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Trust in Digital Health among Older Adults in Remote Areas of Italy: A Latent Class Analysis

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Trust in Digital Health among Older Adults in Remote Areas of Italy: A Latent Class Analysis

ABSTRACT

Background: Digital health technologies have developed and significantly diffused during the COVID-19 pandemic, especially as a solution to reach patients with chronic conditions. Trust in these technologies is a principal component of the interaction and essential for its effectiveness.

For this reason, the study analyzes trust in digital health technologies among older people living in remote areas in Italy to promote access to remote care.

Method: The study is based on a multiple-choice paper-based survey (n = 2073) on the propensity to use digital technologies distributed to the over-65s in remote areas of four regions of Italy in 2022. We evaluated, through a latent class model and a latent class regression model for polytomous outcomes, the probability that they trust health technology tools, inferred from specific behavior and attitude.

Results: Two latent classes were identified, interpreted as higher and lower levels of trust in digital health. The majority of respondents in our sample were classified in the higher-trust group, indicating a generally favorable orientation toward digital health technologies, despite relatively low levels of actual use.

Conclusion: This evidence may inform healthcare policies for older adults living in remote areas, for whom digital health technologies have the potential to support more personalized and accessible care.

Keywords: digital health; trust; older adults; propensity to use; digital health technologies;

Introduction

In recent years, especially with the advent of the Covid-19 pandemic, the use of digital systems for public and private service delivery has dramatically increased (1,2). The need to continue providing essential services has fostered the development of digital technologies and the transformation of different sectors (3–5). In healthcare, the urgency to reach a growing number of people to guarantee service and care delivery has driven the rapid development and adoption of digital health and new telemedicine tools (6–8), especially for patients with chronic conditions (9,10).

Care delivery in public healthcare systems is characterized by efforts to ensure equitable access, cost-effectiveness, and quality outcomes for diverse populations. In this context, digital health technologies — encompassing telemedicine, electronic health records (EHRs), mobile health (mHealth) applications, and wearable devices — offer promising solutions for enhancing healthcare delivery. These technologies have the potential to improve access to health services, streamline care coordination, and reduce healthcare costs while maintaining or improving the quality of care (11,12). For instance, telemedicine has expanded access to care, especially in underserved and remote areas, by reducing geographical barriers (13). Digital tools such as EHRs and e-prescriptions facilitate more efficient data sharing and care continuity (14,15). Wearable devices and mHealth applications empower patients to self-monitor and manage chronic conditions (16,17).

However, despite their potential, implementing digital health technologies in healthcare systems requires careful consideration of factors such as equity of access, technological literacy, and rigorous technology assessment to ensure these tools contribute to sustainable and patient-centered care delivery (18,19). On the population side, the determinant is connected to the willingness to use such technologies, which are perceived to be helpful in the care process. Indeed, in addition to the traditional barriers associated with technology adoption, mainly related to skills and the digital divide (20,21), where difficulties are often observed in the elderly segment of the population (22–24), it is crucial to examine whether, on the part of users, there is confidence in such new tools (25). In particular, older adults (over 65 years of age) are the primary recipients of investments in healthcare for chronic conditions (26–28), and are usually less accustomed to the use of technologies (22,29). Although they have lower digital literacy than younger generations, older adults have been more involved in adopting new health technologies, including using digital services to overcome the pandemic shutdown. This is especially pronounced among those residing in remote areas, who already faced challenges accessing healthcare facilities before the COVID-19 era (30,31).

Although several studies analyze the digital competence barriers of older adults (32,33), to the best of our knowledge, the topic of trust in health technologies and willingness to use them is fragmented. This paper aims to fill the research gap by evaluating trust in digital health technologies among their primary recipients, older adults. More specifically, the study addresses the practical problem of how to promote equitable access to remote and digitally mediated care among older adults living in remote inner areas, considering a population that is at once a primary target of digital health investments and one of the most exposed to the digital divide. Accordingly, the study pursues two objectives: (i) to identify and characterize latent subgroups of older adults according to their level of trust, understood as a general dispositional orientation, in digital health technologies, and (ii) to examine whether socio-demographic and health-related characteristics are associated with membership in these subgroups. The evidence produced is primarily intended to inform policymakers and public healthcare decision-makers designing digital health and telemedicine strategies for remote areas, the public and third-sector organizations delivering digital literacy initiatives, and ultimately the older adults themselves, whose access to care may benefit from trust-informed interventions.

The concept of trust in digital technologies

Trust is defined as a willingness to be vulnerable, based on the positive expectations and characteristics of another party who will perform a specific action necessary to the first party (34–

37). The trustor or trustee can be an individual, organization, institution, or system. Thus, in a broad sense, trust in technology refers to a willingness to depend on the specific technology in a given situation in which negative consequences are possible (38). To be considered trusted, technology possesses the necessary attributes to function as intended. These characteristics include adequate capacity and functionality, sufficient availability, and consistent reliability (39). Furthermore, trust is an essential determinant of users' acceptance and adoption of digital services (40). Indeed, it can be considered a predictor of intended use by the population(41) and the primary construct for understanding users' perceptions of technology (42). However, the concept of trust is tough to quantify, as it is by nature generally considered not directly measurable (43). Indeed, the measurement of trust remains conceptually and methodologically challenging, and there is no single standardized or universally accepted approach, even though there are some suggestions about creating methodologically validated shared indicators to measure trust directly (44). Even the use of specific questions or scales could be interpreted differently by users or still mask the actual response. For this reason, trust can be considered a latent construct that is assumed to be related only to one or more manifest variables, meaning that trust is not directly observable but must be inferred from observable attitudes and behaviors, rather than captured through a single direct question. (45,46). This is also more relevant in complex systems where different determinants can influence the trust in innovative services provided, such as healthcare (43). Factors that influence the introduction of innovations(47) and, in particular, innovative technological tools have been examined several times in the literature (48–50), also regarding the healthcare sector (51,52). Factors such as age, education level, income, technological capabilities, availability, and current use of technologies were highlighted that can undoubtedly influence adoption decisions (53,54). It is highlighted that several models were conceptualized to assess technology acceptance and adoption, such as the Technology Acceptance Model (TAM)(55,56) and, later, the Unified Theory of Acceptance and Use of Technology (UTAUT) (57,58), later revised and adapted over time (59,60). Mainly concerning the age factor, the Senior Technology Acceptance Model (STAM) was formed, a specific model that would consider the older age of individuals faced with the need to provide for the adoption of innovative technologies (61,62). However, none of these original models includes the trust construct (63). Indeed, trust is frequently treated as an extension of existing models such as the TAM and the UTAUT rather than as a central construct (64–66). Existing studies adopt heterogeneous conceptualizations of trust (e.g., institutional vs. technological trust) and rely on diverse measurement strategies, often not directly comparable (67). Individuals may report positive attitudes toward technology without fully trusting it, or conversely, rely on technologies in practice despite expressing uncertainty, especially if they are elderly (68,69). Capturing trust through observable behaviors, therefore, allows a more nuanced interpretation of individuals' relationships with digital health technologies (70). The literature further distinguishes the stage at which trust operates. Before any direct experience with a technology, prospective users form an initial, dispositional trust, grounded in general beliefs, propensity to trust, and the perceived characteristics of the technology, which underpins the intention to adopt it; once the technology has been used, a continuous, experience-based trust develops, shaped by the actual interaction with the tool and expressed as the willingness to keep relying on it (71,72). Although the mechanisms that generate trust differ across these two stages, both rest on a more general dispositional predisposition to rely on digital tools for health. In the present study, trust is deliberately conceptualized at this general dispositional level - as an underlying orientation that precedes and cuts across the adoption and usage stages - rather than as a stage-specific construct, a choice that is coherent with a sample in which actual users represent a small minority. Reference is often made to the concept of utility and perceived ease of use of technology (56,59), but it does not consider that users usually decide, based on their personal experience, beliefs, and general attitudes (73). This primarily affects older people, who have ingrained habits and tend not to recognize the usefulness of technology (63,74), seeing it more as a means of potentially decreasing social contact(33,75) and an increasing perceived risk in relation to limited digital self-efficacy (25,76). Thus, since there is limited research on trust in technology adoption for elderly people, we chose to investigate this issue, with specific reference to digital health, considering that various technologies are specifically designed for them, as a target population mostly living in remote rural areas (13,31,69).

Methodology

Questionnaire and sample

The study is based on a paper-based questionnaire on the digital health gap distributed to the elderly (over 65 years) living in rural remote areas of four Italian regions: Tuscany, Lombardy, Veneto, and Calabria. The sampling was constructed to be regionally representative of the older population living in municipalities identified as remote areas. The municipalities were classified by the National Strategy for Inner Areas (SNAI) criteria (77). The sample size was determined to ensure representativeness of the target population rather than to test a specific statistical hypothesis. The sample size was determined using a precision-based approach aimed at ensuring an adequate level of representativeness of the overall target population, rather than through a conventional power analysis based on a pre-specified effect size. This choice was considered appropriate because the study was exploratory and descriptive in nature and relied on latent class analysis, rather than testing a single primary statistical hypothesis. Latent class analysis is a person-centered modeling approach used to identify unobserved subgroups based on response patterns across manifest variables, with model selection generally relying on fit indices and theoretical interpretability (70,78–80). For the survey component, the required sample size was estimated using the standard formula for proportions in large populations (81). where Z = 1.96 for a 95% confidence level, p = 0.50 represents the most conservative expected proportion, and e = 0.05 is the margin of error. This calculation yielded a minimum required sample size of approximately 385 respondents. The final analytical sample included 2,073 respondents from four Italian regions, largely exceeding the minimum required threshold for the overall study population. Eligibility for the study was defined by explicit inclusion and exclusion criteria. Respondents were included if they (i) were aged 65 years or older, (ii) were resident in a municipality classified as a remote inner area according to the SNAI criteria within one of the four regions considered (Tuscany, Lombardy, Veneto, and Calabria), and (iii) completed the paper-based questionnaire, providing valid answers to the three benchmark items subsequently used to infer trust. Respondents were excluded if they were younger than 65 years, resided outside the targeted remote areas, or did not provide valid responses to all three benchmark items. On this basis, of the 2,188 older adults who took part in the survey in the targeted areas, 115 were excluded because of missing responses to at least one benchmark item, yielding the final analytical sample of 2,073 respondents. The resulting findings apply specifically to community-dwelling older adults living in remote inner areas of the four Italian regions considered and should not be generalized to institutionalized older adults, to younger age groups, or to older adults residing in urban or non-remote areas. The inclusion of respondents from Tuscany, Lombardy, Veneto, and Calabria was intended to capture geographical heterogeneity across different Italian macro-areas. Moreover, the final sample size is appropriate for latent class analysis, which requires sufficiently large samples to ensure stable class estimation and reliable identification of latent response patterns (70,80). For further details, please refer to Vainieri et al.(29,82) where the survey is findable in the supplementary material. Prior to constructing the survey, we conducted a literature review to identify relevant domains. This involved a scoping review of existing literature to ensure all key aspects of the construct, such as intention to use (69), were covered. Moreover, we did a subjective assessment to ensure the questionnaire appears relevant, readable, and clear to our target audience (Italian elderly people living in inner areas). The process includes reviewing the formatting, layout, and clarity of the paper in Italian. The draft survey was assessed on a small sample of the target population, consisting of 10 participants, to identify any confusing, leading, or poorly phrased questions. We found no issues with the questions. The survey was administered in paper form (PAPI - Paper And Pencil Interview) in a large print format to overcome access difficulties for those with digital and readability weaknesses. The survey, consisting of twenty multiple-choice questions and divided into four sections, involved the collection of (I) characteristics of respondents and their health conditions, (II) information on access to digital tools, (III) use of technology for health issues, and (IV) propensity to use them in the present and the future. The survey was not specifically constructed to assess the level of older people's trust in health technologies, but more generally on their actual use, plus the possible digital divide that can arise in the elderly and people living in rural areas. For this reason, the original survey was not specifically designed to directly measure trust through validated psychometric scales. However, in the survey are present specific items that can capture relevant behavioral and attitudinal dimensions (perceived usefulness, current use, and willingness to adopt), which can be interpreted as indirect manifestations of trust in digital health technologies according to existing literature in the field of social sciences (43,67,83,84). We based our research on trust in digital technologies for health on the point that trust is a complex and vague concept that cannot be directly quantified. In line with social science approaches, trust is conceptualized as a latent construct inferred from observable variables. Consequently, it can be seen as a latent phenomenon measured indirectly by manifest variables. Three questions out of twenty were identified within the questionnaire as benchmark indicators of trust in health technologies:

- Question No. 1: Can technology help control your health conditions better?
- Question No. 2: Do you already use health technology tools (apps, sensors, smart watches, etc.)?
- Question No. 3: Would you be willing to experiment with new technological tools to monitor your health conditions?

These questions are interpreted as observable manifestations of underlying trust, as they reflect individuals' willingness to rely on, evaluate, and engage with digital health technologies. Believing useful or using a technology to control one's health, or the propensity to experiment with its use in the future, are specifically representative of the concept of trust in technologies (36,38,39). This approach is consistent with latent variable modeling strategies, where unobservable constructs are estimated probabilistically through response patterns, rather than directly measured. Because the three indicators capture a general, dispositional form of trust rather than a stage-specific one, the analysis intentionally pools respondents who already use digital health tools with those who do not. Indeed, from a theoretical standpoint, dispositional trust is an antecedent common to both the adoption and usage stages, allowing the two subgroups to be meaningfully located on the same latent dimension. The latent construct estimated by the model therefore reflects a general orientation toward digital health technologies rather than an experience-based, usage-stage trust.

Data analysis

The analysis was performed using the R 4.1.1 statistical software (85). Initially, we identified the responses to the three previous questions in the questionnaire as indicators of trust.

The personal characteristics of these respondents were then analyzed by gender, age, education level, any chronic conditions, and geographic origin to provide a complete description of the sample.

Next, polytomous variable latent class analysis (LCA) was conducted to study trust in technologies as the variable of interest (78,79). LCA was chosen as an effective analytical method because it can inform practice in developing strategic policies (67,70). The LCA model aims to partition the cross-classification table of observed variables based on an unobserved categorical variable, which removes any confounding between the manifest variables. Given the values of this latent variable, responses to all manifest variables are assumed to be statistically independent. In essence, the model probabilistically assigns each observation to a "latent class", predicting how that observation will respond to each manifest variable. While the model does not automatically specify the number of latent classes in a given dataset, a range of parsimony and goodness-of-fit statistics can be used to make a theoretically and empirically informed decision. Since the unobserved latent variable represents class membership, which is nominal, the latent class model is a type of finite mixture model. Observations with similar response patterns on the manifest variables tend to cluster within the same latent classes. Analyses were conducted using the R packages “mirt”(86) and “poLCA” (80). Since, in the literature, trust can be considered a latent trait, not directly measurable, and with a fuzzy conceptual definition that can be interpreted differently by different respondents, it was decided to refer to the aforementioned statistical model (79) that can be used to identify clusters of individuals of similar types or observations from multivariate categorical data, to estimate the characteristics of these latent groups, and return the probability that each observation belongs to each group. The model that best fits the data collected according to the AIC and BIC criteria (87,88) and entropy (89) is a model that considers two latent classes (aic=7282.373, bic=7333.104, entropy=0.74) that can be interpreted as trust in technology (Class 1) and non-trust in technology (Class 2).

Accordingly, the various response profiles were investigated, and all possible combinations were identified. Based on the emerging combinations, the conditional probabilities of respondents falling into one of the two previously identified classes were checked.

Finally, Latent Class Regression (LCR) models are applied. LCR is an extension of the basic LC model that allows for the inclusion of covariates to predict latent class membership. In the basic model, each observation has an equal probability of belonging to any latent class before responses to the manifest variables are considered. However, in the LCR model, these prior probabilities differ across individuals based on a set of independent (or concomitant) variables. Due to the small sample size relative to the number of parameters to be estimated in the model, we implemented four independent univariate models in this paper, each using a single auxiliary variable at a time. The four covariates considered are sex, age, educational level, and health conditions.

Findings

A total of 2073 elderly people out of 2188 living in the remote areas of four regions responded to the questionnaire by answering the three benchmark indicators on trust in health technologies reported in the methodology session. The sample size is adequate to obtain results representative of the population considered, with the descriptive and non-inferential purpose of the present analysis. Table 1 shows that among the participants who answered all the questions on trust, most are between 65-74 years old (55.14%), there is gender balance, and most have only had access to primary grades of education, such as elementary school (36.37%) or secondary school (36.47%).

Table 1 *Respondents' characteristics and geographical origin*

Gender	*Men*	*Female*		
	1042 (50,27%)	1031 (49,73%)		
Age	*65-74*	*75-84*	*85+*	
	1143 (55,14%)	707 (34,10%)	223 (10,76%)	
Education	*Primary School*	*Middle School*	*High School*	*Degree or more*
	754 (36,37%)	756 (36,47%)	437 (21,08%)	126 (6,08%)
Chronic diseases	*no*	*yes*		
	846 (40.81%)	1227 (59,19%)		
Regions	*Lombardy*	*Veneto*	*Tuscany*	*Calabria*
	496 (23.93%)	597 (28,80%)	308 (14,85%)	672 (32,42%)

Most respondents (58.03%) recognize that technology can help them control their health, compared with just over one-third who are undecided (36.37%), and only a tiny percentage (5.60%) explicitly declare that they do not consider it worthwhile. The majority of survey participants would be willing to experiment with new health technology systems in the future (69.61%), even though just under one-fifth of them use them in their daily lives (17.12%). Indeed, current users represent only a small minority of the sample, so that the latent structure is overwhelmingly informed by respondents at the pre-adoption stage. Indeed, most of the sample does not already use health technology tools (82.88%). Table 2 shows the data and response rates for the three benchmark questions.

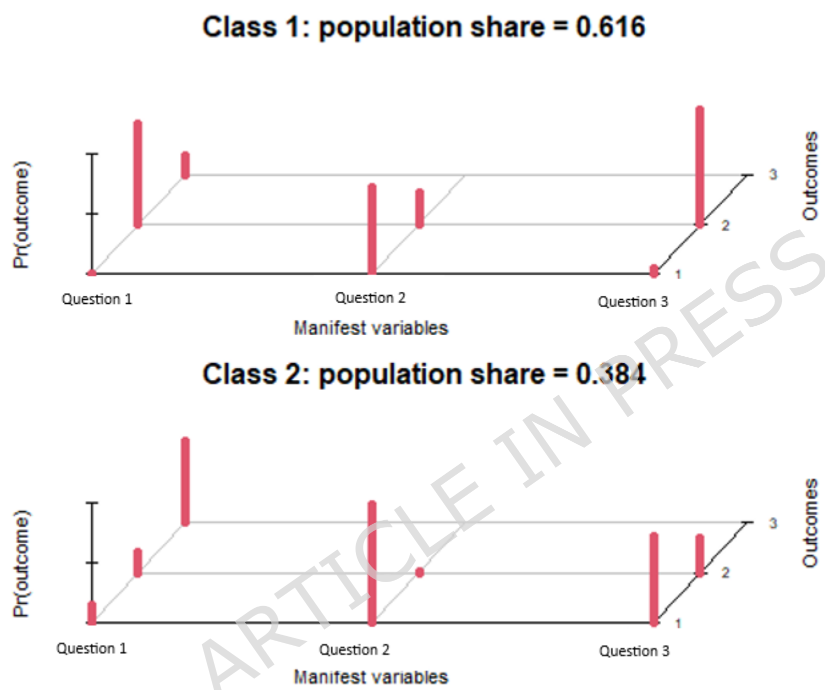
Table 2 *Response data and percentages for the three benchmark questions to assess trust (with variable references).*

Core questions and variables	Answer NO	Percentage of NO (%)	Answer YES	Percentage of YES (%)	Answer DON'T KNOW	Percentage of DON'T KNOW (%)
Question n. 1	116	5.60	1203	58.03	754	36.37
Question n. 2	1718	82.88	355	17.12	----	----
Question n. 3	630	30.39	1443	69.61	----	----

Next, based on the combination of participants' responses to the baseline questions on trust, it was found in which latent variable identified by the latent class model respondents were most likely to be included. Class 1, representing the group that trusts health technologies, included 61% of the sample respondents, while Class 2, or the group of those who do not trust, included 38%.

Figure 1 represents the graphical expression of the probability of being in a given class based on the answers provided in our multidimensional item response theory (MIRT) model.

Figure 1 *Graph expression of the multidimensional item response theory model reporting the probability of being in one of the two classes based on the responses to the trust baseline questions (outcome: no=1, yes=2, don't know=3).*



These analyses, regarding the probability per single answer, are shown in Table 3, and they show how the answers to questions 1 and 3 drive participants to converge in one or the other class. Indeed, the choice of whether to use new health technologies in the future leads to quite opposite solutions: those who answer "yes" have a 95% probability of ending up in the class of those who have confidence in them, those who answer "no" have a 72% probability of being included in the class in which they do not. As for the question assessing the usefulness of technologies for health, on the other hand, those who answered "yes" are 83% more likely to be included in Class 1, while it is interesting to point out that, for Class 2, the answer “don't know” is the most relevant one, being able to comment on how an undecided answer tends to be seen as a lack of confidence. Finally, question 2, regarding the use of health monitoring tools, notes how the “no” answer results in a high conditional probability of being included in both classes.

Table 3 *Conditional probability of falling into any of the two classes based on responses to the baseline questions.*

Questions/Variables	Classes	Answer NO	Answer YES	Answer DON’T KNOW
Question n. 1	Class 1	0.0009	0.836	0.1631
	Class 2	0.1443	0.170	0.6857
Question n. 2	Class 1	0.7282	0.2718	_______
	Class 2	0.9900	0.0100	_______
Question n. 3	Class 1	0.0470	0.9530	_______
	Class 2	0.7161	0.2839	_______

Moreover, eleven possible combinations were found in our data after analyzing all the possible response combinations in the survey. The combination “no, yes, no” is the only one not present in our data; therefore, the model created does not capture it (its probability is equal to zero). The analysis verified that the highest conditional probability of being included in Class 1 is when all questions are answered positively (combination n. 7, p=0.9986). In contrast, the highest conditional probability of being included in Class 2 is combination n. 1, where the answers are always negative.

It should be noted that, as anticipated by the lack of the combination of responses, there are no subjects in the sample who already use health technology tools but feel that they do not help monitor health status and, at the same time, are not inclined to use new ones in the future.

Those who respond positively to the first two questions, regardless of their answer to the third, will fall into Class 1 (combination n. 6 and n. 7). It appears, on the other hand, that those who have doubts about the usefulness of such tools (answer “don't know”), even if they already use them, if they have the propensity to use new ones will fall in Class 1 (p=0.9726), as per combination n. 11. If the last answer is negative, they will tend to fall in Class 2 (p=0.5909), as per combination n. 10. If one answered positively to the first and third, the non-use of technological tools for health does not influence the likelihood of being included in the group in which there is confidence in technologies (combination n. 5, Class 1 p=0.9513). If, on the other hand, although not using such tools, one is likely to use them in the future but does not rate them as helpful in monitoring health status, the respondent will tend to fall into Class 2 (combination n. 2, Class 2=0.9701). See Table 4 for all specific combinations.

Table 4 *Conditional probability of fit into one of the two classes based on the possible answers to the three baseline questions to assess trust.*

Possible Combinations	*Question n. 1*	*Question n. 2*	*Question n. 3*	*Class 1 Trust*	*Class 2 No Trust*	*Total respondents*
1	*no*	*no*	*no*	*0.0006*	*0.9994*	*89*
2	*no*	*no*	*yes*	*0.0299*	*0.9701*	*26*

3	*no*	*yes*	*yes*	*0.5362*	*0.4638*	*1*
4	*yes*	*no*	*no*	*0.2760*	*0.7240*	*133*
5	*yes*	*no*	*yes*	*0.9513*	*0.0487*	*772*
6	*yes*	*yes*	*no*	*0.9346*	*0.0654*	*14*
7	*yes*	*yes*	*yes*	*0.9986*	*0.0014*	*284*
8	*don't know*	*no*	*no*	*0.0181*	*0.9819*	*386*
9	*don't know*	*no*	*yes*	*0.4861*	*0.5139*	*312*
10	*don't know*	*yes*	*no*	*0.4091*	*0.5909*	*8*
11	*don't know*	*yes*	*yes*	*0.9726*	*0.0274*	*48*

To estimate the LCR models, the covariates "Age" and "Education" were redefined as follows. Age has been categorized into two categories (less than 75 years old; 75 and older). Educational level has been rewritten into two categories (elementary and middle school; high school and university degree or more). The health status represented by the variable chronic disease and the variable sex remained unchanged, as it was already a dichotomous variable. In our three different models, the considered covariates are not statistically significant at a 95% confidence level: Age (p-value 0.11), Education (p-value 0.05), Gender (p-value 0.30), and Chronic conditions (p-value 0.17).

Discussion

Our study aimed to analyze the topic of trust in new digital health technologies at the Italian level. Trust plays a vital role in the willingness to embrace technology and rely on it for healthcare needs (76,90–93), on par with other factors such as perceived usefulness and ease of use, might be (55,57), and the technology assessment (18,94). Indeed, the findings show that the older adults in our sample mostly tend to trust digital health technologies, believing they can help monitor their conditions and would be willing to use them in the future. Although only a portion of them responded that they already use wearable devices, this did not influence whether they might decide to use them moving forward. This finding suggests that trust may precede actual use, indicating a latent predisposition toward digital health technologies that is not yet translated into an actual behavior. Definitely, there seems to be a large portion of the older population that appears inclined to adopt and confident in using new technological tools for health, believing that the problems to be overcome in the digital sphere are mostly related to the lack of skills and difficulty in using the technologies themselves(95) and not based on mistrust (96). This analysis indeed provides valuable insights for future policymaking in the realm of digital health technologies for older adults. Educational level showed only a borderline association with trust in our sample ($p = 0.05$), which did not reach conventional statistical significance but points in the same direction as previous evidence (53,97,98). Otherwise, age and health conditions seem not to be a significant moderating factor affecting trust, having to be assumed that the educational level could cover the effect of age and that trust is not directly related to chronic conditions and, consequently, the need for increased use of devices to control it. Compared with other studies, however, no differences were found in gender (99,100). The finding that educational level appears more relevant than age in shaping trust in digital health technologies deserves further consideration. We found a significant negative correlation between age and education level in our sample (Spearman's rho = -0.48, $p < 0.001$), indicating that older participants in our study often have lower educational attainment. While age is traditionally identified as a key determinant of the digital divide, our results suggest that education may play a more direct role in shaping individuals' trust and attitudes toward technology. In particular, education can be interpreted as a proxy for cognitive and digital capabilities, enabling individuals to better understand and interact with digital tools, thereby fostering trust. This interpretation is consistent with the literature highlighting that the digital divide is increasingly shifting from a demographic gap (age-based) to a capability gap (skills-based) (80). In this perspective, older age per se may not directly reduce trust, but rather operates through mediating factors such as lower educational attainment, reduced digital literacy, and limited prior exposure to technology. Moreover, the lack of statistical significance of age in our model suggests that trust in digital health technologies may not be strictly a generational issue, but rather a function of individuals' ability to interpret and engage with innovation. This is particularly relevant in the context of digital health, where perceived complexity requires a certain level of cognitive and informational capacity to be managed. Anyway, we acknowledge that the relationship between age and education is likely intertwined. In our sample, older cohorts tend to have lower educational attainment, reflecting historical differences in access to education. This may partially explain why education emerges as more relevant than age in the model. This evidence could be significant in providing essential insights into the healthcare sector's market and in light of future prospective evaluations on research and development of new digital technologies (63). Indeed, these findings suggest that policies aimed at promoting the adoption of digital health technologies should focus not only on age-related barriers but, more importantly, on strengthening digital health literacy among the population. On the other hand, policies for digitalizing older people should focus on communication, accessibility, and ease of use while promoting technology integration into various aspects of their lives, from healthcare to social interaction (101,102). Therefore, educational campaigns that emphasize the benefits and effectiveness of these tools could be beneficial. Additionally, addressing the skepticism highlighted by those who answer "don't know" might create a more informed population, ultimately leading to higher adoption rates. In this way, technology could become a modality to increase the autonomy of older adults and increase engagement in their own care (103). Indeed, especially those with mobility challenges or those living in rural areas would gain more straightforward access to care without traveling. Digital health technologies could also help with chronic disease management through regular remote video consultation and real-time monitoring of vital signs. Therefore, policies should focus on skill acquisition and establishing tools for the elderly. For instance, specific digital literacy programs(104,105) with the involvement of the third sector could be fostered, especially with the involvement of young digital natives: this is the case with programs that have arisen in the different regions under analysis, where skill enhancement has been encouraged through intergenerational matching. Moreover, public healthcare systems could allocate specific funding to support digital health and telemedicine as essential services for optimizing care delivery. Governments might also implement incentive programs encouraging public healthcare organizations to adopt digital health technologies by providing additional funding or resources for those transitioning to remote care models. In this sense, the Italian government has allocated specific funds to promote digital transformation(106–108) through training programs, acquiring user-friendly devices, and establishing a platform for delivering telemedicine services at a centralized level (109). This also promotes service standardization, ensuring interoperability and easier patient information sharing. Thus, it is a matter of forming a constructive interaction between the health system, private companies, and the nonprofit social enterprise sector in order for all population groups can benefit from digital health technologies.

As a result, older people could secure better access to these technologies and increase their trust by assessing their usefulness. Finally, in terms of regulations, these synergies can produce more secure systems, also regarding data protection, favoring the reduction of privacy concerns and improving trust in the technologies (110).

Limitations and further research

Our study has some limitations. First, we point out that the study is specifically aimed at elderly users living in remote areas, who were targeted because this specific group is the recipient of several policies related to digital health. Therefore, our results should be interpreted cautiously for applications in other populations and age groups. Second, in our study, trust was not directly measured through validated scales, as the original survey was not specifically designed for this purpose. The original survey was designed to explore broader aspects such as digital divide, barriers, and propensity to use technologies; the present study focuses specifically on a subset of variables that are theoretically linked to trust and uses them to model trust as a latent construct. Indeed, it was inferred through proxy variables capturing behavioral and attitudinal dimensions. While this approach is consistent with the treatment of trust as a latent construct, it may not fully capture all its dimensions (i.e., income).

A further limitation concerns the pooling of respondents at different stages of engagement with digital health technologies — the majority who have never used them and the minority who already do. Because the mechanisms underpinning trust may differ between the adoption stage, at which trust reflects an intention to adopt, and the usage stage, at which trust is shaped by direct experience, analyzing the two groups jointly entails a degree of simplification. We mitigated this concern by conceptualizing trust at a general dispositional level and by noting that current use was the weakest discriminating indicator in our model; nevertheless, future studies with larger numbers of actual users could model initial and continuous trust separately, or formally test the stability of the latent structure across user and non-user subgroups.

Future research may focus on trust in healthcare technologies among different population groups. It may also investigate the gaps between the different target groups and the additional factors that could not be tested in this study, such as whether the presence of a social community may change users' attitudes. Moreover, an extension of the model allows for the inclusion of new covariates linked to the literature to predict latent class membership. Furthermore, trust in digital health technologies was inferred through indirect indicators rather than measured using validated psychometric scales. Although this approach is consistent with the conceptualization of trust as a latent construct, it may not fully capture all its dimensions and could introduce measurement bias. This highlights the need for future research to further refine measurement approaches in this field.

Conclusion

Older adults' trust in digital health technologies plays a pivotal role in the effectiveness of health care delivery. While innovations in health technologies have the potential to improve access to and utilization of health services significantly, issues such as technological literacy and perceived complexity may hinder adoption among older adults. Despite these challenges, when trust is established and sustained, it becomes easier to foster change toward digital. Digital health technologies have the potential to support more personalized and efficient care. Our findings suggest that trust in digital health technologies among older adults should not be interpreted as a static attitude, but rather as a latent and evolving disposition shaped by experience, capabilities, and contextual factors. Maintaining this trust and building new ones requires ensuring that technologies are user-friendly and affordable, and that they demonstrate clear benefits in improving health outcomes while addressing older adults' unique needs and concerns. This can foster greater acceptance and utilization of these innovations.

Declarations

Ethics approval and consent to participate.

The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and its subsequent amendments. The present study complies with the ethical standards for human participants in the social sciences and does not concern medical research. In accordance with Law No. 3/2018 and Legislative Decree No. 211/2003, ethics committee approval is not required for anonymous studies that do not involve clinical research in Italy. Participants have been informed and have given their consent to participate by completing the questionnaire. The data collected are anonymous and, therefore, excluded from processing under the GDPR and the Italian Privacy Law.

Consent for publication

Not applicable.

Competing interests

The authors report that there are no competing interests to declare.

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