FinJeHeW Finnish Journal of eHealth and eWelfare

SCIENTIFIC PAPERS

VERTAISARVIOITU
KOLLEGIALT GRANSKAD
PEER-REVIEWED
www.tsv.fi/tunnus

Digital skills and intention to use digital health care and social welfare services among socially marginalized individuals in Finland: A cross-sectional study

Birgitta Tetri[1,2], Teemu Rantanen[1], Anne Kouvonen[2,3]

[1] Laurea University of Applied Sciences, Vantaa, Finland; [2] Faculty of Social Sciences, University of Helsinki, Finland; [3] Centre for Public Health, Queen's University Belfast, Northern Ireland

Birgitta Tetri, MSc, Laurea University of Applied Sciences, Ratatie 22, FI-01300 Vantaa, FINLAND. Email: birgitta.tetri@laurea.fi

Abstract

This article examines the relationship between digital proficiency, trust in service providers, and the intention to use digital health care and social welfare services among prisoners and people with mental health conditions in Finland. Based on cross-sectional data, which includes responses from 225 prisoners and 120 people with mental health conditions between September 2020 and May 2021, a study utilizing latent profile analysis (LPA) reveals that although high digital skills were observed, trust in providers of digital services within the health care and social welfare sector remained low, particularly among younger participants. Despite trust issues, the intention to use digital services remained high, particularly among inmates. This suggests that trust is not the sole factor influencing digital service adoption; age and perceived digital competence also play significant roles. Prisoners demonstrated higher levels of advanced internet skills than individuals with mental health backgrounds, possibly due to overestimating their abilities. Alternative approaches, such as social support and hands-on learning, are vital for enhancing digital skills in socially marginalized groups. Understanding these determinants can guide policymakers and practitioners in developing targeted interventions to promote digital inclusion effectively by considering broadly the factors that promote the accessibility of digital health care and social welfare services. Future research combining objective proficiency testing and self-reported data can offer deeper insights for more successful strategies.

Keywords: digital divide, digital health, mental health, social marginalization, social work

Introduction

The digitalization of society is rapidly transforming citizens' way of life. Digital skills have become part of the civic skills required to manage everyday life. While a large proportion of citizens consider their skills sufficient to use digital devices and services fluently in their daily lives and feel that they benefit from them [1], some are marginalized due to a lack of equipment, digital or other (e.g., language) skills, ill health, and negative attitudes towards technology [2]. This applies particularly to citizens who are economically and socially disadvantaged [3]. The COVID-19 pandemic caused essential health and social welfare services to transition rapidly to online platforms, exacerbating existing inequalities [4].

Citizens' inequalities are manifested as a digital divide, consisting of access and availability of digital services, digital literacy, and skills in the use of services and technology, and the benefits, impacts, and relevance of services [5]. Socially marginalized groups lack economic, cultural, social, and personal resources, exposing them to digital exclusion [2]. Vulnerability within socially marginalized groups results from complex interactions of various factors over the life course [6]. This study examines two socially marginalized groups, prisoners and people with mental health conditions, that face a high risk of being excluded from digital services.

Individuals in these groups share specific characteristics that can make it challenging to acquire digital skills [7] Prisoners often have substance abuse problems, mental health conditions, and somatic diseases [8]. Approximately 32.8% of the prison population in Europe experience mental health disorders, although this percentage likely underestimates the actual prevalence due to potential underreporting [9]. Mental health conditions are associated with reduced functional capacity using digital devices and the internet [10]. Stigma related to prisoners [11] and people with mental health conditions [12] is a well-documented social phenomenon that can significantly impact individuals' lives and their access to resources and support. Exclusion from public services is likely if the prerequisite is independent use of digital services regardless of the person's digital, language, and literacy skills or cognitive and health status [13].

Key concepts

In this study, the concepts of *digital skills, internet self-efficacy, and trust* are essential in determining an individual's *behavioral intention* to use digital health care and social welfare services. Digital skills reflect a user's actual behavior, while internet self-efficacy [14,15] represents their belief in the ability to use the internet effectively. Trust has been shown to influence attitudes toward technology positively and, in turn, affect behavioral intentions [16]. Together, these factors provide an understanding of technology adoption and usage and can guide the design of effective strategies for promoting digital services.

Digital skills, understood as the ability to interact with digital content effectively, are not innate but developed competencies [4]. They are built on the foundation of traditional literacy, which includes reading, writing, and interpreting text [6]. Higher education often correlates with advanced digital skills due to the ample opportunities for digital interaction it provides [6,17]. However, these skills are not solely developed through formal education; informal learning, including self-directed, experiential, and social learning, is also crucial [2].

Internet skills, a subset of digital skills, enable effective engagement with the internet. These can be divided into five types: operational (operating digital devices and software), formal (understanding and using digital systems' structures and conventions), information processing (effectively searching for, evaluating, and using online information), communicative (participating in online communication and collaboration), and strategic (using digital technologies efficiently and goal-oriented) [17,18]. Lower skill levels may limit internet access and usage [17], potentially leading to a digital divide where those with lower digital skills are disadvantaged in areas like education, employment, and social interactions [2].

In digital skills, one's confidence in their abilities is pivotal. Self-efficacy, a belief in one's ability to achieve desired results, is a key determinant of personal agency [19]. It influences the perceived usefulness and ease of use of technology [20]. *Internet Self-Efficacy (*ISE), belief in one's ability to effectively use the internet, is a significant predictor of online behavior and performance [14,15,20]. Application-specific self-efficacy, such as the ability to use health information portals, is crucial for technology adoption and is positively associated with internet use and consumer acceptance of health portals [14,15,20,21].

When discussing digital skills and internet self-efficacy, it's important to consider the role of *trust*. It is a state of mind involving expectations, beliefs, and risk-taking crucial in online contexts for security and protection against exploitation [22]. Confidence in one's skills, trust in internet security, and the service provider are prerequisites for using digital services [4,23]. Trust can influence the adoption and effective use of digital services [16,24,25]. However, certain populations, such as prisoners and people with mental health conditions, may lack trust in technology due to various factors, including privacy concerns and negative experiences [26,27].

Behavioral intention is essential in understanding how individuals make decisions about using digital services and technology. As Ajzen [28] defined, behavioral intention refers to an individual's stated willingness to engage in a specific behavior, such as utilizing digital services, in a particular context. The Technology Acceptance Model (TAM) [29] is a more specific model that concentrates on the determinants of computer technology acceptance and usage. Both the theory of planned behavior [28] and the TAM [29] aim to explain the relationship between behavioral intentions and the actual use of services. Research has demonstrated a strong correlation between behavioral intentions and actual behavior, which leads to the use of behavioral intentions as a predictor of future behavior [30].

While prior research has explored trust in service providers and the internet [23,27] however, user profiling of digital skills among socially marginalized groups such as prisoners and people with mental health conditions has not been investigated before. Understanding individuals' skill levels and their link to digital service use can guide effective digital support strategies. By better identifying the needs of vulnerable individuals, digital services can be more effectively targeted, enhancing client segmentation [31].

Aim and research questions

The primary objective of this research was to discern profiles pertaining to digital skills, internet self-efficacy, and trust in health care and social welfare service providers within socially marginalized cohorts, specifically targeting prisoners and individuals with mental health issues. Additionally, the study sought to explore the potential associations between these identified profiles and individuals' intentions to utilize digital health care and social welfare services. The present study addresses the following research questions:

> RQ 1 What kind of digital skills, internet self-efficacy, and trust profiles can be found among prisoners and adult mental health service users?
>
> RQ 2 How are digital skills, internet self-efficacy, and trust associated with the intention to use digital health care and social welfare services?

Material and methods

Sample

This study, part of a broader research project, investigates digital exclusion in marginalized groups, focusing on prisoners and individuals with mental health conditions. Both groups face societal integration challenges upon release or during daily life due to stigma and discrimination, respectively [11,12]. Despite the survey not directly addressing mental health, it's important to note the shared experiences between these groups, including learning difficulties and mental health disorders. Therefore, the study encompasses both groups, recognizing their shared struggles with societal integration and digital access.

This study's purposive sample included 345 participants, consisting of prisoners and mental health service users, surveyed from November 2020 to May 2021. The 225 prisoners were recruited from eleven Finnish prisons, including six closed and five open facilities, with a response rate of 19.9%.

The remaining 120 participants, individuals with mental health conditions, were sourced from four organizations in southern Finland that provide community-based mental health services. Most (64%) were from a medium-sized NGO, supplemented by members from three other NGOs offering rehabilitation and peer support. The public service provider NGO had a response rate of about 25%, while the rates for individually invited participants from other organizations are unknown.

Data were collected through a questionnaire, available in paper or digital format. However, in prisons, only paper responses were collected and returned anonymously in provided envelopes.

The study was conducted according to the guidelines of the Finnish National Board on Research Integrity [32], based on voluntary participation and informed consent. Stringent measures were implemented in accordance with the General Data Protection Regulation (GDPR) to ensure the preservation, handling, and storage of the data used in this study. Ethical approval was obtained from the Ethics Committee for Humanities at the Uni-versities of Applied Sciences in the Helsinki Met-ropolitan Area (Decision 6/2020; September 25, 2020). To ascertain effectiveness and accessibility, considering that prisoners and people with mental health conditions may encounter cognitive and literacy challenges, the questionnaire was tested with 11 individuals who have a criminal background. The test data was included in the analysis.

Instruments

The complete questionnaire comprised 24 questions, most containing several items and statements. This study focuses on five questions with 32 statements. Demographic questions of gender, age, and educational level were also included. The educational level variable was dichotomized into two categories: secondary education and no secondary education. As background information, the participants were asked two additional questions about the use of the internet and the types of devices and services they have at their disposal.

Basic digital skills and activities were measured with 12 items from the Australian Digital Inclusion Index (ADII) [33]. The ADII measures basic digital skills related to general internet use, mobile phone, banking, shopping, community, and information skills. Activities scale items comprise streamed, played, or downloaded content online, audio-visual communication via the internet, internet transaction or payment, purchased or sold online products, created, or managed sites or blogs, and searched advanced information. Likert scale response options ranged from 1 ("no level of competence") to 5 ("high level of competence"). If the participant was unfamiliar with the activity, "I do not know" was an option.

The internet self-efficacy scale, adapted from the Eastin and LaRose [14] study, consists of eight items that measure beliefs about the use of internet hardware and software at a general level. The measure of trust, which contains seven items, is based on the research by Carter and Bélanger [24]. This measure assesses trust in both the internet and in health care and social welfare service providers. A 5-point Likert scale was used for response options, ranging from 1 (“totally disagree”) to 5 (“totally agree”). This scale was applied to both the internet self-efficacy and the trust measures.

The measure for behavioral intention with five items on a 5-point Likert scale was planned based on previous studies on health technology [20,34]. A person’s overall readiness to use digital health care and social welfare services and the likelihood of future use of digital services were measured with two items. How eager the respondent was to apply for social welfare benefits or deal with health-related matters over the internet was measured with two questions, and the preference between remote and face-to-face appointments with health and social care professionals with one question.

Statistical analysis

The descriptive statistics were computed using IBM SPSS (version 28), and latent profile analysis was performed with Jamovi (version 2.3.18). The study analyzed the sample's demographics, internet access, and digital product usage. Exploratory factor analysis identified the best measurement model for digital skills, self-efficacy, trust, and intention to use digital health and social services. Harman's one-factor test addressed common method bias in scale variables, with the variance attributed to the initial factor below the 0.5 threshold, indicating no common method bias.

The digital skills (Australian Digital Inclusion Index) revealed two factors: basic skills (Skills B) with seven statements and advanced skills and activities (Skills A) with five statements, with a KMO of 0.934. Internet self-efficacy (ISE), trust, and intention yielded one-factor solutions. Average indices were calculated, and internal consistency was estimated with Cronbach’s alpha. Skills B, Skills A, ISE, and trust measures were compared across demographic variables (setting, gender, education) using the Mann-Whitney U test.

The number of profiles generated with latent profile analysis (LPA) was chosen according to the ones that best fit the data structure (i.e., goodness-of-fit indices). The fit indices were the Bootstrapped Likelihood Ratio Test (BLRT), the Akaike Information Criterion (AIC), the Approximate Weight of Evidence (AWE), the Consistent Akaike Information Criterion (CAIC), the Bayesian Information Criterion (BIC), the Sample Adjusted Bayesian Information Criteria (SABIC) and entropy (an overall measure of all posterior probabilities). Lower values of AIC, AWE, CAIC, BIC, and SABIC indicate greater model fit. Entropy values range from 0 to 1, and higher values indicate a better differentiation between profiles. The BLRT was used to determine whether the k-1 profile model should be rejected in favor of a k-profile model. The profile solution was analyzed further with Kruskal Wallis one-way analysis of variance to examine whether the intention to use digital health care and social welfare services and age varied depending on profile type.

Results

Characteristics of the participants

The study involved 345 participants, aged between 18 and 70 years, with a mean age of 39.9 (SD = 12.3). Most of the participants were men (71.6%), and more than half had secondary or higher education (55.8%). In terms of internet usage, most participants (68.7%) used the internet daily or almost daily, while 22.3% used it weekly to several times a year, and a small proportion (9.0%) used it once a year or never.

Regarding devices and connections, smartphones were the most popular device for internet access (79.7%), followed by personal computers (55.9%) and cable or NBN fixed broadband connections (44.3%). Tablet computers and shared family computers were used by 29.3% and 13.6% of the participants, respectively. Notably, 13.0% of the participants reported not having internet access.

Internal consistencies of the scales

To ensure the reliability of the measurements, the internal consistencies of the various scales used in the study were evaluated using Cronbach's alpha coefficient. This analysis demonstrated that the scales pertaining to basic skills (*N* = 315; *Mdn* = 4.14), internet self-efficacy (ISE) (*N* = 337; *Mdn* = 3.88), and trust (*N* = 342; *Mdn* = 3.86) exhibited satisfactory levels of internal consistency, with Cronbach's alpha values of 0.94, 0.95, and 0.96, respectively. Similarly, the advanced skills (*N* = 283; *Mdn* = 2.80) scale, with a Cronbach's alpha coefficient of 0.87, and the intention scale (*N* = 341; *Mdn* = 3.40), with a Cronbach's alpha value of 0.85, demonstrated acceptable reliability.

Univariate tests

A comparison was made of Skills A, Skills B, ISE (Internet self-efficacy), and trust measures across demographic variables such as setting (mental health and prison), gender, and education level. The Mann-Whitney U test was used to compare these measures across groups (see Table 1). The results showed lower trust scores in the prison group compared to the mental health group and higher trust measures among females than males. Advanced skills scores were lower in the mental health setting, and ISE was higher among males. However, there was no difference in basic skills and ISE between the two settings, nor in basic or advanced skills between genders. Education level had no impact on skills and trust measures.

Table 1. Skills and trust measure comparison between the settings and gender.

			N	*Mdn*	*U*	*Z*	*p*	η^2
Skills B	Setting	Mental Health	119	4.29	12572.5	-.262	.794	.032
		Prison	219	4.14				
	Gender	Male	240	4.14	10483	-.72	.474	.039
		Female	92	4.14				
	Education	No secondary	114	4.14	10663.5	-.30	.763	.017
		Secondary or higher	191	4.14				
Skills A	Setting	Mental Health	119	2.80	12332.5	-.82	.415	.097
		Prison	219	3.40				
	Gender	Male	242	2.80	10164.5	-1.52	.130	.083
		Female	94	2.70				
	Education	No secondary	116	3.10	9913	-1.55	.122	.088
		Secondary or higher	191	2.60				
ISE	Setting	Mental Health	119	3.75	12009	-1.13	.259	.062
		Prison	218	4.00				
	Gender	Male	243	4.00	8906	-3.01	.003**	.164
		Female	93	3.50				
	Education	No secondary	118	3.75	10047.5	-1.39	.164	.079
		Secondary or higher	188	3.94				
Trust	Setting	Mental Health	120	4.07	9333	-4.58	<.001***	.248
		Prison	222	3.50				
	Gender	Male	245	3.57	9377.5	-2.92	.004**	.158
		Female	96	4.00				
	Education	No secondary	118	3.86	10424	-1.18	.237	.067
		Secondary or higher	192	3.79				

ISE = Internet self-efficacy; *Mdn* = the median value of the data set; ** $p < .01$, *** $p < .001$.

Latent profiles

LPA was used to establish a baseline model of user profiles encompassing manifest variables of basic internet skills, advanced internet skills, internet self-efficacy, and trust. Five subsequent LPAs were performed to determine the most meaningful profile model based on the skill dimensions and trust. Table 2 displays the Log Likelihood, AIC, AWE, CAIC, BIC, SABIC, BLRT, and entropy values for the one to five profile solutions. The four-profile solution showed the lowest AWE, BIC, and CAIC values. A significant BLRT value (*p* <.05) indicates that the four-profile model was superior to the five-profile solution. LL and AIC kept descending slightly with an additional profile. However, the four-profile model was chosen as it showed the highest entropy and differed only in the overall level of the two indicators compared to the five-profile model.

Table 2. Information criteria values for different profile solutions.

K	LL	AIC	AWE	BIC	CAIC	SABIC	pBLRT	Entropy
1	-1623	3262	3357	3290	3298	3265	0.010	1.000
2	-1390	2807	2964	2854	2867	2813	0.010	0.885
3	-1279	2594	2812	2659	2677	2602	0.010	0.893
4	-1213	2472	2751	2555	2578	2482	0.010	0.917
5	-1207	2470	2810	2571	2599	2482	0.050	0.887

K = number of latent profiles in the model; *LL* = Log-Likelihood; *AIC* = Akaike Information Criterion; *AWE* = Approximate Weight of Evidence criterion; *BIC* = Bayesian Information Criterion, *CAIC* = Consistent Akaike Information Criterion; *SABIC* = Sample-size Adjusted *BIC*; *pBLRT* = Bootstrapped Likelihood Ratio Test. Values in bold indicate the best-fitting model.

Figure 1 presents the breakdown of standardized skills, ISE (Internet self-efficacy), and trust scores over the four profiles generated. The first cluster (labelled "Digitally unskilled but more trust profile"; *Median* = 1.89) consisted of 27 participants who reported the lowest levels for three dimensions of skills but relatively higher levels of trust. The second cluster ("Digitally adequate and confident profile"; *Median* = 2.94) comprised 53 participants who reported moderately low scores in skill dimensions but higher trust scores. The third cluster ("Digitally proficient but lack of trust profile"; *Median* = 4.50), also the largest one, consisted of 104 participants who were confident in all skill dimensions but scored lower on trust. The fourth cluster ("Digitally able and steady trust profile"; *Median* = 3.62) comprised 86 participants who reported even scores in all dimensions except advanced skills, which was slightly lower.

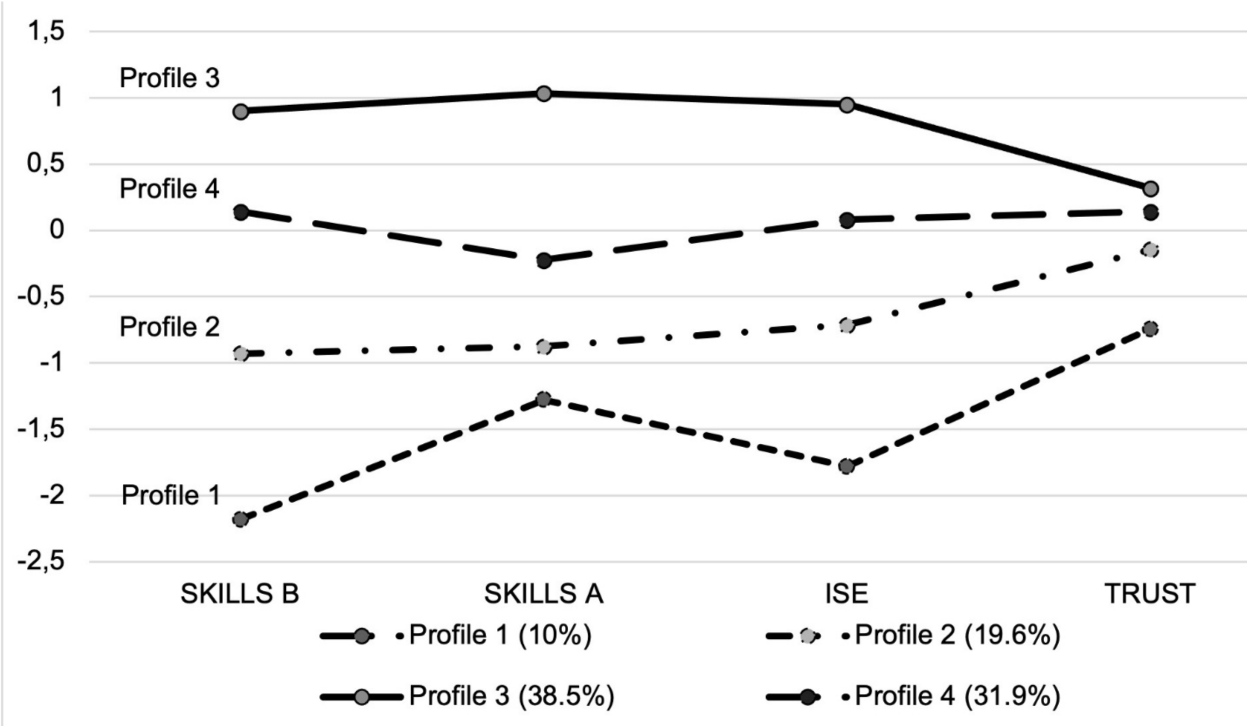

Figure 1. The four digital ability skill profiles with z-scores identified by latent profile analysis.

Note. The model indicators are on the x-axis, whereas the y-axis represents the z-scores. The four profiles were defined by the crisscrossing lines. The profile labels are listed at the bottom, with relative profile sizes presented in percentage (%) in parenthesis.

The profiles generated were further scrutinized to ascertain whether there was a significant variation in the intention to utilize digital health and social welfare services, as well as age, within the profiles. The demographic variables of gender and educational level were excluded from the analysis due to the small effect size of gender and the lack of association between educational level and any of the measures in the univariate tests. A Kruskal-Wallis test unveiled a statistically significant difference in both intention and age across the four profiles, as detailed in Table 3. Eta squared (η2), which measures the proportion of the total variance in a dependent variable that is associated with the membership of different groups, indicated a large effect in relation to both intention and age. The intention to use digital health care and social welfare services was higher in profile 3 compared to profiles 4, 2, and 1. Furthermore, participants in profile 3 were younger than those in profiles 1, 2, and 4.

Table 3. Differences in intention and age across the four skills and trust profiles.

	Profile 1 (N = 27)		Profile 2 (N = 53)		Profile 3 (N = 104)		Profile 4 (N = 86)		Post-hoc	Kruskal-Wallis	
	Mdn	*SD*	*Mdn*	*SD*	*Mdn*	*SD*	*Mdn*	*SD*	Comparison	F (3, 267)	η^2
Intention	2.30	1.10	3.20	.90	4.00	.89	3.40	.91	1, 2, 4 < 3	54.93***	.20
										F (3, 236)	η^2
Age	53	9.5	46	11.2	31	9.2	41	12.3	2, 3, 4 < 1	58.98***	.24

Mdn = the median value of the data set ; ***p < .001

Discussion

The research identified four distinct profiles of digital skills, ISE, and trust, with varying levels of skill and trust among participants. The study investigated the relationship between these profiles and the intention to use digital health care and social welfare services, finding statistically significant differences in intention across the four profiles. Additionally, age and gender were found to vary among the generated profiles.

Among the identified profiles, the largest group, "Digitally proficient but lack of trust" (profile 3), exhibited high confidence in basic and advanced digital skills and internet self-efficacy. Despite this proficiency, trust in service providers was quite low compared to their skills scores. However, interestingly, their intention to utilize digital health and social welfare services was the highest among all profiles. This profile was characterized by a relatively young age structure, suggesting that younger individuals comprised a significant portion of this group.

The second largest group, labelled "Digitally able and steady trust" (profile 4), demonstrated a balanced profile across all dimensions. They displayed a consistent inclination towards using digital services and were the second youngest group among the four profiles. The third largest group, "Digitally adequate and confident" (profile 2), fell between the characteristics of profiles 1 and 4 regarding digital skills, trust, intention, and age levels. Conversely, the smallest group, designated as "Digitally unskilled but more trust" (profile 1), scored the lowest in digital skills and intention levels. Additionally, this group consisted of older individuals with higher levels of trust in digital service providers despite their limited digital skills.

Regarding the intention to use digital services, it was found that age significantly influenced digital skill profiles. The two largest profile groups demonstrated high levels of internet self-efficacy, a factor known to promote the adoption of digital services [21]. The largest profile is of particular interest, characterized as "Digitally proficient but lack of trust," which exhibited low trust in digital service providers but showed a high intention to use digital services. Furthermore, younger participants displayed a higher intention to use digital services irrespective of trust issues, indicating their greater openness to digital technology utilization. These overall findings of low trust scores within the profiles are consistent with prior research findings [10,23].

A significant finding in this study pertains to the association between trust in online service providers and the propensity to utilize digital health care and social welfare services. Earlier research has demonstrated that individuals with greater trust in digital service providers are more likely to engage with these services [24,25]. However, trust scores were comparatively lower among the prisoners who participated in the study. Despite this, the intention to use digital services remained high, particularly among the younger inmates. This suggests that while trust plays a pivotal role in fostering the adoption of digital services, additional factors, such as age and individuals' beliefs in their own digital skills, may also influence inmates' willingness to embrace digital technologies.

Overall, 60% of the total profile members in this study scored lower in advanced digital skills. It is noteworthy that despite the common occurrence of learning difficulties among prisoners [35], this study surprisingly revealed that prisoners exhibited higher levels of advanced internet skills than individuals with mental health backgrounds. This finding suggests that inmates may tend to overestimate their level of advanced digital skills compared to their actual proficiency.

One of the main problems with self-assessment data is positivity bias, where participants tend to assess themselves too positively and may claim to possess traits or perform actions that they do not actually have or do. Previous research has revealed that around 20% of participants exhibited positivity bias in self-assessment data, where some participants falsely claimed comprehension of fictional digital competence terms (i.e., foils) [36]. Complete elimination of positivity bias may not be feasible, as it is a common cognitive bias. However, awareness of its potential presence and adopting these strategies can help mitigate its impact and lead to more accurate self-assessments.

Limitations

The study was conducted in Finnish community-based mental health services and prisons. It faced data collection challenges due to the COVID-19 pandemic, which resulted in a low response rate. The sample may lack diversity, as the survey may not have reached individuals with severe mental conditions, literacy difficulties, or those in non-conducive prison environments. Furthermore, individuals with digital devices and better internet skills were likely more inclined to participate. To ensure broader participation, researchers offered both paper and electronic questionnaires. The small sample size and these biases limit the study's generalizability. The study relied on self-reports, making it susceptible to biases like satisficing and social desirability. However, the anonymous and partially online survey format could mitigate these biases.

Conclusions

The dominant cluster of survey respondents displayed elevated levels of digital proficiency but expressed lower trust in service providers. Nevertheless, they were strongly inclined to embrace digital health care and social welfare services, particularly among the younger participants. These findings imply that trust alone does not exclusively govern digital service adoption. Instead, other factors such as age and individuals' perceived digital competence also play pivotal roles in shaping their willingness to adopt digital technologies. Surprisingly, despite the prevalence of learning challenges among prisoners, this study uncovered that inmates exhibited higher levels of advanced internet skills than individuals with mental health backgrounds. This observation suggests that prisoners may overrate their proficiency in advanced digital skills relative to their actual abilities. By comprehending the determinants influencing digital service adoption, policymakers and practitioners can develop more targeted interventions to enhance digital proficiency. Further research that merges empirical skill assessments with self-reported data could provide a more profound understanding of the discrepancies between perceived and actual digital competencies. Eventually, this combined methodology could lead to the development of more efficient approaches to promote digital inclusivity and enhance the adoption of digital health care and social welfare services.

The declaration of conflicting interests

The authors declare that there is no conflict of interest.

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research was conducted as a part of the "Towards a Social-ly Inclusive Digital Society: Transforming Service Culture" project (DigiIN) and was funded by the Strategic Research Council at the Academy of Fin-land [grant numbers 327169, 327145, 327148, 352501 and 352504].

References

[1] European Commission. Special Eurobarometer 503 - Attitudes towards the impact of digitalisation on daily lives [Internet]. Vol. Digitalisa, European Commission; 2020 [cited 2022 Sep 12]. Available from: https://europa.eu/eurobarometer/surveys/detail/2228

[2] Anrijs S, Mariën I, De Marez L, Ponnet K. Excluded from essential internet services: Examining associations between digital exclusion, socio-economic resources and internet resources. Technol Soc. 2023 May 1;73:102211. https://doi.org/10.1016/j.techsoc.2023.102211

[3] Helsper E. The digital disconnect: The social causes and consequences of digital inequalities. London: Sage; 2021. https://doi.org/10.4135/9781526492982

[4] Kaihlanen AM, Virtanen L, Buchert U, Safarov N, Valkonen P, Hietapakka L, Hörhammer I, Kujala S, Kouvonen A, Heponiemi T. Towards digital health equity - a qualitative study of the challenges experienced by vulnerable groups in using digital health services in the COVID-19 era. BMC Health Serv Res. 2022 Feb 12;22(1):188. https://doi.org/10.1186/s12913-022-07584-4

[5] Hänninen R, Karhinen J, Korpela V, Pajula L, Pihlajamaa O, Merisalo M, et al. Digiosallisuuden käsite ja keskeiset osa-alueet [Internet]. Digiosallisuus Suomessa -hankkeen väliraportti. Valtioneuvoston selvitys- ja tutkimustoiminnan julkaisusarja 2021:25. Helsinki: Valtioneuvoston kanslia; 2021 [cited 2022 Dec 7]. Available from: http://urn.fi/URN:ISBN:978-952-383-287-9

[6] van Deursen AJAM. Digital Inequality During a Pandemic: Quantitative Study of Differences in COVID-19-Related Internet Uses and Outcomes Among the General Population. J Med Internet Res. 2020 Aug 20;22(8):e20073. https://doi.org/10.2196/20073

[7] Heponiemi T, Kujala S, Kouvonen A, Taipale S, Rantanen T, Topo P, et al. Palvelukulttuuria uudistamalla kaikki mukaan digitaaliseen yhteiskuntaan [Internet]. Helsinki; 2019 [cited 2023 Jul 19]. Available from: http://hdl.handle.net/10138/317762

[8] World Health Organization. Status report on prison health in the WHO European Region 2022 [Internet]. WHO; 2022 [cited 2023 Jul 19]. Available from: https://www.who.int/europe/publications/i/item/9789289058674

[9] World Health Organization. One-third of people in prison in Europe suffer from mental health

disorders [Internet]. WHO; 15 February 2023 [cited 2024 Apr 6]. Available from: https://www.who.int/europe/news/item/15-02-2023-one-third-of-people-in-prison-in-europe-suffer-from-mental-health-disorders

[10] Greer B, Robotham D, Simblett S, Curtis H, Griffiths H, Wykes T. Digital Exclusion Among Mental Health Service Users: Qualitative Investigation. J Med Internet Res. 2019 Jan 9;21(1):e11696. https://doi.org/10.2196/11696

[11] Feingold ZR. The Stigma of Incarceration Experience: A Systematic Review. Psychology, Public Policy, and Law. 2021;27(4):550–69. https://doi.org/10.1037/law0000319

[12] Rössler W. The stigma of mental disorders: A millennia-long history of social exclusion and prejudices. EMBO Rep. 2016 Sep;17(9):1250-1253. https://doi.org/10.15252/embr.201643041

[13] Buchert U, Kemppainen L, Olakivi A, Wrede S, Kouvonen A. Is digitalisation of public health and social welfare services reinforcing social exclusion? The case of Russian-speaking older migrants in Finland. Crit Soc Policy. 2022 Jul 3;43(3): 375-400. https://doi.org/10.1177/02610183221105035

[14] Eastin MS, LaRose R. Internet self-efficacy and the psychology of the digital divide. Journal of Computer-Mediated Communication. 2000;6(1):1–23. https://doi.org/10.1111/j.1083-6101.2000.tb00110.x

[15] Zoubir T. Self-efficacy as a construct for understanding teachers and students' engagement with Web 2.0 technologies. In: Proceedings of Global Learn: Global Conference on Learning and Technology Berlin, Germany. Association for the Advancement of Computing in Education (AACE); 2015 [cited 2024 Apr 6]. p. 152–7. Available from: https://www.learntechlib.org/primary/d/150858

[16] Kamal SA, Shafiq M, Kakria P. Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM). Technol Soc. 2020 Feb;60:101212. https://doi.org/10.1016/j.techsoc.2019.101212

[17] van Deursen AJAM, van Dijk JAGM. Modeling Traditional Literacy, Internet Skills and Internet Usage: An Empirical Study. Interact Comput. 2016;28(1):13–26. https://doi.org/10.1093/iwc/iwu027

[18] van Laar E, van Deursen AJAM, van Dijk JAGM, de Haan J. Determinants of 21st-Century Skills and 21st-Century Digital Skills for Workers: A Systematic Literature Review. Sage Open. 2020 Jan 1;10(1). https://doi.org/10.1177/2158244019900176

[19] Bandura A. Self-efficacy: the exercise of control. New York: Freeman; 1997.

[20] Tao D, Shao F, Wang H, Yan M, Qu X. Integrating usability and social cognitive theories with the technology acceptance model to understand young users' acceptance of a health information portal. Health Informatics J. 2020 Jun;26(2):1347-1362. https://doi.org/10.1177/1460458219879337

[21] Tetri B, Juujärvi S. Self-Efficacy, Internet Self-Efficacy, and Proxy Efficacy as Predictors of the Use of Digital Social and Health Care Services Among Mental Health Service Users in Finland: A Cross-Sectional Study. Psychol Res Behav Manag. 2022 Feb 15;15:291-303. https://doi.org/10.2147/PRBM.S340867

[22] Dhagarra D, Goswami M, Kumar G. Impact of Trust and Privacy Concerns on Technology Acceptance in Healthcare: An Indian Perspective. Int J Med Inform. 2020 Sep;141:104164. https://doi.org/10.1016/j.ijmedinf.2020.104164

[23] Rantanen T, Gluschkoff K, Silvennoinen P, Heponiemi T. The Associations Between Mental Health Problems and Attitudes Toward Web-Based

Health and Social Care Services: Evidence From a Finnish Population-Based Study. J Med Internet Res. 2021 Sep 21;23(9):e28066. https://doi.org/10.2196/28066

[24] Carter L, Bélanger F. The utilization of e-government services: Citizen trust, innovation and acceptance factors. Information Systems Journal. 2005;15(1):5–25. https://doi.org/10.1111/j.1365-2575.2005.00183.x

[25] Lattie EG, Stiles-Shields C, Graham AK. An overview of and recommendations for more accessible digital mental health services. Nat Rev Psychol. 2022 Feb;1(2):87-100. https://doi.org/10.1038/s44159-021-00003-1

[26] Rantanen T, Järveläinen E, Leppälahti T. Prisoners as Users of Digital Health Care and Social Welfare Services: A Finnish Attitude Survey. Int J Environ Res Public Health. 2021 May 21;18(11):5528. https://doi.org/10.3390/ijerph18115528

[27] Reisdorf BC, DeCook JR. Locked up and left out: Formerly incarcerated people in the context of digital inclusion. New Media Soc. 2022 Feb 11;24(2):478–95. https://doi.org/10.1177/14614448211063178

[28] Ajzen I. The theory of planned behavior. Organ Behav Hum Decis Process. 1991 Dec;50(2):179–211. https://doi.org/10.1016/0749-5978(91)90020-T

[29] Davis FD. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly. 1989 Sep;13(3):319-340. https://doi.org/10.2307/249008

[30] Fishman J, Lushin V, Mandell DS. Predicting implementation: comparing validated measures of intention and assessing the role of motivation when designing behavioral interventions. Implement Sci Commun. 2020 Sep 28;1:81. https://doi.org/10.1186/s43058-020-00050-4

[31] Virtanen L, Kaihlanen AM, Isola AM, Laukka E, Heponiemi T. Mielenterveyskuntoutujien kokemuksia etäpalveluiden hyödyistä COVID-19-aikakaudella: Laadullinen kuvaileva tutkimus. Sos Laaketiet Aikak. 2021 Oct 5;58(3). https://doi.org/10.23990/sa.107405

[32] Finnish National Board on Research Integrity. The ethical principles of research with human participants and ethical review in the human sciences in Finland. TENK guidelines 2019 [Internet]. Finnish National Board on Research Integrity; 2019 [cited 2023 Aug 4]. Available from: https://tenk.fi/en/advice-and-materials

[33] Wilson CK, Thomas J, Barraket J. Measuring Digital Inequality in Australia: the Australian Digital Inclusion Index. Journal of Telecommunications and the Digital Economy. 2019 Jun 30;7(2):102–20. https://doi.org/10.18080/jtde.v7n2.187

[34] Alanazi M, Soh B. Behavioral Intention to Use IoT Technology in Healthcare Settings. Technology & Applied Science Research. 2019;9(5):4769–74. https://doi.org/10.48084/etasr.3063

[35] Morken F, Jones LØ, Helland WA. Disorders of Language and Literacy in the Prison Population: A Scoping Review. Educ Sci. 2021 Feb 14;11(2):77. https://doi.org/10.3390/educsci11020077

[36] Muszyński M, Pokropek A, Castaño-Muñoz J, Vuorikari R. Can Overclaiming Technique Improve Self-Assessment Tools for Digital Competence? The Case of DigCompSat. Soc Sci Comput Rev. 2022 Aug 31;41(6):2318–41. https://doi.org/10.1177/08944393221117269