Understanding the Implications of Information Literacy in Obesity and Health

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Abstract

The purpose of this study was to investigate the relationship between computer expertise and health in the Black Belt region of Alabama. A Pearson correlation indicated a small, negative relationship (r(304)=.-161, p=.002) between basal metabolic index (BMI) and computer expertise (CE) score. After controlling for demographic variables, search engine knowledge, laptop use, and obtaining health information from television were found to be significant predictors of BMI. With the abundance of health information now available on the Internet, knowing how to use a search engine is a key aspect of health literacy. Since basic literacy is a foundation of both health literacy and information literacy, the results of this study emphasize the importance of various types of literacy in improving health and overall quality of life.

Keywords: health literacy, obesity, computer literacy, information literacy, quality of life, Understanding the Implications of Information Literacy in Obesity, Health, and Overall Quality of Life

1. Introduction

1.1 Basic Literacy and Health Literacy

Health literacy has been defined as a measure of patients' ability to read, comprehend, and act on medical instructions (Schillinger, et al.,2002). Health literacy is dependent on basic literacy, information literacy and the skills associated with it. According to the National Assessment of Adult Literacy, approximately 11 million adults in the U.S. are considered non-literate in English. An additional 19 million are unable to perform more than the most basic literacy tasks. Demographic differences in literacy rates are similar to the differences found in obesity rates and computer usage. Researchers have suggested that poor literacy is a factor contributing to noncompliance with doctor's recommendations and that this noncompliance may be associated with reduced health overall (Weiss, Blanchard, McGee, &D'Estelle, 1994). Additionally, literacy has been found to have a significant association with health knowledge and disease management skills(Williams, Baker, Honig, Lee, & Nowlan, 1998).

Patients lacking basic literacy skills have less exposure to traditional health education and also reduced ability to act on the information they receive from their health care provider (Nutbeam, 2000). Low literacy has been found to be a barrier to seeking treatment for disease (Fortenberry, 2001). Young, Weinert, and Spring conducted an intervention study to improve health literacy among older rural residents in Montana (Young, Weinert, & Spring, 2012). A key component of the intervention was instruction in computer literacy to teach participants how to find, evaluate, and use online health information. The researchers found that computer skills, confidence in searching for health information, and overall health knowledge increased.

1.2 Information Literacy

A 2010 survey for the Pew Internet and American Life project revealed that 80% Internet users look for health information online(Fox, 2011). Specifically, they found that health information was the third most popular search overall and diabetes was the ninth most popular search on WebMD.com in 2010. A majority of those searching for health information online are looking for information on how to treat a specific disease, information about medicine, and ways to prevent illness (Brodie et al., 2000). However, fewer than half of minorities, low education, and low income households look for health information online (Fox, 2011). Past Pew studies have also shown that mobile device users are more engaged than other users and that the use of these devices is growing more rapidly for minority groups (Horrigan, 2009).

The variety, amount of information available, 24/7 access, and up to date nature of the information on the Internet makes it different from traditional forms of health communication media (Cotten, Gupta, 2004). Understanding the relationship between technology and health, will improve society's potential to reach vulnerable populations.

1.3 Health and Obesity

Over the last several decades, obesity levels in the United States have risen dramatically. In 2010, Flegal and colleagues reported that 68% of adults were overweight (BMI>25) or obese (BMI>29.9) compared to 44.8% in 1962(Flegal, Carroll, Ogden, & Curtin, 2010; Wang, Beydoun, 2007). Obesity is considered a leading indicator of overall health and is associated with increased risk of coronary heart disease, endometrial cancer, diabetes, high blood pressure, high cholesterol, asthma, arthritis, and poor general health status (Galanis, Harris, Sharp, &Petrovitch, 1998; Weiderpass et al., 2000; Mokdad et al., 2003). In addition to increased morbidity, obesity is associated with higher mortality. An estimated 111,909 additional deaths occur each year in the United States due to obesity related illnesses (Flegal, Graubard, Williamson, & Gail, 2005). Furthermore, obesity related morbidity and mortality costs the United States economy 147 billion dollars a year (Finkelstein, Trogdon, Cohen, & Dietz, 2009). In the state of Alabama the problem is even more prevalent. In 2009, 31% of the population was obese and in the Black Belt region of Alabama specifically, the obesity rate was 41.2% or 54% higher than the national average (Centers for Disease Control and Prevention [CDC], 2009; CDC, 2008; U. S. Census Bureau, 2010).

The Black Belt region of Alabama includes 12 counties that share similar physical and cultural characteristics: Bullock, Choctaw, Dallas, Greene, Hale, Lowndes, Macon, Marengo, Perry, Pickens, Sumter, and Wilcox. Demographic differences can partially explain the elevated obesity rates. The Black Belt has a high proportion of minorities, low education levels, and high numbers of older adults compared to state and national averages (U. S. Census Bureau, 2010). Non-hispanic blacks, Hispanics, those who did not graduate from high school, low income individuals, and older adults are affected by obesity to a greater degree than other groups (Wang, &Beydoun, 2007; CDC, 2010).In part, the disparities in obesity rates among demographic groups may be explained by the lack of availability of healthy foods in predominantly minority neighborhoods. Morland, Wing, Roux, and Poole studied the distribution of grocery stores in poor versus wealthy neighborhoods and white versus African American neighborhoods (Morland, Wing, Roux, & Poole, 2002). These researchers found that there were four times more supermarkets in white neighborhoods and three times as many supermarkets in upper income neighborhoods. They found an increase in fruit and vegetable consumption for those living in close proximity to a grocery store. This effect was more pronounced in the minority population compared to the white population (Morland et al., 2002). The relationship between food access and obesity is complicated because no one environmental or social factor appears to have a direct causal relationship to obesity rates. Research indicates that individuals with less access to grocery stores consume fewer fruits and vegetables and that consumption of fruits and vegetables is associated with obesity (Morland et al., 2002; Zenk et al.,2005; He et al., 2004).

1.4 Information Literacy and Quality of Life

On the surface information literacy and obesity may seem unrelated. However, Internet use has been associated with a plethora of positive outcomes related to overall quality of life. For example, increased voter activity and civic engagement were found when community members had access to political candidate information online(Tolbert, & McNeal, 2003). Similarly, in a study of low-income breast cancer patients the use of an online support system resulted in increased social support, reduced negative emotions, increased participation in health care, and improved information competency (Gustafson et al., 2005).In addition, studies conducted as part of the Pew Internet and American Life Project provide strong evidence that knowing how to use technology can encourage engagement an many aspects of everyday life (Hampton, Sessions,Her, &Rainie, 2009).

Additional support for an association between information literacy and obesity is suggested by demographic trends. Fox indicated increased computer use among all segments of the population; however, minorities and low-income populations lag behind in adopting some of these technologies (Fox, 2011). Home broadband usage across all segments of the population averages 66% while only 56% of African American's, and 45% of low income families have broadband Internet access at home (Smith, 2010). Similar demographic trends exist for obesity rates (CDC, 2012; Jolliffe, 2011).

2. Methods

2.1 Survey Instrument

The survey instrument used in this study was modified from one originally developed by Arning and Zieflein the Human Technology Center of Auchen University (Arning, &Ziefle, 2008). The survey was translated into English by a native German speaker and then checked for clarity. The original survey, designed to assess the computer expertise of older adults, consisted of 18 total items. Nine items were used to operationalize theoretical computer knowledge. Nine items were used to operationalize practical computer knowledge. The theoretical and practical computer scores were summed for the computer expertise (CE) score. Demographic questions were added to obtain information on age, race/ethnicity, gender, socioeconomic level, and education. The 18 questions that assessed computer expertise were multiple-choice with five choices. In order to discourage guessing, the fifth answer for each question was “I don’t know”. Arning and Ziefle assessed the reliability and validity of the instrument (Arning, &Ziefle, 2008). These researchers found the instrument to be appropriate for older adults with limited computer knowledge and experience. External validity was assessedby relating the survey scores to performance outcomes (Arning, &Ziefle, 2008). Computer expertise and performance were found to be strongly correlated ($r=0.77$, $p<0.01$). Additionally, six questions were added to elucidate how participants obtained health related information, one question was added to give an estimate of overall quality of life, and participants were asked their height and weight to calculate BMI.

2.2 Data Collection

The target population fordata collection was adult residents of the Black Belt region of Alabama. Participants were recruited at events in which the Alabama Cooperative Extension System was a partnerbecause this organization strives to serve all demographic groups in its programming. Thus, the sample is not meant to represent a stratified random sample, but rather it is a sample purposefully intended to represent all demographic groups. A total of 352 participants attempted to complete the survey. Thirty-one surveys were discarded because the participants lived outside the target area, the survey was less than 50% complete, or participants did not report their height and weight. Three hundred twenty-one surveys were used in the analysis.

2.3 Data Analysis

Basil Metabolic Index was calculated for each participant by multiplying weight in pounds by 703 and dividing by height in inches squared (BMI=(pounds*703)/inches2). Average scores for theoretical and practical computer knowledge were assessed for differences using a paired samples t-test. The scores were not significantly different, $t(320)=.53$, $p=.594$. Additionally, Pearson correlation showed that knowledge, $r(320)=.925$, and practical, $r(320)=.940$, scores were highly correlated with the computer expertise (CE) score. For these reasons, the correct responses to the theoretical and practical questions were summed for the CE score and the CE score was used in subsequent analysis. Analysis of variance was conducted to reveal differences in CE scores and BMIs among groups. Multiple regression was conducted to reveal relationships among the grouping variables, BMI, and computer expertise scores. A two way chi square with Pearson phi coefficient was used to identify differences between groups. Residuals were used to identify differences between groups when the Phi coefficient indicated differences existed. Differences were considered significant when the probability value of .05 or smaller was obtained. For demographic variables that have more than two groups (age, education, and income), Fisher's least significant difference (LSD) test was used to identify differences between individual groups.

3. Results

3.1 Demographic Relationships

The demographic makeup of participants is presented in Table 1. Although an effort was made to sample the population in a way to represent all segments, the sample contained younger participants, more females, more educated individuals, and higher income individuals than the general population of the Black Belt.

Approximately two thirds (62%) of the population sample was female. When male and females were compared, analysis of variance showed no differences between mean BMI, $F(1, 304)=.48$, $p=.488$) or CE scores, $F(1, 304)=1.14$, $p=.320$). When all races/ethnicity groups were compared, analysis of variance showed differences between mean BMI, $F(5,304)=4.66$, $p<.001$) and CE scores, $F(5,304)=6.56$, $p<.001$). Post hoc tests were not appropriate because several groups had less than three individuals in a group.

Participants were predominantly African American and Caucasian (96%). A t-test was performed to identify differences in BMI and CE scores between these two groups specifically. The analysis revealed differences in BMI, t(304)=4.56, p=.042) and CE scores, t(304)=4.94, p=.009). Caucasian participants had significantly lower BMI and higher CE scores. A more detailed analysis of the data reveals that the race/ethnicity difference in BMI is primarily accounted for by differences between African American (M=31.23, SD=6.83) and Caucasian (M=27.03, SD=5.71) women. In men, the difference in BMI between African Americans (M=30.46, SD=5.99) and Caucasians (M=28.50, SD=4.64) was smaller.

About a third (34%) of the participant population was low income. When income categories were compared, analysis of variance showed no differences in mean BMI, F(279)=1.74, p=.158). Significant differences in CE scores were found, F (279)=24.19, p=<.001). Post hoc analysis showed that lower income participants had significantly lower CE scores than participants who reported higher incomes.

The average age of participants was 46.09 (SD=15.25). When age categories were compared, analysis of variance failed to reveal differences in mean BMI, F(4,303)=1.34, p=.257. Significant differences in CE scores were found, F (4,317)=17.08, p=<.001. Post hoc analysis indicated a general trend toward lower scores for older participants. Participants that were 65 years of age or older had significantly lower scores compared to other age groups.

When education categories were compared, analysis of variance failed to detect differences in mean BMI, F (6,298)=1.85, p=.104). Significant differences in CE scores were found, F (6,313)=31.59, p=<.001). Post hoc analysis showed that CE scores were significantly higher for participants with a college degree. Participants who did not finish high school had significantly lower scores compared to all other groups.

In order to further define the relationship between obesity and the demographic variables, Pearson correlations were calculated and a multiple regression analysis was completed. Pearson correlations revealed that race/ethnicity, education, and income were negatively associated with BMI (see Table 2). Multiple regression revealed that only race/ethnicity was a significant predictor of BMI when all demographics were taken into consideration together, B=-1.17, t (250)=-3.89, p<.001.

3.2 The Relationship between Information Literacy and Obesity

Pearson correlation indicated a small, but statistically significant negative relationship (r(304)=.-161, p=.002) between BMI and CE score. Regression analysis revealed that CE score was a significant predictor of BMI, B=-.23, t (302)=2.84, p=.005.

A multiple regression analysis was conducted to identify the contribution of CE score to BMI when race/ethnicity was included in the model. Age, sex, income, and education were not included because they were not found to be significant predictors of BMI in this study. Multiple regression statistics are presented in Table 3. Computer Expertise score failed to predict BMI when race/ethnicity was included in the model, B=-.12, t(299)=-1.49, p=.137. However; a more detailed analysis of the individual responses that make up the CE Score was conducted. When responses to individual questions that make up the CE score were analyzed for relationships with BMI, search engine knowledge was found to predict BMI, β=-2.26, t(301)=-2.99, p=.003. Those who exhibited knowledge of how to use a search engine were more likely to have a lower BMI. Because the knowledge question directly related to search engines was associated with BMI, multiple regression analysis was then completed with this variable and race/ethnicity. Search engine knowledge was found to predict BMI when race/ethnicity was included in the model, B=-1.96, t(299)=-2.68, p=.008. Having search engine knowledge and being Caucasian was associated with having a lower BMI.

3.3 The Relationship between Health Literacy and Obesity

Participants were asked what type of media they received information from the last time they had a health issue. The distribution of the type of media that participants use to obtain health information and multiple regression statistics for these variables and BMI is presented in Table 4. The majority (73%) of participants obtain their health information in person from a health professional. Pearson correlations showed relationships between BMI and three types of media. Obtaining information online was negatively associated with BMI, r(301)=-.13, p=.011. Obtaining information from television was positively associated with BMI, r(301)=.13, p=.014. Obtaining information by other means was positively associated with BMI, r(301)=.10, p=.042.

Comments indicated that those who obtained information from other sources use support groups and coworkers as sources of health information. These results indicate that obtaining information online was associated with lower BMI, while obtaining information from television or in groups was associated with higher BMI. Multiple regression of the three ways to obtain health information that were associated with BMI shows that where participants get their health information explains a significant portion of the variance in BMI, $R2=.04$, $F(3, 299)=4.34$, $p=.005$.

The majority (66%) of participants had high-speed Internet access at home. When connection categories were compared, analysis of variance showed no differences in mean BMI $F(3,304)=.21$, $p=.809$). Significant differences in CE scores were found, $F(3,320)=22.07$, $p<.001$). Post hoc analysis showed that CE scores were significantly higher for participants with high-speed Internet access.

The majority (72%) of participants looked online for health information. When participants who looked for information online were compared to those who did not, analysis of variance showed no differences in mean BMI, $F(1,303)=.36$, $p=.549$. Significant differences in CE scores were found, $F(1,319)=129.53$, $p=<.001$. Those who looked online had significantly higher CE scores.

Participants were asked to rate the quality of life for them and their families. The majority (90%) of participants reported that their quality of life was good, very good, or excellent. When quality of life categories were compared, analysis of variance showed no differences in mean BMI ($F(5, 302)=1.51$, $p=.198$). Significant differences in CE scores were found, $F(5, 302)=10.67$, $p=<.001$). Post hoc analysis revealed that CE scores were significantly higher for those who reported a higher quality of life. Regression indicated similar results. Quality of life failed to explain a significant amount of the variation in BMI, $R2=.01$, $F(1,303)=1.44$, $p=.23$. Quality of life explained a significant amount of variation in CE score $R2=.09$, $F(1,317)=29.87$, $p<.001$.

Of the factors included in this study, race/ethnicity, search engine knowledge, obtaining information online, and obtaining information from television were found to predict BMI when included in a multiple regression with similar factors. The factors were then included in a multiple regression equation together. The results are presented in Table 5. Search engine knowledge, race/ethnicity, and obtaining health information from television explained a significant portion (11%) of the variance in BMI, $R2=.11$, $F(4, 295)=8.64$, $p<.001$.

4. Discussion

This study has several limitations:

1. Data were collected in the Black Belt region of Alabama; therefore, inferences made herein may not be generalizable to groups in other areas.
2. Because the survey was administered in an English written format, generalizations may not be extrapolated to populations which are not literate in the English language.
3. Since variations in BMI do not account for individual differences in muscle mass, this measure may over or underestimate obesity in some individuals.

Pearson correlation indicated a small, but statistically significant negative relationship between BMI and CE score. Regression analysis revealed that CE score was a significant predictor of BMI and explained a statistically significant portion of the variance in BMI. These results are not surprising since both lack of computer use and obesity are associated with low income and low education(Fox, 2011; Wang, &Beydoun, 2007). In contrast, Chatterjee and DeVol predict an increase in BMI with more time spent on screen time activities such as playing video games, watching television, and using computers (Chatterjee&DeVol, 2012). Since having more computer expertise was associated with lower levels of obesity in this study, it may be important to make a distinction between watching TV and using computers. It is plausible that computer users are more engaged with the activity and less likely to snack during screen time compared to television watchers.

Pearson correlation failed to detect a relationship between type of Internet access and BMI. It is possible that in this age of rapidly changing technology, having Internet access at home is less important than it once was. According to Fox, minorities are more likely than Caucasians to use a cell phoneto look up health information (Fox, 2011). Since the majority of participants in this study were African American, it is reasonable to conclude that they may be accessing the Internet using mobile technology and not necessarily at home.

CE score failed to predict BMI when race/ethnicity was included in the model. The computer expertise questionnaire may have been too broad an instrument to measure the computer skills specific to finding health information on the Internet. However, the finding that search engine knowledge was associated with reduced obesity indicates that information literacy may be an important factor in solving the very complex obesity challenge. Just as Davis, Crouch, Wills, Miller, and Abdehou noted that basic literacy is key to patient understanding of written health information materials (Davis, Crouch, Wills, Miller, &Abdehou, 1990).The findings in this study support the idea that information literacy is key to finding health information online.

The finding that higher CE scores were associated with improved quality of life is supported by studies conducted by the Pew Internet and American Life Project (Hampton et al., 2009). The pew report indicates that internet use in particular is associated with larger and more diverse social networks. Internet users were also found to be more likely to belong to a civic organization. Since computer expertise would be a prerequisite for internet use, it is a key component of the increased engagement found by the PEW researchers. The current study adds to the growing body of evidence that suggests technology is an important factor in many aspects of our lives.

When the relationship between demographic variables and BMI was assessed, Pearson correlation initially revealed that race/ethnicity, education, and income were associated with obesity. However, multiple regression indicated that only race/ethnicity accounted for a significant amount of variation in BMI. These results are consistent with other studies which suggest that where BMI is concerned race is robust to the effects of education and income (Burke&Heiland, 2008; Burke&Heiland, 2011). Additionally, Lovasi, Hutson, Guerra, and Neckerman found that even after controlling for socioeconomic status and education, African Americans tended to live in areas with fewer grocery stores and places to exercise (Lovasi, Hutson, Guerra, &Neckerman, 2009). These environmental factors may lead to further disparity in obesity rates. In this study, the association among race/ethnicity, education, and income indicated that in the population sampled, African Americans had a lower level of education and income. This relationship may have masked independent effects of income and education on BMI.

4. Implications

Since basic literacy is a foundation of both health literacy and information literacy, the results of this study emphasize the importance of various types of literacy in improving health and overall quality of life. Governments and consumer groups tackling health challenges should pay specific attention to information availability and the ability of the clientele to access the information.

The results of this study support the conclusions and recommendations given by Nutbeam who argued that improving access to health information and the ability to use the information was key to empowering people to improve their own health (Nutbeam, 2000).Nutbeam recommended that community based outreach efforts focus on better equipping people to overcome barriers to healthier lives. Clearly information literacy is important to improving access to health information. One way to empower individuals might be to teach community members the specific skills associated with information literacy thereby enabling participants to find the information that they need to improve their health and quality of life.

The population of focus in this study was predominantly African American and Caucasian, with the highest levels of obesity found in African American women. Minority non-black populations have varying cultural influences, education and economic situations. Although each population struggles with obesity, the cultural factors surrounding the issue may be different. Therefore, investigation into the relationship between computer literacy and obesity in minority non-white populations is recommended. It is likely that the participants in this study were more highly educated, higher income, and predominantly women because these groups are more likely to be in locations where the written survey was administered. Additionally, individuals with low literacy skills who were in the locations surveyed would have been less likely to volunteer to attempt the survey. Repeating this study using random sampling of participants and an oral survey would help further define the obesity causing parameters of the Black Belt population.

5. Conclusion

In this study, relationships were identified between BMI and several variables: CE score, race/ethnicity, where participants get their health information, laptop use, and several individual items that make up the CE score.

Multiple regression identified three factors that were significant overall predictors of BMI: search engine knowledge, race/ethnicity, and obtaining information from television. Participants who lacked search engine knowledge, were African-American, and obtained health information from television were more likely to be overweight compared to participants who were not in these groups. Although computer expertise failed to significantly predict obesity when demographic variables were taken into consideration, the relationships identified in this study help elucidate the complex issue of how people get their health information and how that impacts their overall health.

Despite attempts to reduce obesity levels in the United States, the current trend indicates that levels continue to rise (CDC, 2010). As technology infiltrates every aspect of life, computer expertise becomes increasingly important. This information may help educators and policy makers reduce public health disparities which plague our most vulnerable citizens. Using the information gleaned from this study, educators will be better able to design curriculum to help members of our community become more information and computer literate. Working with disadvantaged populations to develop these skills will help reduce disparities associated with education and poverty.

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Table 1. Population Differences

Demographic	This study	Black Belt	United States
Age 65 +	9.4%	15.5%	13.3%
Male	32.7%	47.5%	49.2%
Female	62.3%	52.5%	50.8%
African American	62.3%	65.8%	13.1%
Caucasian	34.0%	32.5%	78.1%
Hispanic	.6%	1.5%	16.7%
Native or American Indian	.6%	.16%	1.2%
Asian	.3%	.21%	5.0%
High school diploma	90.6%	74.3%	85.4%
College degree	35.8%	13.3%	28.2%
Median income	$40,000	$27,790	$52,762

Table 2. Pearson Correlations for Demographic Variables and BMI

Variable	Age	Sex	Race	Education	Income
BMI	.003	-.049	-.267***	-.126*	-.112*
Age		-.009	.013	-.062	.056
Sex			.184**	.018	.159**
Race/ethnicity				.228***	.467***
Education					.471***

**P*<.05; ***P*<.01; ****P*<.001

Table 3. ***Summary of Multiple Regression Analysis for Variables (CE score and Race/ethnicity) Predicting BMI***

Variable	*B*	*SE B*	β
CE score	-.122	.082	-.086
Race/ethnicity	-1.027	.256	-.233***
R^2		.087	
F		3.853***	

**P<.05; **P<.01; ***P<.001*

Table 4. ***Summary of Multiple Regression Analysis for Variables Predicting BMI (Media Type)***

Preferred media	% of sample	B	SE B	β
Online	33.3%	-1.678	.796	-1.21**
In person	73.2%			
In print	8.4%			
Television	5.3%	3.910	1.648	.135**
Other	5.9%	2.537	1.671	.087
R^2			.042	
F			4.343**	

**P*<.05; ***P*<.01; ****P*<.001

Table 5. ***Summary of Multiple Regression Analysis for Variables Predicting BMI***

Variable	B	SE B	β
Search engine knowledge	-1.949	.730	-.149**
Race/ethnicity	-.910	.257	-.206***
Obtaining information online	-.857	.780	-.063
Obtaining information from television	3.435	1.567	.121*
R^2		.105	
F		8.637***	

**P*<.05; ***P*<.01; ****P*<.001