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Trust Divide in Health Information Sources? Investigating the Role of Techno-Capital and Social Capital: A Comparative Analysis of General and Low-Income Populations

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Trust in the source of health information has become increasingly critical from the advent of the Internet as a primary health information source. Especially as unauthorized entities now have similar gatekeeping powers in health information as health-care professionals. This study strives to conceptualize the factors that affect people's trust in different sources of health information. Specifically, this study proposes ICT usage, digital capabilities and skills conceptualized as "techno-capital," and individuals' health social network behaviors as critical elements explaining one's level of trust. Furthermore, this study addresses the ways in which social inequality interacts with these factors by taking advantage of two

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samples representing different populations within a major U.S. city. Our findings highlight the significance of techno-capital and ICT utilization in explaining the trust of different health information sources as well as the interesting mediating role of health social network behavior in one of the sample populations.

Keywords: health information, health information trust, techno-capital, social capital, ICT, low-income

The rapid spread of ICT has significantly increased the volume and accessibility of information. An important aspect of this transition is the increased accessibility of health information to ordinary people. The "Quantified Self" (Nafus & Sherman, 2014) movement highlights individuals' improved ability to manage health information, enhancing transparency and empowering individual decision making.

Yet, technological development and information availability do not guarantee individual health benefits. Discussions surrounding inequality in the digital society (e.g., digital divide, digital literacy) inform us that not everyone is readily able to fully utilize advanced ICT (Hargittai, Piper, & Morris, 2019). Digital inclusion research has underscored societal inequities in access to technology and connection for maximizing ICT utility (Borg & Smith, 2018). Moreover, literature on digital literacy adds another layer of individual-level skills and capabilities to fully utilize digital information technology (Hargittai et al., 2019).

Another integral aspect is people's evaluation of information trustworthiness, which is related to but not solely dependent on access or comprehension skills. Evaluating information trustworthiness involves complicated factors pertaining to both information quality and source, playing a pivotal role in determining trust (Kelton, Fleischmann, & Wallace, 2008). Such a concept of trust becomes more critical in the context of health. Personal health information is highly private information that has been mostly confined to the doctor-patient relationship (Chin, 2001). Yet, the dynamics of health information seeking have changed with widespread Internet, and trust building and trust perception have been one of the key topics of discussion (Hesse et al., 2005). However, few studies consistently address how social inequality and ICT utilization interact with health-seeking behavior and trust in health information. This study fills such a gap by investigating relationships among individual ICT utilization, technological capabilities, health social network behavior, and trust in different health information sources. Specifically, this study will address the following questions: How does social inequality relate to different patterns of ICT usage and allocation of trust in various health information sources? How do people's use of ICT and their digital capabilities shape their health social network behavior and trust in different health information sources? Does health social network behavior, as a proxy of health-related social capital, play a critical role as a mediator of trust construction? Building on the literatures on technology use, social capital, techno-capital, and trust in the context of health, this study contributes to the literature by incorporating two data sets from the general population[2] and the less-advantaged, low-income population of a major city in Southern United States.

[2] Henceforth, we use "general population" to refer to the general population of a specific U.S. city. Note that we are not claiming that the general population here reflects the general population of the United States.

Literature Review

Technology Use Among Low-Income, Disadvantaged Populations

The rapid diffusion of Internet technology since the 1990s has consistently revealed a gap in the access, use, and capabilities among majority populations and ethnic minorities, low-income populations, and less-educated residents. Studies show that low-income residents frequently have to share phones, start and stop phone and Internet plans, or shift to lower-cost prepaid phones and use the Internet at public access sites due to the difficulty of maintaining monthly payments (Chen et al., 2016). Debates on such digital divides have gone beyond social and physical barriers as scholars have underscored barriers related to industrial structure as well as individual factors such as usage, attitude, skills, and capabilities (van Dijk & Hacker, 2003). Often in lower-income U.S. households that lack access to resources that support digital skills development, parents, children, and siblings become the only sources of such support (Katz, Moran, & Gonzalez, 2018). Access to ICT was found especially critical during the COVID-19 pandemic, and the unresolved problem of the digital divide resurfaced during this period (Roese, 2021). Furthermore, individuals' capabilities of using ICTs were found as substantial factors that promoted the use of telehealth technologies among older citizens during the COVID-19 pandemic (Choi, DiNitto, Marti, & Choi, 2022).

The digital divide extends beyond simple ICT access, involving mental, material, skills, and usage access (van Dijk, 2002). In the context of the COVID-19 pandemic—and health care, more broadly—there can be five digital divide dimensions including infrastructural access, community context, education, economic stability, and health/health-care access (Ramsetty & Adams, 2020). Advocates of the multidimensional concept of digital divide assert that addressing physical access does not guarantee resolutions in other dimensions and that these digital divide dimensions coexist (van Deursen & van Dijk, 2019).

Meanwhile, recent studies show that low-income and minority households turn to cell phones and smartphones to overcome the lack of broadband access and its cost (Tsetsi & Rains, 2017). Furthermore, urban minority youth often secure smartphone access even when parents lack wired Internet access (Lenhart, 2015). Low-income families also rely on smartphones for various family needs, including Internet access to enable schoolchildren to do their homework (Meyer, 2016). Moreover, a study of low-income Latina mothers in Austin, Texas, showed that they relied on smartphones even after receiving computer and Internet training since they felt more competent using smartphones and were more likely to have connectivity for smartphones rather than home broadband to connect a computer (Silva, Mora, & Straubhaar, 2018). However, the debate continues on whether the increased usage of advanced mobile devices significantly reduces digital inequality given persistent issues of affordability, skills, and usage divides (Marler, 2018). In light of such research, our first research question is as follows:

RQ1: How do the general population and the low-income population vary in their use of ICTs?

However, beyond questions of access and usage lie serious questions about people's capability to use various ICTs for activities that are useful or empowering to them.

Techno-Capital and Social Capital

As mentioned above, skills and capabilities are critical factors required for maximizing the utility of ICTs. While digital divide and digital literacy research have addressed the criticality of individual capability (Hargittai, 2005), there is a closely related yet understudied theoretical approach: Bourdieu's theory of capital (Bourdieu, 1986). Bourdieu's theories of economic, social, and cultural capital provide a compelling theoretical framework explaining the factors that can constrain or enable one's wealth, capabilities, social connections, and opportunities (Bourdieu, 1986). In his later work, Bourdieu (2005) expanded on his conceptualizations of capital to include technological capital (i.e., techno-capital), which can be described as literacy and proficiency in utilizing digital tools as shaped by the individual's socioeconomic status.

Meanwhile, as one of the critical forms of capital, social capital can be defined as "the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition" (Bourdieu, 1986, p. 248). Interacting with economic and cultural capital, social capital shapes and influences an individual's social mobility. Broadly, social capital can be understood at two levels: Collective and individual (Lin, 1999). While social capital can be conceptualized as a collective communal asset (e.g., Putnam, 2000), it can also be understood from the individual's standpoint as the social relationships or resources embedded in their social networks (Lin, Fu, & Hsung, 2001). In general, however, social capital is perceived to have several key elements and resources, which are social support, advice, and trust. The extent to which an individual perceives and receives these aspects of social capital has compound influence on the well-being of minority populations (Oh, 2016). Aforementioned forms of capital influence and inform one another with levels of wealth and education positively impacting the expansiveness of an individual's social network and cultural capital (Erickson, 1996). Likewise, an individual's level of techno-capital often reflects earning power, cultural tastes, and social standing, which provide further insight into ICT utilization among different socioeconomic groups (Witte & Mannon, 2010).

In the context of health, studies have considered how digital technologies enable access to health information and influence people's health information–seeking behavior (Lustria, Smith, & Hinnant, 2011), which has implications on individual social capital related to health such as health support or advice network. Social networks provide social capital (i.e., resources), exert social influence, and accompany social support. Social support includes emotional support, instrumental support, informational support, and appraisal support. Regarding health, these resources and support from social networks enable people to acquire both individual coping resources and organizational/community resources related to health (Heaney & Israel, 2008). Several types of social network interventions including enhancing existing network linkages and developing new linkages have been suggested and tested. Studies have found generally positive effects of social network interventions on health behavior–related outcomes as well as considerable heterogeneity among different types of health problems (Hunter et al., 2019; Laranjo et al., 2015).

Health social networks are social networks, online communities, or online support groups that are formed to fulfill emotional support or informational needs (Chung, 2014). Social networks—either general or health-specific—can substantially influence both physical and mental health outcomes by providing social support or informational resources (Franken, Bekhuis, & Tolsma, 2023; Li, Guo, & Shi, 2023; Oktavianus & Lin, 2023). As shown in these studies, online social networks function as important sources of health-related social capital and support. Given this, we define individuals' health social network behavior as the extent of online behavior seeking health information and support.

Although the direction of the contribution of ICT use toward social capital is debatable, it seems there is a consensus that utilizing ICTs, once supported with sufficient access and level of techno-capital, would generally exert a positive influence. In the health context, techno-capital as in digital competence has a positive effect on the use of online health and social care services for older adults (Heponiemi et al., 2022). Furthermore, techno-capital was found to increase the odds of using telehealth during the COVID-19 pandemic (Le, Galperin, & Traube, 2023). Therefore, this study hypothesizes that higher level of ICT utilization and techno-capital would be positively associated with health social network behavior.

RQ2: How does the usage of ICT and techno-capital influence individuals' health social network behavior?

H2.1: ICT utilization factors will be associated with greater health social network behavior.

H2.2: Higher level of techno-capital will be associated with greater health social network behavior.

Health Information Source and Trust

The rapid diffusion of the Internet allowed unprecedented access to health information within reach of the public (Chen & Lee, 2014; Hesse et al., 2005). More than half of U.S. Internet users went online for health information in 2013, and more recently more than 80% of citizens of Austin responded that they had used the Internet to look for health information (Straubhaar et al., 2018).

The Internet has empowered people to consume a wide variety of health information, ranging from information about a specific disease or a certain medical treatment to information on losing weight or food safety (Fox & Duggan, 2013). While this helps people to make more informed health-related decisions, the utilization of health information from the Internet can also be tricky. The uneven quality of health information on the Internet has always been an issue as newly available channels might grant unauthorized persons a gatekeeping role that was once mainly given to physicians or other health-care professionals (Benigeri & Pluye, 2003). With this dilemma, the problem of trust—which source to trust and how much to trust it—has become increasingly crucial. Studies have found that trust in online health information can be determined by various factors related to individual differences, website-related features, and user-website interaction-related variables (Kim, 2016). Generally, better website design, a clear layout, interactivity, website owner/author authority, and ease of use enhance the trust or credibility of online health information (Sbaffi & Rowley, 2017). A recent study found that users generally are skeptical about the health information from crowdsource-based platforms (e.g., Wikipedia). However, the interactive content-editing features offered by these platforms could raise their trust or credibility assessments as they spark the sense of self as the information source itself (Huang & Sundar, 2022). In sum, various individual- and website-related factors could influence the trustworthiness of online health information, and the extent of interactive affordances on different platforms may add complexity to the trust assessment dynamics.

As such, the introduction of new technologies raises different challenges for individuals in evaluating the trustworthiness of online health information. However, most of the aforementioned studies presumed their respondents were already digitally literate and put less focus on individuals' technological capabilities as predictors of online health information trust. With the vast range of information, diverse sources, and the resultant quality concerns, individuals are expected to acquire techno-capital as a prerequisite for effective online health information seeking. Lack of digital access and digital skills could limit ICT-based health knowledge transfer and dissemination (Benigeri & Pluye, 2003; Chen & Lee, 2014).

Given such discussions connecting the use of technology and techno-capital with the level of trust, we argue that a higher level of ICT utilization and techno-capital would be positively associated with the extent of trust in different health information sources. There are various sources of health information. For instance, the National Cancer Institute's Health Information National Trends Survey (HINTS) includes doctors, family/friends, government health agencies, charitable organizations, religious organizations and leaders, and scientists as health information sources (National Cancer Institute, 2022). A study analyzing the trend of this specific question in HINTS between 2005 and 2015 found that doctors were the most trusted health information source while religious organizations and leaders were the least trusted. However, variance existed as the study found that the non-Hispanic Black population and those with lower education reported higher trust in religious organization sources (Jackson, Peterson, Blake, Coa, & Chou, 2019). Other health information sources that should be considered are online sources including information shared by people on social media, health websites, and health applications on mobile devices. We investigate both traditional sources that resemble the HINTS options and online sources. Furthermore, we posit that ICT utilization factors and techno-capital are related to the traditional sources as well because of the fact that even information from doctors or government health agencies is delivered through online platforms.

H3.1: ICT utilization factors will be positively associated with trust in different health information sources.

H3.2: Techno-capital will be positively associated with trust in different health information sources.

Trust in health information sources can also be associated with social support in one's network according to the social capital theory (Bourdieu, 1986; Chen, Lee, Straubhaar, & Spence, 2014) and the social exchange theory (Li, 2015). According to these theories, both social support and trust can reflect material or psychological investments and returns or rewards from the process of interpersonal interactions and social exchanges. Although a large body of literature has discussed the relationship between social support and positive health outcomes (Chen et al., 2014), few examined the joint mechanism of social support and trust in the context of online health information search. Previous studies have found the predictive effects of the family's social support on trust in health information from family members (Yang, Chen, & Muhamad, 2017) and the role of physician's supportive communication on patients' trust (Ommen et al., 2008); thus, this study hypothesizes that more social support from one's network members is likely to facilitate greater trust in health information sources. Furthermore, we intend to explore the extent to which support network plays a mediating role between technology factors and health information source trust.

H4: *Health social network behavior will be positively associated with trust in different health information sources.*

RQ3: *How does health social network behavior potentially mediate the effect of technology factors on trust in different health information sources?*

Finally, we intend to investigate how trust in health information sources as well as the relationships constructed by the aforementioned hypotheses vary between the general population and the disadvantaged, low-income population. Several studies have investigated how sociodemographic factors such as race and income have differentiating effects on people's trust in different health information sources (Somera, Lee, Badowski, & Cassel, 2016) partly due to poor quality of communication between physicians and social minorities. Taking advantage of the availability of comparable samples, we will explore the following research questions. Figure 1 visualizes the conceptual framework.

RQ4: *How differently or similarly do the general population and the low-income population of Austin trust different health information sources?*

RQ5: *How do the relationships among technology factors, health social network behavior, and health information source trust vary between the general population and the low-income population of Austin?*

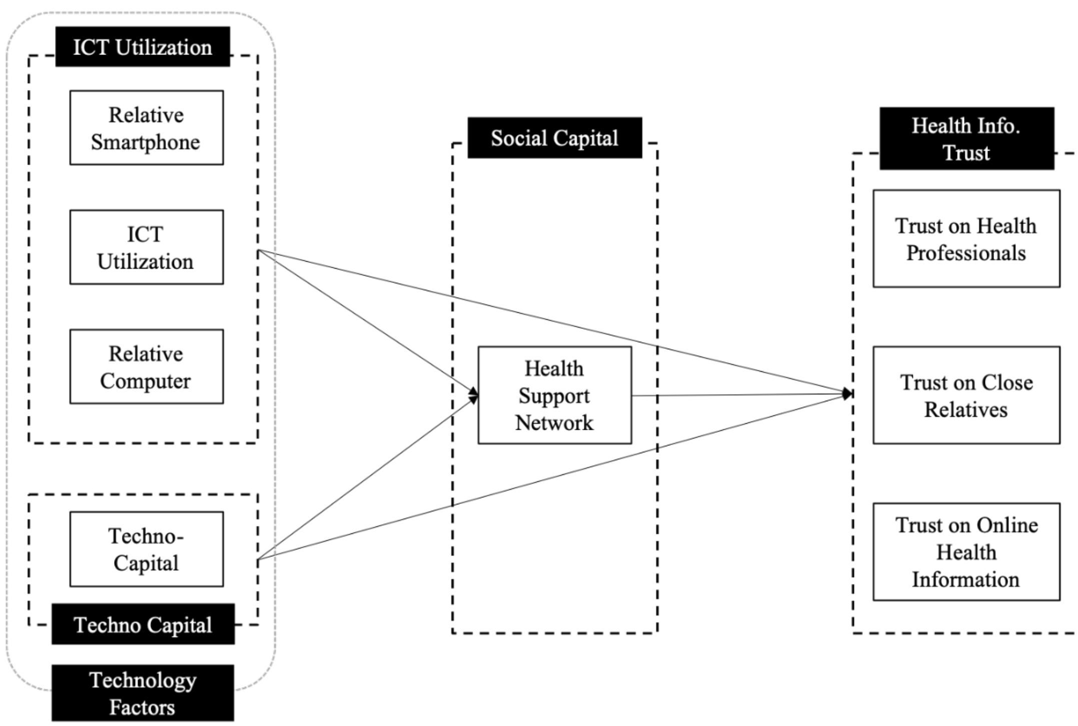

Figure 1. Simplified structural model depiction.

Methodology

This study used two data sets collected through two separate surveys using mostly identical questionnaires. The second-wave questionnaire had the same set of questions with a few item statements that measured similar concepts deleted due to length constraints. Both surveys were part of an ongoing citywide research on digital technology access and usage jointly conducted by the City of Austin and the University of Texas at Austin. We conducted descriptive comparative analyses as well as statistical analyses to investigate the hypotheses.

Data Collection

Representative Random Sample (Data Set 1)

The first data were collected through a self-administered mail survey. Our sample population consisted of a random sample of 11,000 adults residing in Austin. Among them, 8,000 surveys were randomly distributed across the entire city area, and another 3,000 were distributed to purposefully selected areas,[3] which would ensure representation of the most disadvantaged people. We first mailed a postcard notifying potential participants that a survey would be mailed to them in a few weeks. Participants were also provided with a link to an online version of the survey, giving them the option to respond online. Data were collected between April 1 and August 1, 2018. All participants were given a chance to enter a raffle to win one of three Dell tablets, as a means of compensation.

A total of 643 surveys were mailed back, and another 354 were submitted online. The response rate was 8.31% for the 997 valid surveys. Our sample overrepresented a certain demographic profile (i.e., non-Hispanic White with higher income). Therefore, we rake weighted the data set with the 2016 American Community Survey numbers (race and income distributions) to offset overrepresentation and better reflect the population of Austin.

Purposive Selective Sample (Data Set 2)

The second data were collected as a follow-up, aiming to examine the underrepresented population. The second survey was distributed to those who were using public access and training services offered by several major city partners (i.e., Housing Authority of the City of Austin [HACA], Austin Free-Net [AFN], Foundation Communities [FC], and El Buen Samaritano [EBS]) to the more disadvantaged, low-income group of people. The partners voluntarily participated in this study and decided on the method of distribution in collaboration with us.

The cooperating partners represented several kinds of less-advantaged groups in Austin. The Housing Authority of the City of Austin represents people making less than $18,000 and in need of subsidized housing. Austin Free-Net, while serving a variety of groups, reached out to the homeless who use two of their public access computer labs. Foundation Communities, which provides various programs with subsidized housing, reached out to those in single-resident housing for this survey. El Buen Samaritano

[3] These residential addresses were randomly sampled from zip codes that belong to the city’s most disadvantaged neighborhoods based on the census and the city authority’s own data.

serves low-income Latinos with computer labs, training, and English classes; it administered the questionnaires to students in computer-training and English classes. As a result, a total of 692 observations were used, which consisted of 20 recruited by EBS, 50 by AFN, 69 by FC, and 553 by HACA. Table 1 summarizes the sample characteristics.

Table 1. Demographic Characteristics of the General Population Sample and the Low-Income Sample.

		General Population Sample (%, *N* = 997)	Low-Income Sample (%, *N* = 692)
Race and Ethnicity			
	White (non-Hispanic)	52.7	35.4
	Hispanic	32.1	15.3
	African American	7.6	43.4
	Asian	6.8	2.3
	Other	.9	3.5
Gender			
	Male	47.9	37.6
	Female	51.5	58.8
Educational Attainment			
	Less than high school	12.0	27.2
	High school	16.4	39.8
	Some college	23.9	22.3
	College degree	30.2	7.3
	Postgraduate/professional degree	17.5	3.4
Age (18+)			
	18–24	14.5	3.7
	25–34	28.1	15.0
	35–44	20.0	19.2
	45–54	15.2	17.7
	55–64	12.1	21.7
	65–74	6.1	16.7
	75–84	2.7	4.7
	85+	1.2	1.3

Note. Only 0.1% selected the nonbinary option for gender in the general population sample, while 3.5% did so in the low-income sample.

Data Measurement

ICT Utilization

An index for overall ICT utilization was created summing up 10 dichotomous items asking whether the respondents used smartphone, computer, or tablet devices in the past six months for various reasons

(Table 2). Respondents could choose multiple devices. Using this as an individual ICT utilization score, rate variables were calculated by dividing the sums of smartphone and computer use by the overall ICT utilization score. The overall and relative scores are original measurements calculated using basic frequencies.

Health Information Source Trust

Trust in health information was measured using eight items, asking respondents to indicate the degree of trust in health information from different sources on a 4-point Likert-style scale (1—"Not at all" to 4—"A lot"). Eight items are originally developed taking available surveys as references (e.g., National Cancer Institute, 2022). The items were used in previous rounds of annual surveys conducted by our institution and the city government. Three of these items measured health information trust in professional/official sources such as doctors, government health agencies, and health organizations (Data Set 1: Cronbach's α = .62, *M* = 3.6, *SD* = 0.47; Data Set 2: Cronbach's α = .84, *M* = 2.2, *SD* = 0.98). Two items measured trust in close social networks such as close friends, family members, or relatives (Data Set 1: Cronbach's α = .72, *M* = 3.3, *SD* = 0.58; Data Set 2: Cronbach's α = .84, *M* = 2.3, *SD* = 0.93). Another three items measured trust in health information from online sources such as websites, mobile apps, and social media (Data Set 1: Cronbach's α = .52, *M* = 3.2, *SD* = 0.67; Data Set 2: Cronbach's α = .88, *M* = 2.6, *SD* = 0.95). For the last items measuring trust in online sources, we excluded one item from Data Set 1 that substantially compromised reliability. Average scores for these broad subcategories of health information sources were used.

Health Social Network Behavior

We used 10 binary items to assess health social network behavior. Respondents were asked to answer whether they used the Internet for the purposes of each item. The items included health social network behaviors such as, "Looked for health or medical information for myself," "Participated in an online forum or support group for people with a similar health or medical issue," "Shared health information on social media sites, such as Facebook or Twitter," "Exchanged support about health concerns with family or friends." An index was created by summing up respondents' health-related online activities in the past six months.

Techno-Capital

Techno-capital was measured using five questions assessing individuals' basic capabilities of using information technologies (e.g., uploading content on a website, comparing different sites to check information accuracy, etc.). The items recorded respondents' capabilities on a 5-point Likert scale (1—"Strongly disagree" to 5—"Strongly agree"). An average score was calculated for further analyses (Data Set 1: Cronbach's α = .88, *M* = 4.2, *SD* = 0.92; Data Set 2: Cronbach's α = .93, *M* = 2.9, *SD* = 1.3).

Data Analysis

For data analysis, first, we conducted a comparative analysis of descriptive statistics of the two samples to address *RQ1* and *RQ4*. Secondly, we employed structural equation modeling to test the hypotheses. We fit the same model separately for the two samples and conducted a simple comparison of significant paths rather than conducting multigroup comparisons or moderation.

For data handling and descriptive analysis, this study used R and SPSS 25. Incomplete responses were excluded from the analysis. For testing the hypotheses, this study employed partial least squares structural equation modeling (PLS-SEM) using SmartPLS3 software. While the covariance-based SEM has been more widely used in social science, PLS-SEM is an increasingly popular alternative in the early theory-building stage in which the theoretical relationships have been relatively understudied and is more appropriate when dealing with complex latent variables and data non-normality (Hair, Risher, Sarstedt, & Ringle, 2019). While our hypotheses are grounded in findings from previous literature, the model has exploratory elements, and one of our samples deals with purposively targeted populations, thus, justifying the use of the PLS-SEM approach.

Results

ICT Utilizations and Health Information Trust of the Two Different Populations

ICT Utilization of Low-Income Sample and General Population Sample

Research Question 1

For ICT usage, the respondents from the low-income population were found to use smartphones more than computers for most daily activities. Such prevalent use of smartphones by the low-income population extends into types of activities that the general population perceives as the domain of computers (e.g., paying city bills, completing forms for health/other services, most work-related tasks; Table 2).

Table 2. Device Use by Activities Among Low-Income Sample (N = 692) Versus General Population Sample (N = 997).

	Smartphones (%)		Computers (%)	
	Low-Income	General Population	Low-Income	General Population
Use city services				
Pay city bills	35	31	21	58
Get public transportation info.	44	38	22	19
Get info. on or apply for govt. services	40	25	30	30
Contact ride-sharing services	41	47	15	3
Check city info. and resources	44	42	28	43
Work-related				
Complete work for current job	26	38	23	61
Learn job-related skills	27	22	28	45
Find/apply for a new job	37	24	28	38
Health				
Get info. about health	44	57	28	56
Complete forms for health/other services	37	26	28	55

Examining the overall ICT utilization and the relative prominence of smartphones and computer use, we found corroborating evidence of higher smartphone dependence in the low-income population (Table 3). Overall average ICT utilization was slightly higher for the general population (8.03) compared with the low-income population (6.84). The low-income people (3.74) utilized smartphones more than the general population (2.71), while the general population utilized computers (4.41) more. Relative prominence reinforces such findings as relative smartphone prominence in daily activities was far greater for the low-income people (0.576) compared with others (0.301). In contrast, the general population relatively used computers more (0.599) than the low-income population (0.348).

Table 3. ICT Utilization Indices of Low-Income Sample (N =692) Versus General Population Sample (N = 997).

	Overall ICT Utilization	Smartphone Utilization	Computer Utilization	Relative Smartphone	Relative Computer
General population	8.03	2.71	4.41	0.301	0.599
Low-income	6.84	3.74	2.48	0.576	0.348

Health Information Trust of Low-Income Sample and General Population Sample

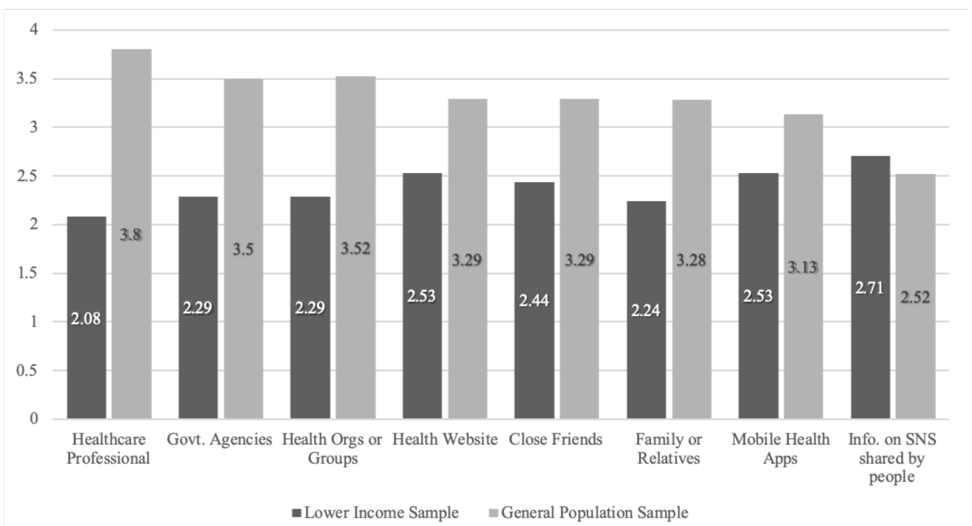

Figure 2. Trust in health information sources—Mean scores of trust (1 = Not at all, 2 = A little, 3 = Some, 4 = A lot).

Research Question 4

Overall, the low-income sample showed lower levels of trust in health information from all sources (M = 2.39, SD = 0.76) compared with the general population (M = 3.29, SD = 0.38). Furthermore, we witnessed a contrasting pattern of health information trust in different sources (Figure 2). Relatively, the low-income sample indicated higher trust in online health information (M = 2.59, SD = 0.94) than information from health-care professionals or other health-related authorities (M = 2.22, SD = 0.97; Figure

3). Interestingly, the low-income sample perceived health information from close friends, family, or relatives as more trustworthy (*M* = 2.34, *SD* = 0.93) than from health-care professionals. In contrast, the general population sample indicated the highest level of trust in health-care professionals and organizations (*M* = 3.6, *SD* = 0.47), and the lowest trust in online health information sources (*M* = 2.98, *SD* = 0.68). For them, health information from close relatives and friends was more trustworthy (*M* = 3.28, *SD* = 0.58) than information from online sources, but not so much as information from health professional communities.

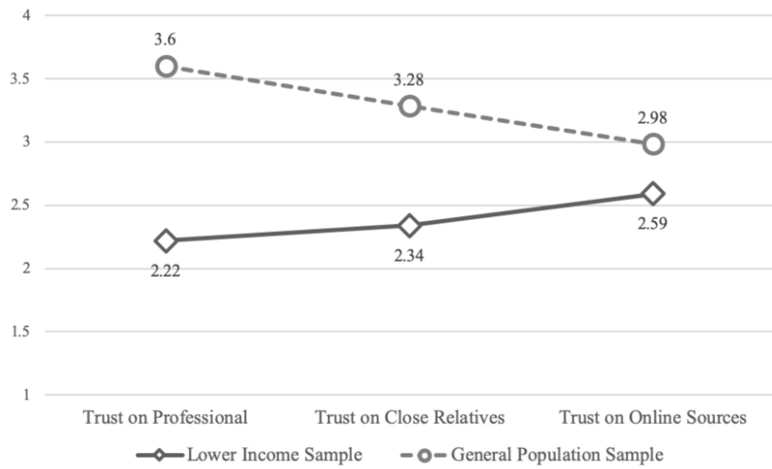

Figure 3. Average trust in three health information sources.

Influence of ICT Factors, Techno-Capital, and Health Social Network Behavior on Health Information Trust

In this section, we report the PLS-SEM results testing our hypotheses (*H2.1* and *H2.2* under *RQ2*, *H3.1*, *H3.2*, and *H4*) and the remaining research questions (*RQ3* and *RQ5*).

Measurement Model

The measurement model of latent constructs in PLS-SEM is assessed using three concepts: Internal consistency, convergent validity, and discriminant validity. The internal consistency is evaluated by the composite reliability measure provided by SmartPLS3, complemented by Cronbach's alpha. The composite reliability is considered a more precise measure of reliability as the items are weighted based on the indicators' individual loadings (Hair et al., 2019). Internal consistency for all latent variables included in the model was in an acceptable range in terms of Cronbach's alpha and composite reliability measures. A few concerning exceptions were relatively low Cronbach's alpha for the trust in health information from online and professional sources in the general population sample data. As mentioned above, we decided to delete one of the indicators of online health information trust to bolster the reliability. Although the resulting Cronbach's alpha was still in a relatively low range, the composite reliability scores indicated high internal consistency for all variables in both data sets.

Convergent reliability was assessed by examining the average variance extracted (AVE). All variables showed AVE greater than the generally accepted threshold of .5, except the health social network behavior in both data sets. While the AVE was not too far off for the low-income sample (.439), it was considerably low (.279) for the general population sample data. However, as the variable successfully established internal reliability and discriminant validity, we maintained its presence in the model (Wong, 2016).

Discriminant validity was established by comparing the square root of the AVE with the correlations of latent variables (i.e., Fornell-Larcker criterion; Hair et al., 2019). The square roots of AVE scores were larger than the correlations across latent variables. Furthermore, the heterotrait-monotrait (HTMT) ratio of the correlations for all the variables in both data sets did not exceed .9, therefore the discriminant validity was successfully established. Table 4 summarizes the assessment criteria of the measurement model.

Table 4. Composite Reliability, AVE, and HTMT Scores of the Latent Variables.

General Population										
Composite Reliability	AVE		Trust-C	Trust-O	Trust-P	HSN	ICT	Rel-C	Rel-S	TC
.871	.774	Trust-C								
.799	.674	Trust-O	.218							
.798	.569	Trust-P	.119	.294						
.791	.279	HSN	.113	.227	.190					
NA[*]	*NA*	ICT	.084	.250	.214	.742				
NA	*NA*	Rel-C	.017	.148	.017	.333	.220			
NA	*NA*	Rel-S	.003	.152	.038	.252	.072	.700		
.921	.699	TC	.050	.337	.264	.488	.552	.211	.189	
Low-Income Population										
Composite Reliability	AVE		Trust-C	Trust-O	Trust-P	HSN	ICT	Rel-C	Rel-S	TC
.946	.897	Trust-C								
.942	.845	Trust-O	.515							
.914	.780	Trust-P	.655	.450						
.875	.439	HSN	.209	.462	.219					
NA	*NA*	ICT	.081	.247	.184	.673				
NA	*NA*	Rel-C	.143	.033	.129	.287	.064			
NA	*NA*	Rel-S	.139	.039	.090	.316	.116	.855		
.960	.828	TC	.240	.370	.336	.449	.357	.068	.120	

Note. [*]*NA* has been introduced because these three variables have only a single indicator.
Trust-C = Health information trust in close relatives; Trust-O = Health information trust in online sources; Trust-P = Health information trust in professional sources; HSN = Health social network behavior; ICT = Overall ICT utilization; Rel-C = Relative computer usage; Rel-S = Relative smartphone usage; TC = Techno-capital. The numbers in the matrix represent HTMT scores, which should not exceed .9.

PLS-SEM Path Analysis

A bootstrapping procedure to statistically test the path coefficients was conducted with 5,000 bootstrap subsamples.[4] Similar to conventional regression analysis, the R^2 value of the endogenous variables indicates the variance explained by the exogenous variables. For the general population sample, our model successfully explained 8.6% and 4.7% of the variance in the level of trust in health information from online and professional sources, respectively; ICT utilization factors and techno-capital together significantly explained 45.9% of the variance in health social network behavior. The model failed to statistically significantly explain trust in health information from close relatives of the general population sample. For the low-income sample, the model successfully explained 6.3%, 21.2%, and 10.8% of the variance in the trust in health information from close relatives, online sources, and professional community, respectively. The ICT utilization factors and techno-capital significantly accounted for 39.4% of the variance in health social network behavior. Figure 4 and Figure 5 visually depict the PLS-SEM path analysis results using the general population sample and the low-income sample, respectively.

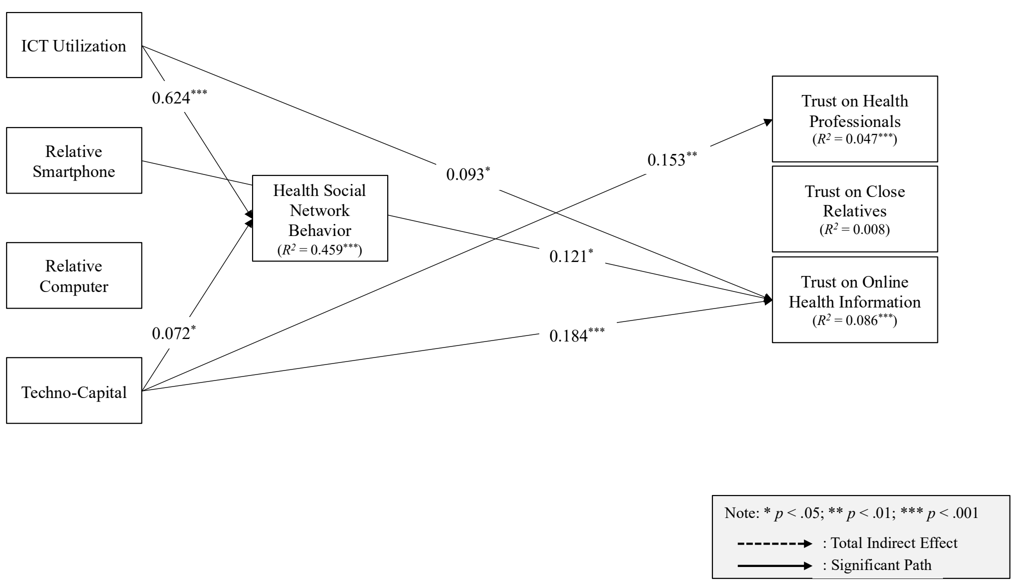

Figure 4. PLS-SEM on the general population sample.

Technology Factors and Trust in Different Health Information Sources

First, we examined the direct relationship between ICT factors, consisting of the extent of ICT utilization and techno-capital, and the trust in different health information sources. Our hypothesis was that greater level of ICT utilization (both overall and relative prominences; H3.1) and techno-capital corresponds to greater trust in the health information obtained from diverse sources (H3.2).

[4] Bootstrapping is a required procedure in PLS-SEM to test the statistical significance.

For the general population, we found partial support for hypotheses H3.1 and H3.2. The overall ICT utilization (β = .093, *p* = .025), the relative prominence of smartphones (β = .121, *p* = .010), and techno-capital (β = .184, *p* < .001) were positive predictors of trust in online health information. Furthermore, techno-capital was significantly related to trust in health information originating from professional health-care communities (β = .153, *p* = .001) adding to the partial support for H3.2.

In the low-income sample, we found significant evidence supporting H3.2, with partial support for H3.1. The relative prominence of computers in their daily ICT usage was a significant predictor of trust in health professionals (β = .213, *p* = .002). While there were no significant direct effects of ICT utilization on trust in different health information sources, techno-capital was found to be a highly influential predictor of one's trust in health information from close relatives (β = .170, *p* < .001), health professionals (β = .272, *p* < .001), and online sources (β = .204, *p* < .001).

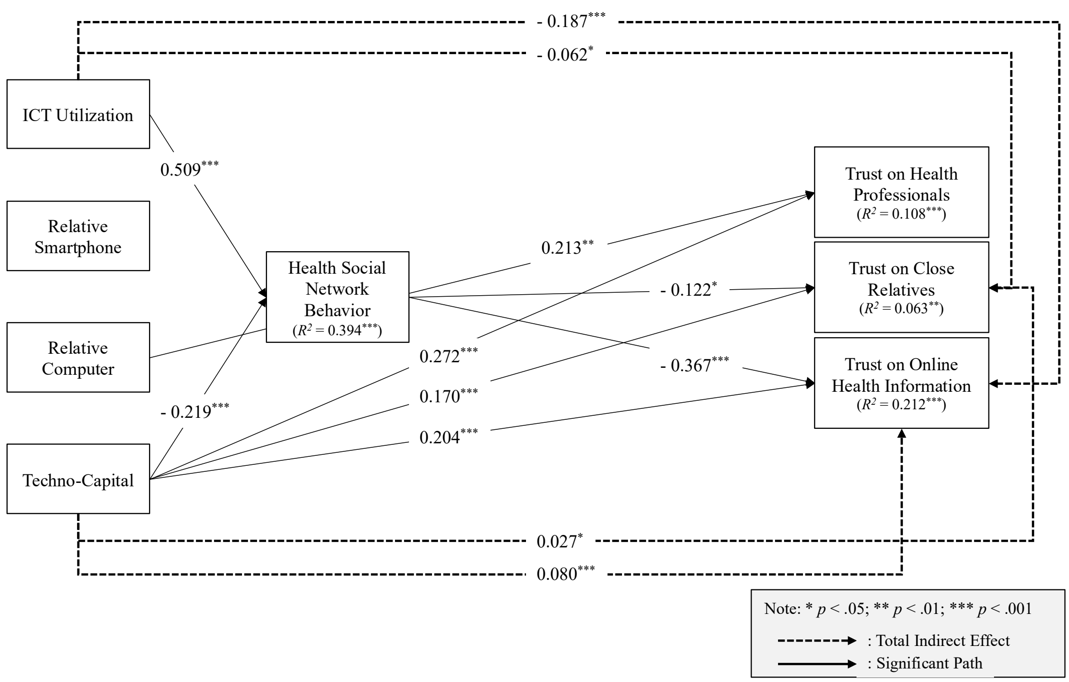

Figure 5. PLS-SEM on the purposive low-income sample.

Technology Factors and Health Social Network Behavior

Second, we investigated the relationship between individuals' utilization of ICT and techno-capital with health-related social capital represented by support network (H2.1 and H2.2). The PLS path analyses revealed both corresponding and contrasting results between the general population sample and the low-income sample.

For the general population sample, our results support H2.1 and H2.2. Overall ICT utilization was a significant predictor of greater health social capital (β = .624, p < .001). Furthermore, individuals' techno-capital had a significant relationship with their health social capital (β = .072, p = .014). In other words, those who utilized ICT more and had higher basic technological capability had a higher probability of acquiring bigger health social network behavior (RQ2, H2.1, and H2.2).

We found a contrasting relationship for the low-income sample. The results support H2.1, but an inverse relationship was found for H2.2. To illustrate, the results corroborate the relationship between overall ICT utilization and one's health social network behavior (β = .509, p < .001). However, techno-capital was found to influence health social network behavior negatively (β = –.219, p < .001).

Health Social Network Behavior and Trust in Different Health Information Sources

For the general population sample, the results indicated no significant direct relationships between health social network behavior and trust in different health information sources. Therefore, we failed to accept H4.

In contrast to H4, the analysis of the second data set indicated several significantly negative relationships between health social network behavior and health information source trust. We found that greater range and magnitude of health social network behaviors were a significantly negative predictor of trust in health information from close relatives (β = –.122, p = .012) and online sources (β = –.367, p < .001).

Research Question 3

Investigation of the potential mediating effect of health social network behavior on health information source trust was done by examining indirect effects coupled with the process of determining the existence and type of mediation suggested by other scholars (Zhao, Lynch, & Chen, 2010). For the general population sample, there were no mediation effects as there were no significant direct effects of health social network behavior on the health information source trusts. That is, for the general citizens of Austin, their degree of trust in health information sources was most likely influenced by their ability and actual utilization of information technologies.

On the other hand, for the socially disadvantaged population of Austin, we found several significant indirect effects. To elaborate, there were significant positive indirect effects of techno-capital on trust in health information from close relatives (β = .027, p = .022) and online sources (β = .080, p < .001). Considering that the direct effects of techno-capital on these two constructs of health information source trust were statistically significant, and the product of path coefficients was positive, there was a complementary partial mediation of health social network behavior. Furthermore, there were significant negative indirect effects of ICT utilization on trust in health information from close relatives (β = –.062, p = .012) and online sources (β = –.187, p < .001). In this case, there were no direct effects of ICT utilization on both trust in close relatives and online sources. Therefore, the effects of ICT utilization on both trust constructs were fully mediated by the individual's health social network behavior.

Discussion and Conclusion

This study examined the complex relationships among ICT usage, techno-capital, health social network behavior, and trust in different sources of health information. Drawing on literatures on digital inclusion, social/techno-capital, and trust, we constructed an exploratory conceptual framework. Furthermore, we examined differences between the general population and the disadvantaged, low-income population of a major U.S. city. Specifically, we compared their ICT usage as well as the degree of trust in different sources of health information.

Our findings identify two key factors affecting one's health social network behavior and trust in health information sources: Overall ICT utilization and techno-capital. Firstly, individuals' overall ICT usage in various domains of daily tasks was a substantial predictor of their health social network behavior for both populations. Capabilities of using information technologies (i.e., techno-capital) also significantly impacted health social network behavior. However, the direction diverged as the effect was positive in the general population and negative in the lower-income sample. Such counterintuitive results could be a result of the bias inherent in the nature of purposive sampling or other unidentified factors. For instance, it could be possible that the low-income people who responded had accrued a substantial level of techno-capital through training sessions offered by partner organizations but did not have sufficient access to devices or the Internet, prohibiting them from actively engaging in health social network behavior. This echoes some of the recent studies highlighting the lingering physical access problems for underserved communities during public health crises such as the COVID-19 pandemic (Eruchalu et al., 2021; Pandit et al., 2023).

Another key finding is that techno-capital was significantly related to the perceived trustworthiness of various health information sources. Except for the trust in close relatives for the general population, techno-capital positively influenced health information trust. This underscores the importance of acquiring sufficient capabilities to use ICTs and navigate and discern information. Especially, as we witness the relatively greater impact of techno-capital on the low-income population than the general population, one can infer how the educational effect of teaching digital capabilities might be greater for the less-advantaged population.

We also found that health social network behavior was related to a less extent to health information trust for the general population, whereas it played an intriguing mediating role for the low-income population. This could imply that individual health social network activity is not very integral for most people but is pivotal for socially disadvantaged people. In other words, for most people with middle-class socioeconomic status, actively seeking out health information and supportive actions matters less compared with those with lower socioeconomic status.

Another possible explanation is that for the low-income population, there are more financial and societal barriers that prohibit them from reliable, consistent relationships with health-care professionals, making them more reliant on close social networks or available information from online resources. Such barriers and poor communication with professionals might be sone of the influential factors affecting the contrasting patterns of trust in different sources of health information that were found in our analyses. This suggests that there is a higher probability of unvetted health misinformation among the less advantaged, and policy makers and regional stakeholders should pay particular attention to this. Additionally, practitioners should strive to provide more access to tools and build individual capabilities for the disadvantaged as studies show the adoption of health informatics that provides direct communication with health professionals, such as telehealth, can be enhanced even for the older population, who tend to refrain from using such types of service (Heponiemi et al., 2022).

Last, but not least, we found that the relative prominence of smartphones and computer devices in their ICT battery influenced trust in online health information and health professionals in the general population and low-income population, respectively. One possible explanation could relate to the difference in ICT usage between the two populations. Aligning with previous studies, our results indicate that the low-income population tends to use smartphones more in most daily activities compared with conventional computer devices. On the other hand, the general population used computer devices relatively more than smartphones (Tables 2 and 3). Such a predisposition could be a reason why the impact of relative computer usage emerged as a significant factor for the low-income population whereas the effect of relative smartphone usage surfaced for the general population.

This study touches on many important issues related to our ICT-permeated information environment, particularly in the context of health information dissemination. Most importantly, we take advantage of comparable data sets and offer a valuable empirical investigation of groups of people that are relatively understudied. Our study may offer insights for policy makers and health-related organizations on how relatively disadvantaged parts of our society use technologies and trust their information sources differently. Moreover, our findings suggest that investing in promoting their techno-capital could potentially contribute to elevating trust toward public health-care professionals.

Our findings are not without limitations. First, our model only examined one form of social capital (i.e., social support network), which showed few issues regarding its measurement as well. A better and more comprehensive operationalization of social capital would have bolstered our results. Second, the bias from the sampling methods employed for the second data set might have cast an undetected influence on our model. Although PLS-SEM offers flexibility in dealing with non-normal data, our data for the low-income population sample were strictly purposively selected. Finally, there would always be other critical factors and variables that the conceptual model proposed in this study might have ignored. We encourage future studies to expand and advance the model for a better understanding of relationships among technology, social capital, and trust.

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