovic et al., 2007).

The path analyses reported in the present paper were conducted on participant data aggregated across three studies (Azevedo et al., 2017; Azevedo & Morrow, 2018; Morrow et al., 2019). While the formats of the test result messages varied across the three studies, the scenarios, measures and procedures were identical. Because message format had little influence on the primary variables analyzed in the present study other than message memory, the analyses reported in the present paper collapsed over format to increase statistical power. Cholesterol messages were presented in all three studies while diabetes messages were not presented in some of the studies due to time constraints.

Method

Participants

Participants were 216 community-dwelling older adults (average age of 71.3 years, range 60-94 years 69.9% females). All older adult participants were native English speakers, predominantly Caucasian/White = 91.2%, with no cognitive, physical or visual/auditory impairments that could restrict participation. 14.8% had a high school level of education or lower, 10.6% had some college education and 74.5% had at least a college degree (See Table 1 for additional demographic information). The study was approved by the UIUC and Carle Hospital Foundation IRBs and participants provided consent before participation. Smaller sample sizes (n=147; n=108) in Human Factors and Health Care

Table 1
Demographic characteristics

Age	71.3 years, range 60-94
Gender	
Female	151 (69.9%)
Male	65 (30.1%)
Education	
High school or lower	32 (14.8%)
Some college/Associate degree	10 (10.6%)
Bachelor's degree	58 (26.9%)
Master's degree	82 (38.0%)
Doctoral degree	21 (9.7%)
Race/Ethnicity:	
Asian or Pacific Islander	0 (0.0%)
Asian Indian	0 (0.0%)
Black or African American (non-Hispanic)	13 (6.0%)
Caucasian/White	197 (91.2%)
Native American	1 (0.5%)
Latino/Hispanic	2 (0.9%)
More than one race:	3 (1.4%)

studies were able to detect significant differences in health behavioral measures examining older adults' responses that were modeled using path analysis (Conn, 1998; Xie & Kalun Or, 2021) and adopted same measures (n=85, Petrova et al., 2023; Study 3). Furthermore, based on Da Tao, Yuan, & Qu's (2018) reported data (n=72), our sample size allows detection of fixed effects (e.g., verbatim comprehension task based on comparable clinical test result formats) with a power of .8, alpha level =.05, for a small effect size (f = 0.16) (Cohen, 1988).

Materials and Design

Participants were presented with hypothetical patient scenarios that contained six messages describing cholesterol (n=216) varying in level of risk (lower, borderline, higher). These messages were presented in blocks, in which each block included a message at each level of risk in a random order. A subset of participants (n=180) were also presented with six additional scenarios describing diabetes test results, with analogous procedure. Hence, there was an equal number of messages reporting test results from each level of risk for both the cholesterol and diabetes messages (i.e., two scenarios at each level). When both types of scenarios were presented in the same study, the cholesterol scenarios were always presented first. Message format was randomly assigned to participants (that is, a between-group variable) in all studies. These scenarios and materials were developed in collaboration with two physicians from our partner health care institution to ensure realism (for more information see: Morrow et al., 2017; Morrow et al., 2019). The physicians also determined the cut-off values that defined the risk-based categories in the test result messages, based on recommendations from the National Institutes of Health, National Heart, Lung, and Blood Institute (2001). Messages for cholesterol and diabetes test results were selected because these chronic illnesses are common and often co-morbid with other illnesses.

Measures

Fig. 2 describes the direct and indirect relationships among the variables as motivated by our framework (Fig. 1), as well as the four predictions to be evaluated.

Gist memory for risk information. Gist memory both before and after the summary statement for each message was scored for accuracy (correctly identifying whether risk was lower, borderline, or higher). This question evaluated how well participants could extract the overall gist only from the component scores indicated in the message (e.g., *"Considering Jennifer's cholesterol test results, her overall level of risk indicated by the set of results in the message was = ___ [ordinal level gist: low/borderline/high]")*. In our models, we associated all the answers for the modeled variables (see Fig. 2) with the correct answer of each message. For gist memory, that association in our path analysis could be interpreted as a measure of accuracy (correctly identifying, before the summary was given, whether risk was lower, borderline, or higher).

Affective reactions. Participants indicated their integral affective response[1] to the messages, ranking to what extent they experienced seven negative and seven positive emotions (Berlin Emotional Responses to Risk Instrument - BERRI; Petrova et al., 2023). For each emotion, participants ranked on a 9-point scale, as follows: *"If you were the patient Jennifer, how would you feel as you watched this message? Indicate the extent that you felt: (assured, calm, cheerful, happy, hopeful, relaxed, and relieved; or anxious, afraid, discouraged, disturbed, sad, troubled, and worried"* (Garcia-Retamero & Cokely, 2011). As in Garcia-Retamero and Cokely (2011) and Morrow et al. (2019), a composite score was created by reverse scoring negative emotion ratings and combining with the positive emotion ratings. The composite score ranged from 1 (most negative) to 5 (neutral) to 9 (most positive).

Risk perception. Risk Perception was measured by asking participants to rank on a 9-point scale (1= Very unlikely; 9 = Very likely) the likelihood of developing heart disease and heart-related complications if nothing was done to reduce the reported cholesterol levels, if they were the patient in the scenario (Garcia-Retamero & Cokely, 2011). This measure reflects the perceived risk associated with the reported test results.

Attitude toward taking medication. Attitude towards taking medications was measured by asking participants to rank on a 9-point scale (1 = not at all; 9 = very much) how favorable they would feel about taking medications prescribed for lowering cholesterol, if they were the patient in the scenarios (Garcia-Retamero & Cokely, 2011).

Intention to perform self-care behaviors. Similarly, behavioral intentions were measured by asking participants to rank the following on a 9-point scale (1 = I have no intention of doing this; 9 = I am certain that I would do this): If they were the patient in the scenario, (1) how likely were they to take medication prescribed to reduce cholesterol; (2) how likely were they to change their diet; and (3) how likely were they to increase their level of exercise? (Adapted from Garcia-Retamero & Cokely, 2011).

In the present analysis, we converted the 9-point scale measures described above, mapping the scores into the three ordinal levels of risk adopted to measure gist memory (1,2,3 as low risk; 4,5,6 as borderline risk; and 7,8,9 as high risk). Then we compared these scores with the three levels of risk to score participants' accuracy. For each message, accuracy was either 1 (accurate) or 0 (inaccurate). The overall accuracy score for each participant was then computed by averaging across messages, resulting in an accuracy score between 0 and 1. In this way gist memory, affect, behavioral attitude, and behavioral intention were all scored on a scale between 0 (inaccurate) and 1 (accurate). We used this scoring approach for two reasons. First, it allowed us to include all modeled variables on the same scale. Second, it represented the extent to which participants (users of health information) correctly identified whether risk was lower, borderline, or higher on each scenario.

Participant Ability Measures. In addition to general education level, we collected several ability measures to characterize our participant sample. Measures of vocabulary ability (Ekstrom et al., 1976) and literacy (Author Recognition test, Stanovich, West, & Harrison, 1995) were collected to create a verbal ability/literacy construct. Letter and Pattern Comparisons Tests (Salthouse & Babcock, 1991) were collected to create a processing speed/capacity construct. Finally, both subjective numeracy (Fagerlin et al., 2007) and objective numeracy (Berlin Numeracy test, Cokely et al., 2012) were measured.

Procedure

After providing consent, participants completed demographics and vocabulary ability (Ekstrom et al., 1976) measures. Then, they viewed messages describing test results. Participants viewed six cholesterol messages embedded in patient scenarios after one practice trial (for more information see: Morrow et al., 2019). A similar trial structure was used for the diabetes messages, for those participants who saw both types of messages. For each message, scores for individual components of the test were first presented followed by a summary of risk associated with the total set of scores for that message. Gist memory for risk information was measured both before and after this summary statement for each message. Participants identified whether the risk indicated by each component score was lower, borderline, or higher. Furthermore, the questions about global gist before the summary statement required participants to integrate information across the component scores (e.g., total cholesterol, triglycerides, HDL, and LDL) to remember whether risk associated with the complete message was lower, borderline, or higher, while the after-summary questions essentially measured memory for

[1] Integral affect is defined as experienced feelings about a stimulus, in contrast to incidental affect, which is defined as mood states and feelings that are independent of a stimulus. The latter can be misattributed to the stimulus and likewise can influence the decision-making process (Peters et al., 2006).

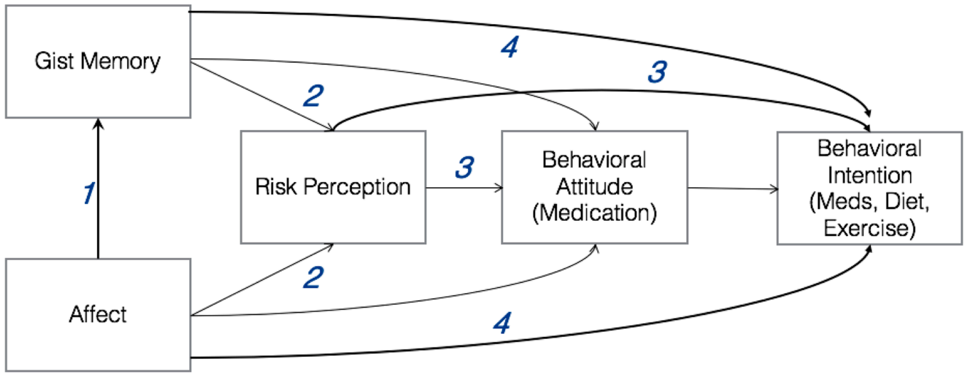

Fig. 2. Variables modeled and predictions evaluated

global gist identified in the summary statement. For each scenario, after the summary statement was presented, additional questions measured participants' risk perception, affective response, attitude towards taking medication prescribed, and intent to perform self-care behaviors (take medication, change diet, exercise). A measure of literacy (Author Recognition test, Stanovich, West, & Harrison, 1995) was included after the test results scenarios.

For the subset of participants who also saw the diabetes test result messages, the first part of the message included the single diabetes test component score (HbA1c). Hence, while the diabetes screening tests reflect a single percent score (HbA1c scores), cholesterol messages described complex patterns of scores on multiple tests (total cholesterol, triglycerides, HDL, and LDL), that suggest lower, borderline or higher risk for cardio-vascular illness.

All other individual difference measures were collected at the end of the study visit (Letter and Pattern Comparisons; Salthouse & Babcock, 1991; subjective numeracy; Fagerlin et al., 2007; and objective numeracy Berlin Numeracy test, Cokely et al., 2012).

Analysis plan

To evaluate the predicted associations among the message response variables (gist memory, affective responses, risk perception, behavior attitude, and behavior intentions), we conducted a multivariate path analysis to explore direct and indirect links among the key concepts. We modeled the variables, as illustrated in Fig. 2, and input all the hypothesized relationships, with alpha values of .05, using the package lavaan in R (Rosseel, 2012)[2].

The structure regression equations of our first (full) model are composed by the following six regressions:

$$(\widehat{Gist\ Memory}) = \beta 0 + \beta 1\ (Affective\ Response)$$
$$(\widehat{Risk\ Perception}) = \beta 0 + \beta 1 (Gist\ Memory) + \beta 2\ (Affective\ Response)$$
$$(\widehat{Behav.\ Attitude}) = \beta 0 + \beta 1 (Gist\ Memory) + \beta 2\ (Affective\ Response) + \beta 3 (Risk\ Perception)$$
$$(\widehat{Beh.\ Int.\ Exercise}) = \beta 0 + \beta 1 (Gist\ Memory) + \beta 2\ (Affective\ Response) + \beta 3 (Risk\ Perception) + \beta 4\ (Behav.\ Attitude)$$
$$(\widehat{Beh.\ Int.\ Diet}) = \beta 0 + \beta 1 (Gist\ Memory) + \beta 2\ (Affective\ Response) + \beta 3 (Risk\ Perception) + \beta 4\ (Behav.\ Attitude)$$
$$(\widehat{Beh.\ Int.\ Meds}) = \beta 0 + \beta 1 (Gist\ Memory) + \beta 2\ (Affective\ Response) + \beta 3 (Risk\ Perception) + \beta 4\ (Behav.\ Attitude)$$

The present analyses focus on gist memory for risk information before the summary statement because accuracy for this measure was lower and more variable than for the after-summary statement measure (Azevedo et al., 2017; Morrow et al., 2019). To decide between nested competing models and to evaluate our predictions, we excluded (or included) additional paths in the structural model, and compared these nested models using the general regression test (aka extra sum of squares test) (McDonald & Ho, 2002). In the spirit of exploratory/confirmatory analysis, we first conducted these model comparisons only on the cholesterol test results dataset, and then, to validate the re-specified final model proposed, we fit the same revised model to a new dataset (diabetes data).

Results

Participant Sample

Simple correlations among the participant ability measures replicate patterns found in the cognitive aging literature (see Appendix B). Measures of vocabulary ability (Ekstrom et al., 1976) and literacy (Stanovich, West, & Harrison, 1995) were correlated (r=.65, p<.001), suggesting a verbal ability construct, and measures of processing speed (Letter Comparison and Pattern Comparison tests, Salthouse, 1992) were correlated (r=.92, p<.001), suggesting a fluid mental ability/processing capacity construct. Older adults in the sample performed more poorly on the processing capacity measures (r= -.38, p<.001) while age was not correlated with verbal ability (r=-.096, p>.10). Verbal ability also correlated with education (r= .47, p <.001). Thus, while the sample was generally well educated, the sample was fairly representative of older adults in the population. Finally, subjective numeracy (Fagerlin et al., 2007) and objective numeracy (Berlin Numeracy Test, Cokely et al., 2012) were moderately correlated (r=.29, p<.001).

Correlations between the modeled variables are included in Table 2. Note that because the affective response composite score was created by reverse scoring negative emotion ratings and combining the positive emotions ratings, the association between risk level and the composite

[2] Because including message format as a moderator in the path models did not improve model fit, the analyses reported in the present paper were collapsed over format.

Table 2
Correlations

Observed variables	1. Gist Memory	2.Affective Response	3. Risk Perception	4. Behavioral Attitude (Meds)	5. Behavioral Intention (Exercise)	6. Behavioral Intention (Diet)	7. Behavioral Intention (Meds)
1. Gist Memory	1	-0.76***	0.77***	0.66***	0.41***	0.43***	0.57***
2. Affective Response		1	-0.77***	-0.69***	-0.42***	-0.45***	-0.62***
3. Risk Perception			1	0.71***	0.46***	0.49***	0.63***
4. Behav. Attitude (Meds)				1	0.53***	0.55***	0.88***
5. Behav. Intention (Exercise)					1	0.88***	0.51***
6. Behav. Intention (Diet)						1	0.53***
7. Behav. Intention (Meds)							1

Note: † p<.10; * p<.05; ** p<.01; *** p<.001.

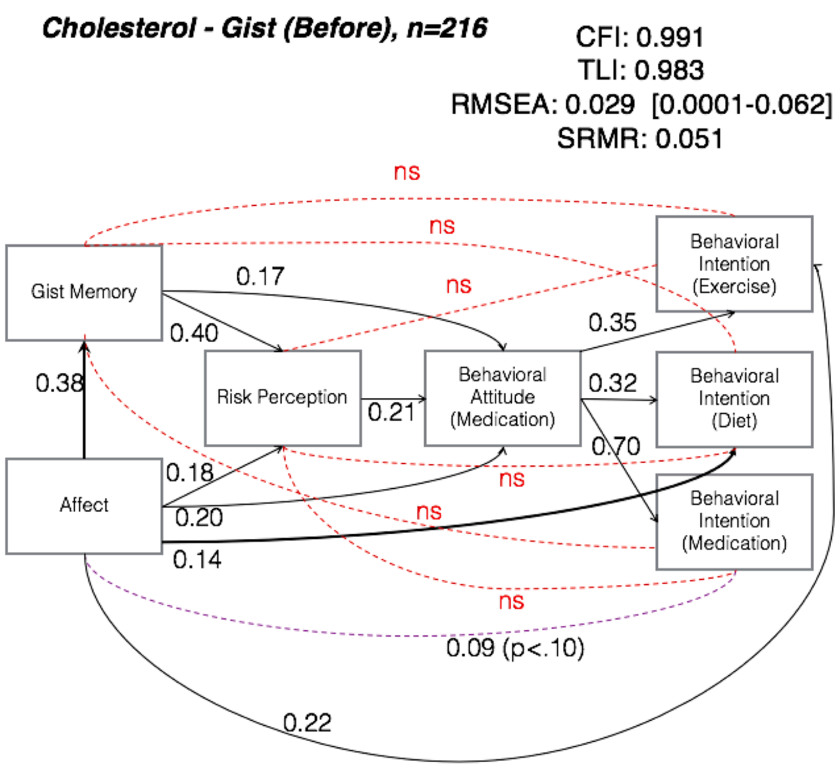

Fig. 3. Initial Path Analysis: Cholesterol data

affective response variable is negative. As risk associated with test results increased, positive affect decreased whereas negative affect increased, as predicted by behavioral change theories.

Path Models

The framework motivating our study suggests that understanding and remembering self-care information at a gist level incorporates affective as well as cognitive interpretation of risk, and influences risk perception, which in turn influences decision-making (e.g., attitudes toward and intentions to perform behaviors) that may mitigate risk.

Our initial model contained several non-significant direct paths, as shown in Fig. 3. Consistent with prediction #4 (*While gist memory should influence behavioral intentions only indirectly, affective response should have a broader influence, with direct as well as indirect effects on intentions*), gist memory influenced behavioral intention only indirectly (non-significant direct effects on behavioral intention to exercise, change diet and take medication), while affective responses had broader effects, with direct and indirect links to behavioral intention (although the direct effect of affective responses on intention to take medication only trended toward significance, p<.10). Furthermore, the model suggests that only part of prediction #3 (*Risk perception should relate to behavioral attitudes and behavioral intentions*) was supported, because risk perception related directly to behavioral attitude, but not to behavioral intentions.

Based on these initial results, we followed a post-hoc model re-specification process considering a) the regression estimates of the constructs from the initial model and b) the R-square of each construct from the initial model (McDonald & Ho, 2002). For our first model re-specification, we tested an alternative nested model removing the direct links of gist memory on the intention to perform self-care behavior variables. That re-specification directly tested part of prediction #4 (*While gist memory should influence behavioral intentions only indirectly, affective response should have a broader influence, with direct as well as indirect effects on intentions*). The result of this model comparison suggests that these models were not significantly different in fit ($F(30,33) = 2.15$, $p > .10$). Hence adopting a parsimonious modelling strategy, this

Table 3
Model Fit Indices

Models	TLI	RMSEA	SRMR	AIC	BIC
Original framework (based on Fig. 2)	0.983	0.029	0.051	3783.79	3874.92
Gist Memory ~ Affective Response		90% CI [0.001 – 0.062]			
Risk Perception ~ Gist Memory + Affective Response					
Behav. Attitude ~ Gist Memory + Affective Response + Risk Perception					
Behav. Intention (Exercise) ~ **Gist Memory** + Affective Response + Risk Perception + Behav. Attitude					
Behav. Intention (Diet) ~ **Gist Memory** + Affective Response + Risk Perception + Behav. Attitude					
Behav. Intention (Medication) ~ **Gist Memory** + Affective Response + Risk Perception + Behav. Attitude					
First Re-specification	0.987	0.025	0.049	3779.94	3860.95
Gist Memory ~ Affective Response		90% CI [0.001 – 0.058]			
Risk Perception ~ Gist Memory + Affective Response					
Behav. Attitude ~ Gist Memory + Affective Response + Risk Perception					
Behav. Intention (Exercise) ~ Affective Response + **Risk Perception** + Behav. Attitude					
Behav. Intention (Diet) ~ Affective Response + **Risk Perception** + Behav. Attitude					
Behav. Intention (Medication) ~ Affective Response + **Risk Perception** + Behav. Attitude					
Second Re-specification (Proposed Model, Fig. 4)	0.992	0.020	0.049	3775.31	3846.19
Gist Memory ~ Affective Response		90% CI [0.001 – 0.054]			
Risk Perception ~ Gist Memory + Affective Response					
Behav. Attitude ~ Gist Memory + Affective Response + Risk Perception					
Behav. Intention (Exercise) ~ **Affective Response** + Behav. Attitude					
Behav. Intention (Diet) ~ **Affective Response** + Behav. Attitude					
Behav. Intention (Medication) ~ **Affective Response** + Behav. Attitude					
Model without Affective Response on Behav. Intention	0.976	0.034	0.061	3779.37	3840.12
Gist Memory ~ Affective Response		90% CI [0.001 – 0.062]			
Risk Perception ~ Gist Memory + Affective Response					
Behav. Attitude ~ Gist Memory + Affective Response + Risk Perception					
Behav. Intention (Exercise) ~ Behav. Attitude					
Behav. Intention (Diet) ~ Behav. Attitude					
Behav. Intention (Medication) ~ Behav. Attitude					

Note: Bold variables indicate changes in the framework and variables subsequently removed for model comparisons.
Tucker-Lewis Index (TLI): > 0.95 acceptable, > 0.97 good fit (Bentler, 1990; Hu & Bentler, 1999)
Root mean square error of approximation (RMSEA): < 0.10 good, <0.05 very good (Steiger, 1989)
Standardized Root Mean Square Residual (SRMR): <0.08 adequate fit (Hu & Bentler, 1999).
Akaike information criterion (AIC) and Bayesian Information Criterion (BIC): lower values indicate a better fit.

analysis suggests that while gist memory had a direct impact on the behavioral attitude measure, it did not impact directly the intention to perform self-care behaviors variables.

Next, we attempted a second re-specification by removing the direct links of risk perception on the intention to perform self-care behavior variables. Once again, the model comparison suggests these nested models were not significantly different in fit ($F(33,36) = 1.37$, $p > .10$). This result supports only part of prediction #3 (*Risk perception should relate to behavioral attitudes and behavioral intentions*), because risk perception related directly to behavioral attitude but not directly to behavioral intention.

Finally, a third re-specification was conducted, removing the extended direct effects of affective responses on behavioral intentions, in order to explore a parallel procedure for this variable similar to what we did with gist memory and risk perception. Notably, this model comparison is significant ($F(36,39) = 10.05$, $p < .05$), suggesting a broader impact of affective responses on behavioral intentions. This finding supports prediction #4 (*While gist memory should influence behavioral intentions only indirectly, affective response should have a broader influence, with direct as well as indirect effects on intentions*) and previous work showing that affective response has direct as well as indirect effects on behavioral intention (Loewenstein et al., 2001; Peters et al., 2006; Slovic et al., 2007). A summary of our models and respective fit indices is presented in Table 3.

The diagram with our proposed revised model is presented in Fig. 4.

Because these model comparisons were conducted only on the cholesterol test result data, we next attempted to validate the re-specified final model on the diabetes test results data (see: Fig. 5). The proposed revised model had a very good fit to both datasets (model fit stats, cholesterol: TLI=0.992, RMSEA=0.02, SRMR=0.049; diabetes: TLI=0.928, RMSEA=0.065, SRMR=0.073).

The path analysis for the diabetes data largely confirmed the model, although the direct association of affect and gist memory to behavioral attitude was not significant. Moreover, the direct association patterns of affect and the behavioral intention variables were replicated. Hence, this confirmatory analysis supported our final re-specified model.

Discussion

We evaluated a framework that suggests memory for and affective response to health information influences health decisions and behaviors (Morrow et al., 2017). The framework emphasizes the importance of presenting health numeric information in ways that support memory, decision making, and action, with implications for improving digital health solutions that present clinical test results to patients. Our earlier studies focused on the impact of message formats on gist memory for and affective response to numeric information (Azevedo et al., 2017; Morrow et al., 2019). The present study evaluated how memory for and affective response to risk information related to those variables conceptualized as closer to decision making and behavior by exploring direct and indirect relationships among these variables through multivariate path analyses (McDonald & Ho, 2002; Rosseel, 2012; Sanchez, 2013; Schreiber et al., 2006).

The results show that the gist memory and affective response variables were associated with each other, supporting prediction #1 *(Affective response should relate to gist memory for the test result messages)*. Both gist and affect in turn predicted risk perception, supporting prediction #2 *(Gist memory and affective response should relate to perception of risk associated with the messages)*. However, prediction #3 (*Risk perception should relate to behavioral attitudes and behavioral intentions*) was only partially supported because risk perception related directly to behavioral attitude toward taking medication, but not to behavioral intentions to perform self-care behaviors. Finally, affective response had a direct effect on behavioral intention while gist memory only indirectly influenced intention, supporting prediction #4 (*While gist memory should influence behavioral intentions only indirectly, affective response should have a broader influence, with direct as well as indirect effects on intentions*).

The findings from modeling the responses to cholesterol test messages were largely confirmed by modeling the responses to diabetes screening messages. However, the direct associations of affect and gist memory to attitude were not significant in the latter analysis. The role of gist memory may have been attenuated for diabetes messages because these messages were simpler and had just one component score (A1C) compared to four scores for the cholesterol messages, possibly producing a ceiling effect on memory for the diabetes scores (see Morrow et al., 2019). Consistent with this explanation, gist memory was greater for the diabetes than the cholesterol messages (86% versus 63% accuracy). In addition, the smaller sample size for the diabetes compared to the cholesterol dataset could have reduced power to detect these relationships, although studies with smaller sample sizes have found significant associations among similar population and health behavior measures (Conn, 1998; Petrova et al., 2023; Xie & Kalun Or, 2020).

Our findings are generally consistent with theories of health communication and memory for health information. The association of affective response with gist memory for risk-related information and the influence of both variables on risk perception support fuzzy-trace theory, which argues that gist memory is often organized around evaluative and affective dimensions (Reyna, 2011; Reyna, 2021; Reyna et al., 2009).

Consistent with work on warning and health labels, we found that gist-based memory for test result messages was associated with intention to perform health behaviors only indirectly, through its impact on risk perception and behavioral attitudes, suggesting that improving message memory has a 'diminishing cascade of effects' on the sequence of processes linking communication to action (Donnelly et al., 2018; Evans et al., 2015; Noar et al., 2016a, 2016b, 2017; Purmehdi et al., 2017). Notably, affective response to the messages had a broader impact on processes more proximal to action, with direct as well as indirect effects on behavioral intentions. These findings were replicated across two types of numeric health messages: cholesterol and diabetes screen test results.

The findings add to evidence that health communication influences behavioral attitudes and intentions in part through affective responses to the communication (e.g., McLean, 2020; van't Riet et al., 2010; also see Rothman & Salovey, 1997). Furthermore, our proposed framework suggests that the influence of integral affective responses to risk-related information extend beyond risk perception to decisions about behavior (see Slovic's Affect Heuristic and risk-as-feelings hypothesis, Loewenstein et al., 2001; Slovic et al., 2002; Slovic et al., 2004; Slovic et al., 2007), perhaps because behavioral attitude and intentions are often based on information organized around affective and evaluative dimensions. If so, accurate affective response may not only directly support older adults' risk perception, but their attitude toward behavior addressing this risk (e.g., increase exercise and/or change diet to decrease risk of cardiovascular diseases) as well (see also: Weller et al., 2019).

Our findings also extend the literature on behavioral decision-making and human factors and ergonomics to the design, implementation, and evaluation of digital health solutions, by showing that affective response to the messages has a broader impact than cognitive/memory responses particularly for more complex health information (e.g., cholesterol test results). We encourage developers to consider our findings to assist successful use of digital health solutions by including designs with color-coded number lines, emojis, the use of conversational agents (CAs), gamification, as well as other features and mechanisms that promote appropriate affective response and gist memory. For example, including features such as color coding and emojis in e-health contexts can influence affective responses and decisions related to risk

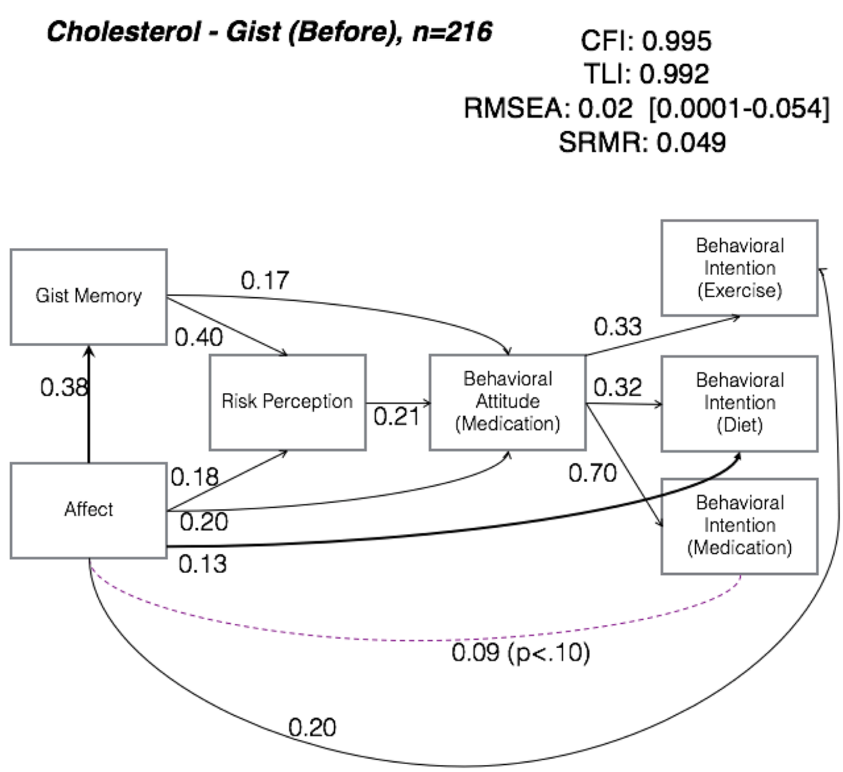

Fig. 4. Proposed Path Model: Cholesterol data

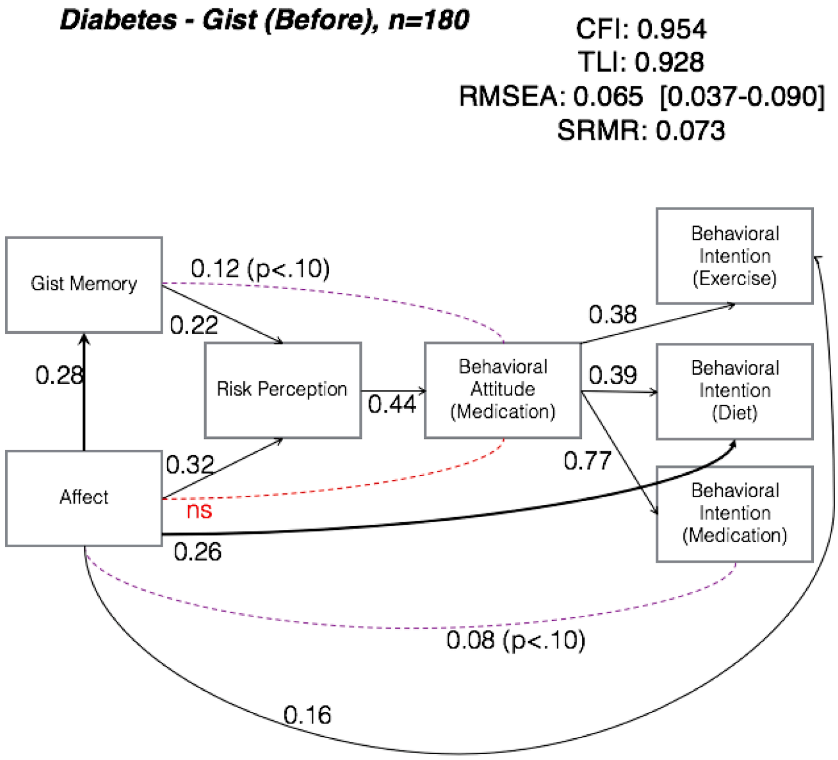

Fig. 5. Path Analysis: Diabetes data

information (e.g., Arcia et al., 2016; Turchioe et al., 2019; Zikmund--Fisher et al., 2017). CAs also support older adults' learning in part by engendering social responses, by using both nonverbal and verbal cues to convey the affective and cognitive meaning of health information (e.g., clinical test results, medication and discharge instructions, etc.; e.g., Azevedo et al., 2017; Desai & Chin, 2023). To integrate these features into health portals, one strategy could involve the utilization of CAs that customize presented information by using either gain- or loss-framed messages (i.e., gain: "if you take your beta blocker you will strengthen your heart"; loss: "if you do not take your beta blocker, you will weaken your heart"), with verbal cues (speech) and verbal cues (facial expressions) reinforcing affective and cognitive aspects of the message (Azevedo et al., 2018). For example, previous, findings show that older adults respond more positively to and better remember to gain- versus loss-framed health messages with(e.g., Azevedo et al., 2018, see also: Liu, Mikels, & Stine-Morrow, 2021).

Furthermore, although not all design and implementation challenges can be addressed solely with well-designed health materials and visualizations, by including mechanisms that promote appropriate affective response, designers can improve users' onboarding and initial experiences with digital health solutions, which is known to be related to technology adoption, perceived ease of use, and usefulness (Mitzner et al., 2019). Designers of health communication can improve users' onboarding and initial experiences with digital health solutions by incorporating interactive processes that guide users through the digital health solution step-by-step, offering both informative and emotionally supportive content. In addition, designers can explore the integration of features that allow users to connect with others who are on similar health journeys (e.g., supportive communities), which can provide valuable information to understand the emotional needs, concerns, and expectations of the target audience.

More generally, the framework tested in the present paper may provide the basis for more comprehensive design and evaluation of patient portals and other types of e-health technology. The framework provides insights that complement technology adoption models that were developed to predict patients' use of technology. These models, like our own framework, are based on health belief and planned behavior theories and assume that use of technology is driven by perceived ease of use and the usefulness of this technology, which in turn drives intentions to use (Venkatesh et al., 2003). This model has been expanded to address older adults' use of technology by incorporating empirical findings related to age differences in abilities and beliefs about health-related tasks (Chen & Chan, 2013). Our framework provides a more fine-grained analysis of the role of cognitive abilities and resources (e.g., processing speed, working memory) involved in remembering health information that may influence the accessibility and use of information provided by patient portals and other e-health technology. Our findings especially highlight the role of affective factors such as the valence (positive versus negative) and the intensity of emotional responses to health information that may influence the use of the technology that delivers this information. It is important for health technology acceptance models to incorporate this information because affect may also drive perceived usefulness of the technology. Our findings about the direct and indirect effects of cognitive abilities and affect on health decisions and behaviors may also guide development of technologies tailored to specific types of patients (i.e., older adults, care takers, patients with cognitive impairments). Finally, and perhaps most generally, our findings also demonstrate the value of a theory-guided approach to designing messages that improve patients' understanding and use of numeric health information in digital health solutions.

Limitations and Future Research

The present study has several limitations. First, the study involved hypothetical patient scenarios, so conclusions regarding improving patient response to digital health solutions (e.g., portal-based information, mHealth apps) and thus improving access to these solutions, must be made cautiously. In that regard, our measure of affective response could be capturing a forecasted affect of a person (future self or another) in that scenario.

Second, because the simulation did not include an actual web-based portal or mHealth environment, our approach may underestimate the cognitive demands of accessing as well as understanding portal messages (e.g., navigation demands may reduce benefits of message formats for comprehension) and other cognitive biases that occur when making forecasts.

Third, because participants did not respond to their actual test results, we may have underestimated the effects of patient health knowledge, beliefs, and affective factors (e.g., stress, anxiety) on responses to portal-based information presented.

Fourth, our sample primarily consists of primarily well-educated individuals who are predominantly white. The sample also included many more women than men, although this gender imbalance is typical of older samples.

Future research could investigate whether other health care professionals (e.g., providers and nurses) respond similarly to patients when assessing risk-related information. It could also evaluate other kinds of digital health-based messages than clinical test results, such as medication and discharge instructions to further investigate the role of affective responses in shaping self-care behavioral intentions and other decision-making processes. Furthermore, as in other studies (e.g., Garcia-Retamero & Cokely, 2011; Morrow et al., 2019), the measure of affective response combines different emotions. Given the importance of affective responses to health messages on self-care behavioral intentions, future studies should explore the differential effects of discrete emotions (e.g., happy vs assured, hopeful vs relieved, afraid vs sad, afraid vs worried, etc.) on health risk judgments and health behaviors.

Our findings suggest the potential of the present framework and approach for guiding researchers and practitioners from human factors and ergonomics, behavioral science, engineering, medicine, and other disciplines to integrate their different theoretical and methodological perspectives in order to meet the complex challenges involved in designing and implementing patient-centered systems, taking into account both the role of patient memory for and affective responses to health messages on self-care. Therefore, by promoting affective responses that shape self-care behavioral intentions and other decision-making process, these digital health solutions could be perceived as more useful and easy to use.

Declaration of Competing Interest

The authors do not have any conflicts of interest related to the research described in the paper.

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Appendix A

Message formats designed to enhance the context of clinical test results.

Component	Your Value (mg/dl)	Range of Scores (mg/dl)
Total Cholesterol	184 **Desirable**	< 200 (Desirable) 200-240 (Borderline) >240 (High)
Triglycerides	42 **Optimal**	< 100 (Optimal) 101-149 (Normal) 150-199 (Borderline) 200-499 (High) >500 (Very High)
HDL Cholesterol	47 **Borderline**	< 40 (Low/Bad) 41-59 (Borderline) >60 (High/Good)
LDL Cholesterol	130 **Borderline**	< 100 (Optimal) 101-129 (Near Optimal) 130-159 (Borderline) 160-189 (High) >190 (Very High)

Verbally Enhanced Message Format. (Morrow et al., 2017; Morrow et al., 2019).

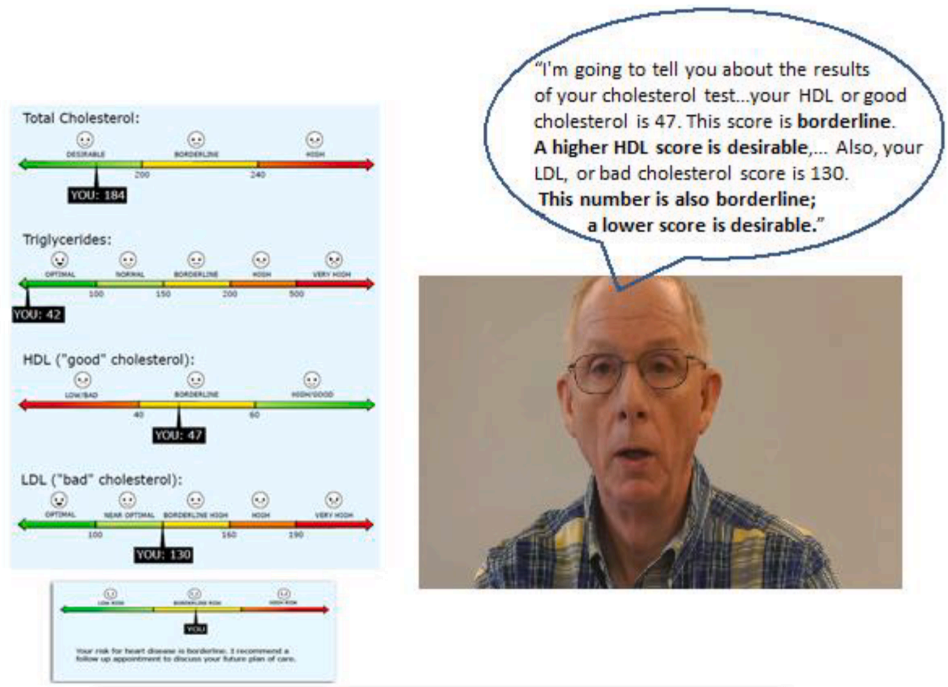

Fig. 6. Video Enhanced Message Format (Morrow et al., 2017; Morrow et al., 2019).

"Your risk for heart disease is borderline. I recommend a follow up appointment to discuss your future plan of care."

Appendix B

Participants Ability Measures - Correlations
Cholesterol Dataset (n=216)

	Gist Memory	Affective Response	Age	Education	Literacy	Processing Speed	Objective Numeracy	Subjective Numeracy
Gist Memory	1							
Affective Response	0.43***	1						
Age	-0.21***	-0.14*	1					
Education	0.29***	0.19**	-0.16*	1				
Literacy	0.24***	0.27***	-0.10	0.47***	1			
Processing Speed	0.14*	0.28***	-0.38***	0.19**	0.26***	1		
Obj. Numeracy	0.18**	0.23***	-0.07	0.13†	0.15*	0.09	1	
Subj. Numeracy	0.30***	0.12†	-0.10	0.39***	0.22***	0.16*	0.29***	1

Diabetes Dataset (n=180)

	Gist Memory	Affective Response	Age	Education	Literacy	Processing Speed	Objective Numeracy	Subjective Numeracy
Gist Memory	1							
Affective Response	0.30***	1						
Age	-0.20**	-0.20**	1					
Education	0.19*	0.13†	-0.23**	1				
Literacy	0.17*	0.29***	-0.15*	0.46***	1			
Processing Speed	0.11†	0.23**	-0.42***	0.19**	0.23**	1		
Obj. Numeracy	0.12†	0.15*	-0.06	0.11†	0.10	0.06	1	
Subj. Numeracy	0.20**	0.10	-0.13†	0.37***	0.21**	0.18*	0.27***	1

Note: † $p<.10$; * $p<.05$; ** $p<.01$; *** $p<.001$.

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