The Influence of eHealth Literacy on Trust in Technology Among People of Older Age

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Abstract

With aging populations leading to a higher prevalence of aging-associated diseases, pressure on healthcare will worsen. eHealth can offer solutions as it can provide relevant information regarding health issues and personalized feedback that enhances one's health and well-being. However, negative associations between age and trust in technology seem to exist, which creates a barrier for older people to use eHealth. This study investigated the relationships between age and trust in technology, as well as between age and eHealth literacy, and an interaction effect between age and eHealth literacy. With simple random sampling, a sample of ($n = 89$) was collected for this cross-sectional correlation study. ($\mathrm{n} = 35$) were men, ($\mathrm{n} = 28$) were women, and the age of all respondents ranged from 17 to 71 years old ($\mathrm{M} = 42.36\ \text{years}, \mathrm{SD} = 38.02$). Findings indicated that age was negatively associated with both trust in technology and eHealth literacy. Indicating that people of older age tend to have less trust in health applications and seem to have lower levels of eHealth literacy compared to younger people. Contrastingly results did not find a significant interaction effect between eHealth literacy and age. Future research should explore further how to increase trust in technology among people of older age. Additionally, new eHealth should be developed that focuses on older people with lower eHealth literacy.

Keywords: gerontology, education levels, mobile and wearable health applications, eHealth,

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Over the past century, the number of individuals aged 65 and older in the Netherlands has increased from three hundred thousand in 1900 to three million six hundred thousand in 2023. On top of this, the proportion of individuals aged 80 years and older within the 65+ group has also been rising in numbers (Stoeldraijer et al., 2021). This aging population increases the workload on the already burdened healthcare organizations. As people get older they are more vulnerable to developing health complications like cardiovascular diseases, cancer, chronic respiratory diseases, and digestive diseases (Prince et al., 2014). Therefore, with an aging population, the disproportion between the number of patients and the available workforce in healthcare facilities will worsen. Not only will the demand rise, but the workforce itself is aging too, leading to a significant increase in work pressure on understaffed and overburdened healthcare (VZinfo, 2023; Jones & Dolsten, 2024).

eHealth has emerged as the potential solution to provide significant support to people of older age with health complications. eHealth comprises all personal eHealth that can be accessed via mobile devices, wearable devices, or web platforms. These technologies, such as web platforms, can be used to find information regarding health issues that an individual may be experiencing. Additionally, mobile or wearable devices, can deliver personalized feedback to enhance individual health and well-being while also playing a preventative role in reducing and preventing hospitalization (Meng et al., 2021; Wilkowska et al., 2023).

Trust in technology and Age

Although this may appear as a promising solution to counter the increased healthcare burden, in reality, the number of older people that actually use these eHealth is limited. (Zulman et al., 2011; Mak, 2019). Several factors can account for the limited adoption of eHealth among older individuals. Firstly, they have poor competence in using these modern technologies compared to younger people (Kim et al., 2021; Lee et al., 2020). As difficulties may arise in

using these technologies, it is more likely they will reach out to easier accessible sources that will fulfil the same purpose. As a result, the second reason for limited eHealth use is the preference in traditional sources like physicians and pharmacists to inform them about health-related information (Zulman et al.,2011; Hesse et al., 2005) Apart from poor competence in eHealth, a key factor in the preferred source of health information, is trust. Overall, people of older age tend to have lower trust in technology as a source of health information compared to younger people (Zulman et al., 2011).

This phenomenon could be partially explained by the human computer trust model (HCTM) (Gulati et al., 2019). This model poses that somebody' trust in technology can be predicted by: perceived risk, benevolence, competence, and reciprocity. The first factor perceived risk can be defined as the user's subjective assessment of the chance of negative consequences from using the technology. A qualitative study by Fox and Connolly (2018) demonstrated that people of older age have high privacy concerns regarding eHealth, which leads to negative intention to use eHealth.

The second factor benevolence can be defined as the ability to provide the user with adequate feedback that will help him. However, eHealth does often not provide feedback that focuses on the specific needs of older people (Mak, 2019).

The last two factors are reciprocity, defined as the relationship in which the user will use and adopt the technological system repetitively when the system helps the user and competence. People of older age are less experienced in using eHealth compared to people of younger age. Hence, they are less competent in using these technologies which leads to resistance to adopting the technology (Zulman et al., 2011; Fox and Connolly, 2018). Overall, literature suggests that there seems to be a negative association between age and trust in technology.

eHealth Literacy and Age

According to the HCTM, to successfully benefit from and use eHealth to improve individual health and well-being, having a competent level of eHealth literacy is essential. eHealth literacy can be defined as the ability to find and analyse health information from digital data to remedy health problems (Park & Chung 2023). Moreover, eHealth literacy is associated with health behaviour, perceived self-management, and a better view on own health situation (Vaart and Drossaert, 2017)

However, over time research has shown that there exists a negative association between age and eHealth literacy. Namely, people of an older age tend to have lower eHealth literacy compared to people of younger age (Paige et al., 2018; Park & 2023). As a result, these people find it more difficult to access and efficiently use eHealth which creates a barrier to adopting the information provided by these technologies (Wong & Cheung, 2019).

eHealth Literacy as a Moderator for Age and Trust in Technology

Research demonstrates that age tends to have a negative association with both trust in technology and eHealth literacy (Zulman et al., 2011; Paige et al., 2018; Park, S.-Y., & Chung, S., 2023). However, eHealth literacy may play a significant role in influencing trust in technology. Given that eHealth literacy is the ability to find and analyse health information from digital data (Park & Chung 2023), it is likely to influence the four factors of the HCTM: perceived risk, benevolence, competence, and reciprocity. First, people who lack eHealth literacy tend to underestimate the privacy of eHealth (Fox & Connolly, 2018). This underestimation contributes to a decrease in trust in technology. Furthermore, for individuals with limited eHealth literacy, evaluating the benevolence and competence of technology becomes challenging (Park, S.-Y., & Chung, S., 2023). As these people will experience difficulty in finding and understanding the feedback of the technology, the two factors will be negatively influenced. Finally, reciprocity is difficult to establish when an individual has a

poor ability to understand and adapt to the feedback given by the technology (Zulman et al., 2011), which might influence trust in technology negatively.

A study by Paige et al. (2016) investigated an interaction effect of eHealth literacy and age on perceived trust in online health communication sources and channels. The study aimed to investigate whether age and levels of eHealth literacy influenced someone's trust in specific sources or channels on the internet. Findings demonstrated a significant interaction effect. Perceived trust in Facebook rose with age among people with low levels of eHealth literacy. However, perceived trust in social support groups decreased with age among people with low levels of eHealth literacy. Interestingly, among people with high eHealth literacy, the differences between the age groups ware reduced. These findings demonstrated that levels of trust in specific sources vary depending on age and eHealth literacy. However, when eHealth literacy is high, differences seem to be less. Hence, we expect that low levels of eHealth literacy will emphasize the difference between age groups regarding trust in technology and higher levels of eHealth literacy will reduce this difference.

Concluding, the aging population enhances pressure on the healthcare systems as older people are more vulnerable for health related diseases (Prince et al., 2014; VZinfo., 2023; Jones & Dolsten, 2024). In theory eHealth seems to be able to provide solutions to this problem as it can can provide relevant information regarding health issues and personalized feedback that enhances one's health and well-being (Meng et al., 2021; Wilkowska et al., 2023; Zulman et al., 2011; Mak, 2019). However, in reality a lack of trust in technology seems to be one of the barriers that hinder people of older age from using eHealth (Zulman et al., 2011). The HCTM by S. Gulati et al. (2019) demonstrates the four predictors of trust in technology, however these seem to be negatively associated with age (Fox and Connolly, 2018; Mak, 2019; Zulman et al., 2011). Besides trust in technology, eHealth literacy also plays a significantly role as a factor contributing to usage of eHealth among people of older age (Park & Chung, 2023; Vaart and

Drossaert, 2017). Low levels of eHealth literacy represent low ability to find and analyse health information from digital data to remedy health problems (Park & Chung, 2023) Age seems to be negatively associated with eHealth literacy (Paige et al., 2018). The study by Paige et al. (2016) showed that levels of trust in online health sources was different among age groups with low eHealth literacy. However, this difference in trust was attenuated when levels of eHealth literacy was high. The levels of trust among the different age groups was moderated by eHealth literacy. It looks like trust in technology and eHealth literacy decrease with age. Additionally, there seems to be a possibility that eHealth literacy and age interact with each other. Therefore the current study proposes the following hypothesis:

Hypothesis I: *Age is negatively associated with trust in eHealth*

Hypothesis II: *Age is negatively associated with eHealth literacy*

Hypothesis III: *The association between age and technology trust is moderated by eHealth literacy*

Method

Participants and Procedure

This study employed a cross-sectional correlational design to examine the effect of age on trust in health and the effect of eHealth literacy as moderator in this relationship. 84 participants were recruited by simple random sampling. The age of the participants in this study ranged from 17 till 71 years old ($M = 42.36$ years, $SD = 38.02$). Of all the participants, 51.5% ($n = 35$) were men, 41.2% ($n = 28$) were woman, 5.8% ($n = 4$) were non-binary, and 1.5% ($n = 1$) preferred to not share their gender identity.

For a period of 3 weeks participants were recruited from a shared pool of individuals approached in public locations in Groningen, including the Forum, Vinkhuizen, Paddepoel, and the Groningen Central Train Station. The researchers approached participants, informed them about the study, and invited them to participate. They were provided with a brief explanation of the questionnaire and the estimated time for completion; approximately 15

minutes. Participants could complete the survey on-site using a tablet provided or scan a QR code to participate at their convenience.

Research information including the research purpose, their rights as participants, and data privacy were provided firstly, then an electronic informed consent was obtained before the participants fill in the questionnaire. Participation was voluntary. Incentives were provided in the form of drinks, snacks and the participation in a raffle with a €5 prize. On the basis of a checklist developed by the EC-BSS at the University of Groningen, the study was exempt from full ethical review (EC code: PSY-2425-S-0063).

Measures

Demographics

Participants demographics were assessed by four questions. The demographics that were measured were age, gender, and social economic status (SES). The first question measured participants age by asking their year of birth. Secondly, participants were asked to fill in their gender by answering the preconstructed answers which were: (woman, man, non-binary, or prefer not to say). Finaly, participants SES was measured by the last two questions. The first question measured participants education level. This was measured by asking the participants to fill in their highest completed degree. The options answers were: elementary school, LBO, VBO, Domestic school, IHNO, VMBO1-3, and MBO1-2 categorized as low level of education. ULO, MULO, MAVO, VMBO-4, MBO-3-4, VWO, Atheneum, Gymnasium, and Havo categorized as medium level of education. University of applied sciences, University, and Post-academic categorized as high level of education. The second question asked the net income of the participants. This was asked with the use of a slider-based item that ranged between 0 and 100 (in thousands).

Human Computer Trust Scale

People's trust in technology was assessed via an adjusted version of the human

computer trust scale (HCTS) by Gulati et al. (2019). The 5-point Likert scale consists of 12 items that aim to visualize trust towards a technology of interest, in this case mobile health applications and wearable technology. The items answers ranged from 1 (strongly agree) tot 5 (strongly disagree). Scores on item 4 till 9 were reverse-coded in the analysis. A higher score indicates a higher level of trust towards health applications. These 12 items together aim to assess the four factors (Perceived risk, benevolence, competence, and reciprocity), of the HCTM by Gulati et al. (2019), where each individual factor is assessed by 3 items each. An example of a question that measured perceived risk is 'I believe that there could be negative consequences when using health applications'. Additionally, an example question that measured benevolence is 'I believe that health applications will do its best to help me if I need help'. Next, an example question that measured competence is 'I think that health applications are competent and effective in monitoring'. Lastly, an example question that measured reciprocity is 'I can always rely on health apps when it comes to a healthy lifestyle'. As the survey was conducted in Dutch while the original scale was developed in English, a back translation procedure was adopted. The internal consistency of the scale in this sample was ($\alpha = .85$).

eHealth literacy

To measure eHealth literacy, we adopted the digital health literacy scale developed by van der Vaart and Drossaert (2017). This scale consists of two parts. The first part is a self-report section which measures subjective digital health literacy skills and consists of 15 items. An example item is 'When you are searching for health information on the internet, how easy or hard is it for you to determine if the information is reliable?'. These items were measured on a 4-point Likert response format (1 = very hard to 4 = very easy). The second part of this scale is a performance-based section which measures objective digital health literacy skill. The items contain screenshots of websites, followed by questions that ask specific operational

tasks. Figure 1, which can be found in Appendix A, shows an example of such a question. Higher scores on the digital health literacy scale indicate a good skill in adequately using technology, and to understand the feedback it gives (van der Vaart & Drossaert, 2017). To keep an adequate length of the questionnaire, six items from self-report measures were removed when it showed the corrected item-total correlation <0.3 in the pilot test. The internal consistency for the scale in this sample was ($\alpha = .88$).

Data analysis

Data preprocessing

Before the start of the main analysis, an accurate inspection of the data was conducted. All statistics were performed using IBM SPSS Statistics (version 27). Firstly, 16 (19%) variables were eliminated due to missing data within the scales of interest. Secondly, the HCTS had to be partially reversed, since the order of the items were not all equivalent to each other. Thirdly, the first part of the eHealth literacy scale had to be reversed in total, making sure higher scores on the scale indicated higher levels eHealth Literacy. The overall score of the eHealth Literacy scale was the combination of the self-reported first part and the performance-based second part.

Statistical Plan

Descriptive statistics was conducted to investigate the sample characteristics. Bivariate Pearson correlation was conducted to test the first and second hypothesis. A multiple regression analysis was conducted to test the third hypothesis.

Power Analysis

The required sample size was analysed using the G*power analysis software program version of Faul et al. (2009). A minimum sample size of 77 participants was required to test a medium effect size $f^2 = .015$ in Power = .80% at a significant level α = .05.

Results

Assumptions

Prior to the analyses assumptions were checked. Firstly, the assumption of continues variables was met for the Pearson correlation. Furthermore, a histogram demonstrated a normal distribution of the variables age and trust in technology (Appendix A, Figure 2). Additionally, the Q-Q plot of Residuals of HCTS on Age shows a straight line of the observation which indicates a linear relationship between age and trust in technology (Appendix A, Figure 3). Moreover, the Scatterplot of Standardized Residuals vs. Standardized Predicted Values of HCTS on Age demonstrates an evenly distribution of the residuals, which demonstrates homoscedasticity (Appendix A, Figure 4). Furthermore, the assumption of outliers was not violated as no significant outliers were observed. Lastly, the multicollinearity assumption was not violated as none of the predictors had a variance inflation factor above five.

Sample Characteristics

An overview of the sample characteristics is provided in **Table 1** and **2**. In the first table age, trust in technology, and eHealth literacy are displayed with numeric descriptives. In the second table gender and education levels are displayed along with the frequencies and percentages.

Table 1

Sample Characteristics - Continuous

	N	Minimum	Maximum	Mean	Std. Deviation
Age	68	1	71	25.5	21.02
HCTS	68	12.00	50.00	36.13	7.62
eHealth literacy scale	68	6.25	18.25	14.78	2.14

Table 2

Factors	N	%
Gender		
Man	28	41.2
Woman	35	51.5

Non-binary	4	5.8
Preferred to not say	1	1.5
Education level		
High	30	44.1
Medium	32	47.1
Low	4	5.9
Preferred not to say	2	2.9

Sample Characteristics - Categorical

Age and eHealth Literacy

The Pearson correlation was used to test the association between age and eHealth literacy. In accordance with our hypothesis, the analysis showed a significant negative association between age and eHealth literacy ($r(66) = -.45, p < .001, 95\%$ CI $[-.62, -.24]$) indicating that people of a older age, scored significantly lower on the eHealth literacy scale compared to participants of a younger age.

The Moderation Effect of eHealth Literacy

A multiple regression analysis was conducted to test the moderation effect of eHealth literacy on the association between age and trust in technology, while controlling for education levels. The multiple regression model was significant ($F(3, 64) = 3.29, p < .05, {R^2}_{adj} = .09$). In contrast to our hypothesis, the interaction term (Age x eHealth literacy) showed no significant effect ($p = .88$). These results indicate that the levels of eHealth literacy, as a moderator, did not significantly influence the association between age and trust in eHealth. Meaning that people of older age with high levels of eHealth literacy did not significantly have more trust in eHealth, compared to people of the same age with low eHealth literacy levels.

Table 5

Multiple Regression of the scores of HCTS

Predictor	B	SE	t	p	95% CI of B
Age	-.23	.07	-.08	.14	[-.20, .03]
eHealth literacy	.14	.60	.51	.40	[-.69, 1.71]

Education (control)	.14	1.92	1.77	.36	[-2.07, 5.61]
Age x eHealth literacy	.02	.02	.003	.88	[-.03, .04]

Discussion

This study examined the trust in health technology and eHealth literacy of people across different ages. The current study found supporting evidence for the negative relationship between age and trust in technology (H1), and age and eHealth literacy (H2). However, results did not indicate a significant moderation effect of eHealth literacy on the negative relationship between age and trust in technology (H3).

Age and Trust in Technology

The findings that supported the first hypothesis align with prior studies which found a negative association between age and trust in technology (Fischer et al., 2014; Paige et al., 2018; Hesse et al., 2005). A possible explanation for this negative association between trust and age could be the lack of experience with technology among people of older age (Zulman et al.,2011). As older generations have been exposed to technology at a later stage of their life, they are less familiar with these novel technologies. They often face difficulties regarding technology use and have apprehensive attitudes towards the privacy and benevolence of health technology (Paige et al., 2018; Zulman et al., 2011). These factors can lead to lower trust in the health technology (Zulman et al., 2011; Gulati et al., 2019). However, according to the extended Technological Acceptance Model (Dicksons et al., 2021), a lack of trust can also hinder one's intention to adopt novel technology. This prevents the possibility of gaining experience and trust in these technologies. This indicates that trust can drive intentions to use novel technology, but using technology can also enhance levels of trust.

Additionally, research demonstrated that older people show greater trust in physicians than in technology as a source of health information (Hesse et al., 2005). For example, people

of older age are highly uncomfortable in situations where they are completely dependent on health technology (Fischer et al., 2014). Given that, they trust health information given by physicians more than by health technology, this may be another reason for the negative association between age and trust in technology

On the contrary, recent research by Ologeanu-Taddei et al. (2022) did not find a negative association between age and trust in technology. Meaning that there was no significant difference found in levels of trust in technology across people of different ages. A possible explanation for this discrepancy can be the fact that the study of Ologenanu-Taddei et al. (2002) was conducted during a worldwide pandemic caused by the COVID-19 virus. The levels of trust in health technologies among people of various ages may have been more similar in times when everyone's health was threatened. Additionally, the health technology that was focused on in the study of Ologenanu-Taddei et al. was the Stop Covid Proximity Tracing Application which was promoted in France by the French government. This promotion of the app done by the government may have influenced people's trust in the app, leading to more uniform levels of trust across people of different ages in contrast to our study where the technology was not promoted by the government.

Age and eHealth Literacy

The findings that supported the second hypothesis align with prior studies which found a negative association between age and eHealth literacy (Park & Chung., 2023; Wong & Cheung, 2019; Magsamen-Conrad et al., 2019; Xu et al., 2024). A possible explanation for the negative association between age and eHealth literacy could be the fact that younger people are significantly more exposed to novel technologies, like smartphones and the internet, compared to people of older age (Magsamen-Conrad et al., 2019; Kim et al., 2023). This may contribute to developing better competence in technology proficiency, which can enhance the eHealth literacy of younger people.

Next, recent research addresses that while new technologies are speeding up, the cognitive abilities of people of older age are slowing down. People of older age often experience reduced vision, attention span, and memory capacity. This may hinder their abilities to effectively use health technologies which can restrict their eHealth literacy (Lee et al., 2020).

Another explanation for the negative association between age and eHealth literacy could be that older people might feel a lack of confidence in technology due to inexperience with technology, which has a negative effect on their eHealth literacy (Kim et al., 2023; Lee et al., 2020). While social support can enhance this experience and confidence in technology, people of older age seem to get insufficient support from the people around them compared to people of younger age (Magsamen-Conrad et al., 2019). These factors may contribute to a negative association between age and eHealth literacy

The moderation Effect of eHealth Literacy

Contrary to the first two hypotheses, our results did not support a significant moderation effect of eHealth literacy on age and trust in technology. Despite the little research that has been done on this specific effect, one study by Paige et al. (2016) did find, in contrast to our findings, a significant interaction effect between eHealth literacy and age on trust in technology. A reason for this contrast could be the fact that the study focused on levels of trust in different sources (government agencies, charitable organizations, religious organizations, healthcare providers, and family/friends) and different channels (Facebook, Twitter, Pinterest, Online blog, Online support group, YouTube, General online newspaper), that provided the online health information. Our study on the other hand, measured levels of trust in the health application itself. Trust in sources and channels where personal health data was not collected might have a different mechanism compared to health applications and wearables where personal health data was collected. This may have influenced the association between eHealth literacy and age, and explain the contrasting results between our studies. Additionally, the

current study had a sample size that was significantly smaller compared to this study. This is a factor that can contribute to the reason for opposite findings among the studies.

Another reason for the results found in our study could be that the factors of the HCTM like perceived risk and competence of technology are not directly influenced by someone's eHealth literacy. As eHealth literacy may improve abilities to find and analyse health information from digital technologies (Park & Chung., 2023), it may not directly lead to improved attitudes towards the competence and perceived risk of that technology, which improves ones trust. Moreover, some people of older age have high privacy concerns that might not be easily attenuated by high levels of eHealth literacy.

Implications

The findings of this study have important practical implications as older people showed to have lower levels of eHealth literacy and trust in technology. While these people are more vulnerable to developing health implications like osteoarthritis, strokes, coronary heart disease, dementia, and diabetes (Prince et al., 2014), health technology can significantly support them in daily life by supporting a healthy lifestyle to avoid health issues (Meng et al., 2021; Milkowska et al., 2023). Future research and practitioners could take the findings of this study as a starting point to establish improved health technology specifically targeted to older people with lower trust in technology and support the ease of use for older people with lower eHealth literacy. Besides, findings from this study can be used to further expand the theory about trust in technology as trust plays a big part of the acceptance in technology (Dicksons et al., 2021). Furthermore, Future research should aim to investigate a best possible way to educate people with poor eHealth literacy, with the purpose to improve their eHealth literacy.

Limitations and Future Research

Despite the findings of this study, several limitations merit consideration. Firstly, the sample size of this study was relatively small. This may have potentially led to Type II errors, where significant effects remain undetected. Next, the generalizability of the study is limited due to the narrow geographical scope of data collection. Data collection was exclusively done in, or around the city centre of Groningen, resulting in a sample predominantly representing participants residing in or near Groningen. Given that Groningen is part of the highly educated regions in the Netherlands, generalizing these results to all the Dutch people may lead to biases regarding the education levels (VZinfo, 2024). On top of that, Given that the Netherlands scores above average among European countries with the highest levels of education, generalizing these findings to the rest of the world can again result in generalizability problems with regard to education levels (VZinfo, 2024).

Besides the sample size and generalizability, the way the survey was conducted can have had a possible negative impact on the validity. Namely, researchers conducted the survey verbally for older people. However, with regard to the self-report section of the eHealth literacy scale, the older participants may have deliberately overstated their eHealth literacy skills due to possibly feeling ashamed of their actual poor eHealth literacy skills in the presence of a researcher. Hence, the overall score of the scale would be inflated for people who overstated answers and the validity of these scores would be threatened.

Given the studies limitations, future research should aim to conduct a similar study with a significantly increased sample size. This will enhance the power and limit the possibility of random error, leading to more precision and accuracy in result. Moreover, future research should aim to improve generalizability. Collecting participants in a wide variety of places in the Netherlands to ensure different levels of education are evenly distributed over the sample. This will resemble a more representative sample with more variety and will limit the possibility of a sampling bias as different subgroups may be evenly present in the sample. As

a result the generalizability of the study's findings will increase. Lastly, future research should aim to limit the possibility of overstating in self-report section. Thus, maintaining appropriate validity of the scale while offering support for individuals with poor eHealth literacy. Possibly by focussing more on the performance-based section as this cannot be influenced by purposely overestimating ones abilities.

Conclusion

This study aimed to shed light on predictors of trust in technology. It was found that age is negatively associated with trust in technology. Additionally, age was negatively associated with eHealth literacy. The relationship between age and trust in technology was not moderated by eHealth literacy. Despite the studies limitations, findings can be used as a basis for future research to further expand the theory on predictors of trust in technology among older people to eventually improve their acceptance of eHealth. And develop health technology that supports people with low levels of eHealth literacy.

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Appendix A

Figure 1

Example question from the performance-based section of the eHealth literacy

Figure 2

Histogram of Residuals of HCTS

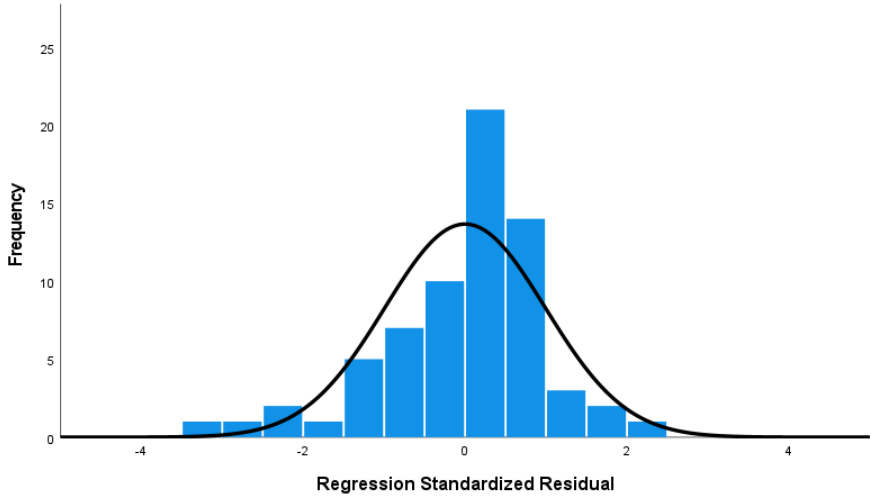

Figure 3

Q-Q plot of Residuals of HCTS on Age

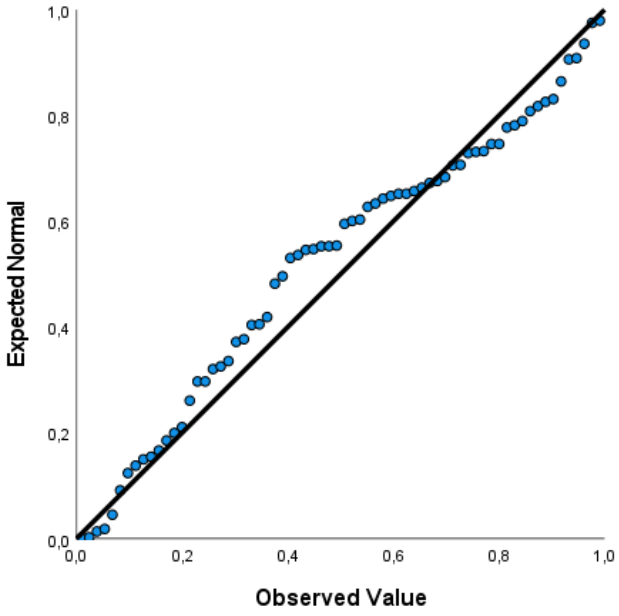

Figure 4

Scatterplot of Standardized Residuals vs. Standardized Predicted Values of HCTS on Age


Regression Standardized Predicted Value
1
0
-1
-2
-4
-2
0
2
Regression Standardized Residual