Information, Communication & Society

ISSN: 1369-118X (Print) 1468-4462 (Online) Journal homepage: www.tandfonline.com/journals/rics20

The digital health capital framework: cross-cutting digital health inequality and smart-aging in post-COVID Hong Kong

Fen Lin , Pei Zhi, Yulu Ouyang , Xiaohui Wang , Bo Wen & Yi-Hui Christine Huang

To cite this article: Fen Lin , Pei Zhi, Yulu Ouyang , Xiaohui Wang , Bo Wen & Yi-Hui Christine Huang (29 Jun 2026): The digital health capital framework: cross-cutting digital health inequality and smart-aging in post-COVID Hong Kong, Information, Communication & Society, DOI: 10.1080/1369118X.2026.2689041

To link to this article: https://doi.org/10.1080/1369118X.2026.2689041

INFORMATION, COMMUNICATION & SOCIETY
https://doi.org/10.1080/1369118X.2026.2689041

The digital health capital framework: cross-cutting digital health inequality and smart-aging in post-COVID Hong Kong

Fen Lin[a], Pei Zhi [a], Yulu Ouyang[a], Xiaohui Wang[a], Bo Wen[b] and Yi-Hui Christine Huang[a]

[a]Department of Media and Communication, City University of Hong Kong, Hong Kong SAR; [b]Faculty of Social Sciences, University of Macau, Macau SAR

ABSTRACT

The COVID-19 pandemic has accelerated the adoption of e-health technologies while simultaneously amplifying existing digital health disparities. To identify the digital health divide, we propose the Digital Health Capital (DHC) framework, an integrated multidimensional measure including usage, literacy and transformative capacity, to scrutinize the digital health divide in the emerging technology landscape. Utilizing a mixed-mode dataset that combines a quota-sampled online survey with an offline sample of elderly participants, we apply this framework to examine the digital health capital divide in post-COVID Hong Kong. Our data reveals three findings. First, consistent with previous studies, substantial disparities in DHC scores correlated with socioeconomic status (SES): individuals with higher education, wealthier, and employment consistently exhibit stronger digital health capacities. Second, the impacts of SES on the divide vary by different dimensions of DHC, revealing that the mechanisms driving inequalities in transformative capacity differ significantly from those affecting usage and literacy. Third, the findings challenge the stereotype of the homogeneity of digital disadvantage among the elderly and highlight the overlooked disadvantage faced by the middle-aged 'sandwiched generation.' These findings call for more refined policies for smart aging initiatives, emphasizing the need for targeted strategies to bridge the digital health capital divide when developing techcare for diverse demographic groups.

ARTICLE HISTORY
Received 19 June 2025
Accepted 9 June 2026

KEYWORDS
Digital health; digital health capital; extended digital divide; smart-aging; entropy weight method

1. Introduction

For decades, telemedicine and digital health tools have been widely adopted to tackle an imbalance in public access to medical resources (Budd et al., 2020). During the COVID-19 pandemic, the use of e-health tools expanded widely due to quarantine and social

CONTACT Pei Zhi peizhi2-c@my.cityu.edu.hk Department of Media and Communication, M3052, City University of Hong Kong, Run Run Shaw Creative Media Center, 18th Tat Hong Avenue, Kowloon Tong, Hong Kong SAR.
Supplemental data for this article can be accessed online at https://doi.org/10.1080/1369118X.2026.2689041.

distancing policies (e.g., Bokolo, 2021). This acceleration in e-health development has deeply integrated technology into the healthcare sector (Magsamen-Conrad et al., 2020), transforming digital competence from a mere technical skill into an important form of health capital. However, while this technological advancement has empowered patients by creating a more inclusive, participatory healthcare environment, digitalization of healthcare has also simultaneously exacerbated exclusion among the digitally disadvantaged, especially the elderly (Kaihlanen et al., 2022). Thus, mitigating the digital health divide requires not just observing who uses technology, but to understand the evolving, multidimensional capacity of individuals to navigate this digital health landscape.

To this end, existing digital divide research and health literary studies have developed various concepts and tools. However, existing research is not adequate to address the evolving complexity of the digital health field for two reasons. First, the concept of e-health and its variations were developed along with different types of technology. For example, the concept of e-health has evolved alongside technological shifts – from early telehealth relying on telephone wires or radio (Gershon-Cohen & Cooley, 1950) to mobile health utilizing wireless networks (Istepanian et al., 2006). These technologies have various features and require different skills and knowledge when applied to healthcare. With the advancement of emerging technology landscape characterized by algorithmic information and data-driven services, we need updated concepts and measures to adapt to emerging technologies.

Second, with the evolving digital health landscape, researchers cannot afford treating digital engagement in isolation. Existing digital literacy studies distinguishes between digital access (the first level digital divide; van Dijk, 2006) and digital competence (the second level digital divide; Büchi et al., 2018; van Deursen & van Dijk, 2014). While the most recent digital divide literature has further emphasized a third-level divide: the disparity in translating digital resources into tangible offline outcomes (Lin et al., 2025; Ragnedda, 2017; Ragnedda et al., 2020; Stern et al., 2009; van Deursen & van Dijk, 2014), current instruments rarely capture the interplay of these levels (Norman & Skinner, 2006; Vaart & Drossaert, 2017). The digital divide is not a series of isolated gaps but a sequential process: usage is the prerequisite for skills, which in turn functions as a converter to generate health outcomes. Existing studies that focus on a single dimension capture specific stages of engagement but may overlook the cumulative nature of digital advantage. A comprehensive framework is thus needed to integrate this cumulative digital repertoire, identifying where the chain of conversion breaks down for vulnerable groups.

Therefore, our research aims to update and integrate the existing literature on the digital divide, digital literacy, health literacy, and then polish the concept of 'digital health capital', and develop an analytical framework to gauge the patterns of the digital divide in the health arena. This framework conceptualizes digital health capital as a multi-layered construct comprising three dimensions: (1) digital health usage, (2) digital health literacy, and (3) digital health transformative capacity. By aggregating these three dimensions, the DHC can capture the complex, accumulative nature of digital inequality in the current AI-empowered ecosystem.

We empirically examine this framework and identify the patterns of digital health capital divide in post-COVID Hong Kong. Hong Kong serves as a strategic case study due to its unique 'high-tech, high-aging' context: it possesses world-leading digital infrastructure yet faces one of the world's fastest-aging populations (Das, 2023). This context allows us to observe the digital health divide in its most acute form, offering early insights for other developed economies. The analysis is based on a mixed-mode dataset: a representative online survey of Hong Kong residents (N = 1000) supplemented by a face-to-face interview sample of elderly participants (N = 308). This offline sample would better capture the experiences of 'internet minorities' often excluded from digital health research. Our findings call for more refined policies for smart aging initiatives, contributing to developing techcare for diverse demographic groups.

2. Theoretical framework: digital health capital and extended digital divide

2.1 Digital divide in health context

The individual accumulation of digital health resources aggregates into the digital health capital divide across different socioeconomic groups (SES). While digital health has traditionally been viewed as a tool to narrow disparities (Benis et al., 2020), technological advancements may inadvertently widen existing gaps (Chang et al., 2004).

The first level digital divide, defined by physical connectivity ('haves' and 'have-nots') (van Dijk, 2006). Recent data from Hong Kong indicates that physical access is no longer the primary barrier. In 2023, smartphone penetration reached 96.4%, and internet usage hit 96.0% (Hong Kong Census and Statistics Department, 2024). Mere connectivity does not guarantee equitable outcomes (Ramsetty & Adams, 2020), necessitating examination of higher-level divides.

The second level addresses disparities in skills and usage ('knows vs. know-nots') (Büchi et al., 2018; Hargittai, 2010). While basic literacy initiatives have expanded, the increasing complexity of emerging technologies creates new barriers for the digitally illiterate (Hadjiat, 2023; Saeed & Masters, 2021). For example, AI-powered e-health applications often rely on training data that underrepresents socially disadvantaged groups, creating an 'algorithmic divide' where biases favor data-rich population (Wang et al., 2024). This complexity may not be captured, widening the gap for those lacking the specific literacy to navigate these advanced systems.

The third level focuses on the ability to translate digital resources into tangible offline outcomes (Ragnedda, 2017; van Deursen & van Dijk, 2014). Even with similar access and skills, individuals may not achieve comparable health benefits (Ragnedda, 2017), and those who do often experience retroactive benefits that further enhance their digital skills (van & Helsper, 2015). While third-level divides are documented in specific contexts (Alvarez-Galvez et al., 2020; Jin et al., 2022), few studies have offered a comprehensive framework that captures how digital health resources are accumulated across these three levels and converted into tangible health outcomes. This gap is particularly necessary in the health context, because health outcomes depend not only on an individual's digital capabilities but also on institutional healthcare systems.

2.2 Evolution of ICT and concepts of digital health

The 2019 pandemic accelerated the expansion of digital health through quarantine and social distancing policies, establishing digital spaces as a pivotal channel for accessing medical resources in the post-pandemic era (Abernethy et al., 2022). However, the discussion on technology and health has a long history: as summarized in Table 1, each era of digital health is closely linked with the dominant Information and Communication Technology (ICT) of that time. Telemedicine at the early stage, relying on radio and telephone infrastructure (Gershon-Cohen & Cooley, 1950; Murphy & Bird, 1974), centered measurement on availability of remote connections rather than user skills or outcomes. As videoconferencing expanded the scope of services, telehealth shifted attention toward provider-side clinical adoption (Bashshur et al., 2011; Sakumoto & Krug, 2023). The rise of the Internet and mobile communications then brought e-health and m-health into focus, redirecting measurement toward individual user capability to seek and evaluate health information (Istepanian et al., 2006; Norman & Skinner, 2006). Each concept captured a distinct but partial dimension of digital health engagement.

Although these terms are often used interchangeably, their evolution in Tabel-1 reflects both technological advancements and the ongoing integration of technology into healthcare. Thus, in this paper, we adopting 'digital health' as an inclusive term that encompasses disruptive technologies fostering shared decision-making, democratized cafre, and health enhacement in a patient-centered environment (Meskó et al., 2017). However, a gap remains in the theoretical conceptualization. While previous concepts successfully measured isolated dimensions – health infrastructure in telemedicine, health delivery in telehealth, and health literacy and adoption in eHealth and mHealth, there is a lack of a holistic framework that captures the full sequential process from usage and skills to transformative health outcomes. This fragmentation necessitates Digital Health Capital (DHC) framework, which integrates digital health usage, literacy, and transformative capacity into a unified cumulative measure.

2.3 Digital health capital framework: three dimensions

To integrate extended digital divide and evolving digial health technology, we propose digital health capital framework to describe a complex relationship between individual's digital health resources and their capacity to achieve meaningful health outcomes. Unlike previous concepts that view eHealth literacy merely as a technical skill (Norman & Skinner, 2006), we conceptualize DHC as a cumulative resource that individuals acquire and mobilize to achieve health goals. We deliberately adopt the term capital drawing on Bourdieu's (1986) theory of capital forms and its extensions in the digital domain (Ragnedda, 2017; Calderón Gómez, 2021). This framing emphasizes two properties that alternative terms fail to capture: DHC is cumulative, built gradually through consistent engagement; and convertible, in that its value lies in being converted into real-world health outcomes (Calderón Gómez, 2021; Ragnedda, 2017; Ragnedda et al., 2020; Stern et al., 2009; van & Helsper, 2015; van Deursen & van Dijk, 2014). This emphasis on conversion is particularly important in the health context, because health outcomes depend not only on an individual's digital capabilities but also on institutional healthcare systems. This also distinguishes DHC from other forms of capital. Social capital is typically mobilized through networks, while cultural capital is often rewarded through relatively established educational and institutional pathways (Ragnedda, 2018). In digital health, however, resources only matter when they can be translated into meaningful benefits within healthcare systems that are themselves unequal and often difficult to navigate. While

Table 1. Evolution of the eHealth-related concepts and related ICT.

Concepts	Definition	Dominant Technology	Reference	Sample Size	Time of Survey	Area	Measurement			DHC Framework		
							Access	Usage	Skills	Usage	Literacy	Transformative
Tele-medicine	The provision of medical services without the traditional face-to-face interaction between patient and doctor (Murphy & Bird, 1974).	Radio or telephone wires over short or long distances (Gershon-Cohen & Cooley, 1950)	(Harris et al., 2023)	1067 patients	2018	US	√	√	×	√	×	×
Tele-health	Telehealth is a broader ICT health concept, covering areas such as nursing, pharmacy, and rehabilitation (Bennett, 1978).	General ICT (Bashshur et al., 2011)	(Sakumoto & Krug, 2023)	Evaluators (n = 44) and Clinicians (n = 24)	2022–2023	US	√	×	√	×	√	×
Electronic health (e-health)	The economical and safe application of ICT to aid health and health-related areas (WHO, 2006).	Health-related ICT technologies (Bashshur et al., 2011)	(Norman & Skinner, 2006)	664 adolescents	2006	Canada	×	×	√	×	√	×
			(Karnoe et al., 2018)	475 respondents	2011–2016	Denmark	×	√	×	√	×	×
			(Paige et al., 2019)	2100 patients	Not reported	US	×	×	√	×	√	√
Mobile health (m-health)	Mobile technology expansion aids healthcare access, especially in developing nations (Bashshur et al., 2011).	Wireless communication and network technologies (Istepanian et al., 2006)	(Lin & Bautista, 2017)	295 young mHealth app users	Jul-05	Singapore	×	×	√	×	√	×
			(Fu et al., 2021)	5,420 valid responses	Not reported	China	×	×	√	×	√	√
			(Zhang & Li, 2022)	552 + 433	2020–2021	China	×	√	√	×	√	√
Digital health	Digital health leverages disruptive tech to provide caregivers and patients with data, fostering shared decision-making, democratized care, and health enhancement (Meskó et al., 2017).	Cloud Computing, Artificial Intelligence, Machine Learning, Blockchain, and various consumer-facing self-management applications (Abernethy et al., 2022)	(Vaart & Drossaert, 2017)	200 people	Not reported	Dutch	√	√	√	√	√	×
			(Yoon et al., 2022)	590 adults	2020	Korea	×	×	√	×	√	×
			(Rachmani et al., 2022)	383 respondents	Not reported	Indonesia	×	√	√	√	√	√
			This study				√	√	√	√	√	√

(*Continued*)

Table 1. Continued.

Concepts	Definition	Dominant Technology	Reference	Sample Size	Time of Survey	Area	Measurement			DHC Framework		
							Access	Usa-ge	Skills	Usage	Lite-racy	Transfor-mative
Digital Health Capital (DHC) Framework	As a form of capital rather than a tool-specific measure, DHC combines usage, literacy, and transformative capacity, DHC empowers informed decisions, better health management, and communication with providers in the digital age.	Encompasses both traditional ICT widely applied in digital health and emerging technologies such as artificial intelligence, mobile health applications, and wearable devices.		1308 responses (including both online and offline data)	Online and Offline survey in Oct 2023 and Feb 2024	Hong Kong						

this study primarily examines DHC through the lens of digital health inequality, the concept holds broader applicability across health communication contexts, informing research on patient empowerment (Grossman, 1972), culturally sensitive health interventions (Abel, 2008), or telehealth evaluation across diverse populations (Shim, 2010). By framing digital health engagement as capital, researchers are prompted to consider not only whether individuals possess certain competencies but how these resources are accumulated, converted, and distributed into meaningful health outcomes.

To operationalize DHC, we integrate existing literature on the digital divide and digital health literature. Given that basic connectivity is near-universal in Hong Kong, the first-level divide is not the primary concern of this framework. Instead, Digital health usage captures the behavioral dimension of the second-level divide, reflecting differences in the frequency, diversity, and depth of engagement with digital health tools (see Table 2). Digital health literacy corresponds to the cognitive dimension of the second-level divide, and digital health transformative capacity maps onto the third-level divide.

Digital Health Usage reflects the foundational layer of digital engagement. This dimension assesses how often individuals use these tools, the variety of tools they use, and the depth of their engagement with these technologies (Frishammar et al., 2023). This dimension probes the frequency, diversity, and intensity of using digital health tools, underscoring the behavioral aspect of digital health engagement.

Digital Health Literacy represents the cognitive layer. It refers to the ability to seek, appraise and apply health information from electronic sources (Norman & Skinner, 2006). It enables individuals to effectively to navigate, understand, and utilize digital health information to improve their health outcomes (Norman & Skinner, 2006). However, in the era of disruptive technology, this dimension must evolve beyond basic search skills. The digital health literacy now encompasses the competency to navigate complex, often AI-driven information ecosystems, requiring individuals to critically evaluate the validity of algorithmic recommendations and data sources (Saeed & Masters, 2021).

Table 2. Three dimensions of digital health capital framework and divide.

Digital divide level	Dimensions	Definition	Item construction	Cronbach's alpha	Reference
Second divide level	Digital health usage (A)	The frequency, diversity, and intensity with which individuals engage with digital health tools.	8 items (Q5-Q7_6)	.94	Rachmani et al., 2022; Vaart & Drossaert, 2017
Second divide level	Digital health literacy (B)	The ability to seek, understand, and use health information from electronic sources to make informed health decisions and manage personal health effectively.	8 items (Q8_1-Q8_8)	.94	Norman & Skinner, 2006
Third divide level	Digital health transformative capacity (C)	The ability to effectively apply digital tools and resources to enhance real-world health outcomes and lifestyle behaviors, representing the practical impact of digital engagement on improving health.	2 items (Q9-Q10)	.98	Dobransky & Hargittai, 2012; Virlée et al., 2020

Note: Full item wording is provided in Appendix A.

Digital Health Transformative Capacity is the consequential layer, focusing on the conversion of digital resources into real-world outcomes. While access and skills are necessary but insufficient conditions, the ultimate value of digital health lies in its ability to improve lifestyle behaviors and health status (Calderón Gómez, 2021). Thus, such transformative capacity embodies the potential of digital engagement to catalyze positive health transformations (Abernethy et al., 2022; Meskó et al., 2017).

Even though existing studies more or less examined each dimension in isolation, the DHC offers an integrated framework. It posits that these three dimensions are not independent but synergistic: usage builds the foundation for literacy, which in turn enables the transformative capacity required to improve health outcomes. Conceptually, DHC is a composit construct. Each dimension captures a unique and non-substitutable aspect of digital health engagement, rather than interchangeable reflections of a single latent trait (Diamantopoulos & Winklhofer, 2001). This composite approach follows the construction of Digital Capital Index that combined digital access and digital competence to capture individuals' overall digital resources (Ragnedda et al., 2020).

To empirically examine these divides, Hong Kong serves as a strategic context. The city has near-universal digital infrastructure: smartphone penetration reaches 96.3%, and household internet access stands at 96.7% (Census and Statistics Department, 2025), meaning the first-level digital divide is no longer a primary barrier. Health digitalization has progressed rapidly: over 20 telemedicine mobile applications are available, and the HA Go, an official app developed by the Hospital Authority, which had over 3.25 million members (43.9% of the population) by 2025 (Hospital Authority, 2025). Yet Hong Kong simultaneously faces one of the world's fastest aging rates (Das, 2023). This 'high-tech, high-aging' juxtaposition, prevalent across developed Asian societies, makes it ideal for examining how technological acceleration and demographic shifts shape digital health capital distribution and its health consequences.

However, merely identifying the existence of these divides is insufficient; it is crucial to understand who falls on which side of the divide. Digital capital is not randomly distributed but mirrors existing social stratifications. Offline inequalities are often amplified in the digital context (Lin et al., 2025; Ragnedda, 2017). For instance, lower socioeconomic status groups may face an algorithmic divide where their data is underrepresented, leading to poorer health outcomes. Therefore, testing demographic differences is essential for identifying specific vulnerable subpopulations who are systematically excluded from the benefits of digital health.

Echoing the call to address the digital divide in the new media environment (Scheerder et al., 2017), this study adopts the DHC framework to identify digital health divide patterns in Hong Kong:

RQ1: To what extent do sociodemographic disparities exist in the distribution of Digital Health Capital?

RQ2: How does the divide differ across the three dimension of the digital health capital in post-pandemic Hong Kong?

3. Data and method

3.1 Data collection

We collected data through both online and offline approaches. The online survey was conducted in Hong Kong from 20 to 27 October 2023 via a globally recognized data collection company. The company maintains an opt-in list of 56,000 individuals relevant to the study population. Targeting residents aged 18 and above, we employed quota sampling to match geographical and demographic distributions of the 2021 Hong Kong census. Participation was voluntary, incentivized, and anonymous. Ethical approval was granted by the Human Subject Ethics Committee of the authors' institution.

To address the potential exclusion of digitally-abandoned individuals, we then conducted a supplementary offline survey between 20 and 28 February 2024. This face-to-face component targeted areas with high elderly density (Kwun Tong and the New Territories) to include populations typically overlooked by online methodologies. After excluding incomplete responses, the final dataset comprised 1,308 valid responses. Since our survey oversampled elderly citizens and private housing residents, we applied post-stratification weighting to replicate the marginal distributions of the population.[1]

3.2 Measurement

Digital health usage was measured by eight questions accessing the frequency of engagement with digital health tools (Table 1). We updated items to encompass wearable devices and AI-powered tools (e.g., ChatGPT and new Bing)[2] (Abernethy et al., 2022). The score was calculated as the average of these items, with higher scores representing more frequent digital health usage. (Min = 1, Max = 6.75, M = 3.19)

Digital health literacy was assessed using eight items based on established frameworks (Norman & Skinner, 2006) regarding confidence and skills in utilizing online health resources. The score was derived from the average of these eight items (Min = 1, Max = 7, M = 4.82).

Digital health transformative capacity was gauged by two items focusing on the impact of digital health technologies on health behaviors and access to offline medical resources. This two-item measure was designed to capture two distinct theoretical dimensions: health behavior modification and offline service access (Calderón Gómez, 2021; Virlée et al., 2020). Such abbreviated scales are statistically acceptable in large-scale survey to minimize respondent burden while maintaining construct validity (Eisinga et al., 2013). This approach is methodologically acceptable given that the selected items exhibit strong inter-item correlations and high composite reliability, ensuring that the construct is adequately measured without imposing excessive respondent burden. These items capture the extent to which digital health tools facilitate health improvement and service access (Min = 1, Max = 6, M = 3.50).

Demographic variables included age groups (1 = Young (under 45), 2 = Sandwiched generation (45–65), and 3 = Elderly (above 65)) and gender. SES indicators include educational level (1 = secondary level and below and 3 = graduate and above), monthly domestic income (1 = under 30,000 HKD and 3 = above 60,000 HKD),[3] and type of housing (1 = public rental, and 3 = private permanent). Control variables include employment status (0 = unemployment, 1 = employed),[4] marital status (0 = No, 1 = Yes), immigration (1 = born in Hong Kong, 2 = born in Mainland China and 3 = born overseas), and chronic illness record (0 = No, 1 = Yes).

3.3 Comprehensive DHC framework construction

We employed the entropy method to develop the framework of DHC. The entropy method determines the weighting of evaluation factors by leveraging the inherent information within the data itself (e.g. Hua et al., 2023). This data-driven approach minimizes subjective arbitrariness in weight assignment, ensuring that indicators with significant variation receive higher weights as they provide more information (Wang et al., 2017). This weighting approach is consistent with the formative nature of the DHC construct: rather than assuming the three dimensions share a common latent cause, the entropy method preserves their distinct contributions by assigning weights based on each indicator's discriminative power within the dataset.

Following data standardization, we calculate the DHC using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Uzun et al., 2021). Specifically, TOPSIS evaluates individuals by measuring their proximity to an ideal solution (the best possible score) and a negative ideal solution (the worst possible score). Table 3 details the specific entropy values and weights.

4. Results

4.1 Sample representation

The raw data shows that, 41.3% of respondents were from the young generation (under 45 years old), while 40.90% belonged to the elderly generation (above 65 years old). Female respondents accounted for 49.96% of the sample, and 14.32% reported having obtained a graduate degree or above. Regarding the monthly family income, 30.89% of

Table 3. Comprehensive entropy values and weights of DHC.

First-level indicators	Weights	Second-level indicators	Weights	Information entropy value E
A-Digital health usage	.73	A1	.10	.93
		A2	.11	.92
		A3	.04	.97
		A4	.09	.94
		A5	.11	.92
		A6	.10	.93
		A7	.09	.94
		A8	.09	.95
B-Digital health literacy	.10	B1	.01	.99
		B2	.01	.99
		B3	.01	.99
		B4	.01	.99
		B5	.02	.99
		B6	.01	.99
		B7	.02	.99
		B8	.02	.99
C-Digital health transformative capacity	.17	C1	.09	.94
		C2	.09	.94

respondents reported earning less than 30,000 HKD per month, which approximates the median monthly domestic household income in Hong Kong, and 34.25% reported earning over 60,000 HKD. 8.17% of respondents claimed they lived in a public permanent house, 62.2% of respondents reported are employed, and 72.4% of respondents claimed they are married. 99.5% of respondents reported as Hong Kong Permanent Residents. 26.55% of respondents indicated they have chronic illness records. 98% of respondents claimed they have access to the Internet at home.

4.2 Validity of DHC in the Hong Kong context

To ensure the accuracy of the three dimensions of DHC, we initially conducted Confirmatory Factor Analysis (CFA) to test the fit of the data to a hypothesized measurement model. The CFA was conducted to validate the internal measurement model of each dimension. This within-dimension reflective structure is distinct from the between-dimension formative logic of the overall DHC framework, in which the three validated dimensions are aggregated as constitutive components using the entropy method described in Section 3.3. As shown in Table 4, the results demonstrated a high level of internal consistency, with an overall Cronbach's α coefficient of .94. Furthermore, the Cronbach's α coefficient for each dimension exceeded 0.7, demonstrating that the individual digital health scale possesses good reliability.

The CFA also suggests a good model fit (CFI = .985, RMSEA = .043, and TLI = .983). As shown in Table 4, it is evident that the standardized factor loading of the 18 items was greater than .6, which is considered a robust threshold for establishing construct validity in social science research (Hair et al., 2019, p. 103). Additionally, CR of the three factors is greater than .6 and AVE is greater than .5, confirming good convergent validity. Thus, based on the CFA results, the proposed indicator system is reasonable and valid.

The DHC for Hong Kong residents exhibited substantial variation, ranging from .01 to 94.24 (M = 40.94, SD = 24.46). To address RQ1, we examined the distribution of DHC across demographic characteristics (see Table 5).

Table 4. CFA results of DHC in three dimensions.

First-level indicator	Second-level indicator	Mean (S.D.)	Factor load	CR	AVE
A-Digital health usage	A1	3.53 (2.18)	.67	.95	.70
	A2	2.94 (1.86)	.82		
	A3	3.69 (1.51)	.76		
	A4	3.16 (1.80)	.85		
	A5	2.95 (1.84)	.87		
	A6	3.06 (1.77)	.90		
	A7	3.02 (1.76)	.90		
	A8	3.17 (1.69)	.88		
B-Digital health literacy	B1	4.93 (1.22)	.80	.94	.64
	B2	4.74 (1.28)	.82		
	B3	4.90 (1.20)	.78		
	B4	4.85 (1.28)	.82		
	B5	4.90 (1.22)	.82		
	B6	4.81 (1.23)	.80		
	B7	4.74 (1.23)	.79		
	B8	4.69 (1.25)	.77		
C-Digital health transformative capacity	C1	3.71 (.79)	.97	.98	.95
	C2	3.76 (.75)	.97		

Table 5. Descriptive summary of digital health capital divide in three dimensions.

	Digital health usage	Digital health literacy	Digital health transformative capacity	Digital health capital
Mean	3.19 (1.53)	4.82 (1.03)	3.50 (1.85)	40.94 (24.46)
Min	1	1	1	.01
Max	6.75	7	6	94.24
Age group				
Young (under 45)	3.57 (1.30) [b]	4.95 (.85) [b]	3.62 (1.67)	46.42 (20.63) [b]
Sandwiched Group (45-65)	2.93 (1.28) [a]	4.68 (1.01) [a]	3.37 (1.70)	37.16 (20.72) [a]
Elderly (above 65)	2.90 (1.75) [a]	4.75 (1.17) [a]	3.44 (2.06)	37.04 (28.13) [a]
Gender				
Male	3.23 (1.54)	4.88 (1.02) *	3.53 (1.87)	41.76 (24.44)
Female	3.14 (1.53)	4.76 (1.03)	3.48 (1.82)	40.16 (24.37)
Education				
Secondary or below	2.37 (1.26) [a]	4.37 (1.08) [a]	3.00 (1.88) [a]	28.32 (20.70) [a]
Tertiary	3.58 (1.46) [b]	5.06 (.87) [b]	3.68 (1.76) [b]	46.92 (22.94) [b]
Graduate or above	4.11 (1.38) [c]	5.29 (.84) [c]	4.31 (1.64) [c]	56.14 (22.44) [c]
House type				
Public rental	2.45 (1.28) [a]	4.50 (1.07) [a]	2.98 (1.84) [a]	29.50 (20.81) [a]
Subsidized house	3.04 (1.52) [b]	4.72 (1.06) [b]	3.43 (1.87) [b]	38.74 (24.07) [b]
Private owned	3.62 (1.52) [c]	5.05 (.84) [c]	3.83 (1.80) [c]	47.83 (24.14) [c]
Marital status				
Married	3.30 (1.58) ***	4.86 (1.03) ***	3.68 (1.85) ***	43.08 (25.13) ***
Not married	2.87 (1.36)	4.70 (1.02)	3.05 (1.75)	35.31 (21.47)
Employment				
Employed	3.44 (1.41) ***	4.95 (.90) ***	3.66 (1.73) ***	44.94 (22.36) ***
Not employed	2.75 (1.64)	4.61 (1.18)	3.25 (2.00)	34.36 (26.19)
Monthly domestic income				
Under 30,000HKD	2.99 (1.63) [a]	4.64 (1.17) [a]	3.36 (1.87) [a]	37.83 (25.84) [a]
30,000-60,000HKD	3.08 (1.48) [a]	4.84 (.99) [b]	3.35 (1.87) [a]	39.17 (23.56) [a]
Above 60,000HKD	3.46 (1.46) [b]	4.96 (.89) [b]	3.79 (1.78) [b]	45.53 (23.30) [b]
Immigration				
-Hong Kong	3.44 (1.52) ***	5.00 (.91) ***	3.72 (1.79) ***	45.08 (23.97) ***
-Mainland China & Overseas	2.24 (1.18)	4.14 (1.14)	2.71 (1.83)	25.56 (19.43)
Chronic illness record				
-No chronic illness record	3.38 (1.48) ***	4.95 (.90) **	3.59 (1.84)	43.58 (23.83) ***
-Has chronic illness record	2.65 (1.55)	4.46 (1.26) **	3.48 (1.87)	33.90 (24.82)

Note: Reported values are means with standard deviations in parentheses. For variables with more than two categories, superscript letters denote significant differences based on Bonferroni post-hoc tests ($p < .05$); a < b < c. Means sharing the same letter do not differ significantly. Cells without superscripts indicate no significant pairwise differences. For variables with two categories, asterisks indicate that the group mean is significantly higher based on independent-sample t-tests (*$p < .05$, **$p < .01$, ***$p < .001$).

Demographic: A one-way ANOVA revealed a statistically significant difference in DHC across age groups (F (2, 1305) = 24.02, $p < .001$, eta^2 = .04). Post-hoc comparisons using the Bonferroni test indicated that young adults under 45 scored significantly higher on DHC (M = 46.42), than both the sandwiched group (M = 37.16, $p < .001$) and the elderly (M = 37.04, $p < .001$). Regarding gender, male and female had no significant difference on DHC (t = 1.19, $p > .05$).

SES indicators: Education showed a robust positive association with DHC (F (2, 1303) = 150.78, $p < .001$, eta^2 = .19). Post-hoc tests confirmed a stepwise hierarchy: respondents with graduate degrees (M = 56.14) scored significantly higher than those with tertiary education (M = 46.92), who in turn scored significantly higher than those with secondary education or below (M = 28.32, $p < .001$ for all pairs).

Housing type delineated a similarly clear linear relation ($F(2, 1247) = 74.52$, $p < .001$, $eta^2 = .11$): residents in private owned housing ($M = 47.83$) scored significantly higher than those in subsidized housing ($M = 38.74$), who in turn outperformed public rental tenants ($M = 29.50$). Then, household income mirrored this graded pattern ($F(2, 1305) = 12.63$, $p < .001$, $eta^2 = .02$). Post-hoc results showed that the highest income group sat atop the hierarchy ($M = 45.53$), significantly outperforming the lower income groups.

We further conducted the analysis on each dimension of DHC. Not surprisingly, each dimension of DHC has a relatively strong correlation with each other, as shown in Table 6.

To address RQ2, We ran a weighted OLS regression model to examine the impacts of demographic features and SES on DHC, as reported in Table 7.

When controlling for other factors, age remains significant: relative to young adults, the sandwiched generation reports notably lower DHC ($\beta = .20$, $p < .001$). Interestingly, there is also a huge significant difference between the sandwiched generation and those aged above 65 ($\beta = .23$, $p < .001$), suggesting that the middle-aged group may be uniquely vulnerable in digital health engagement, not as digitally fluent as the young, yet not receiving the targeted support often directed at seniors.

Education exerts the strongest effect. Compared to individuals with secondary education or below, those with tertiary education ($\beta = .27$, $p < .001$), and graduate degree ($\beta = .32$, $p < .001$) score significantly higher. Housing type shows a similar pattern: privately owned housing residents outscore public rental tenants ($\beta = .15$, $p < .01$). Notably, once education and housing are controlled, household income loses statistical significance, suggesting that in Hong Kong's property-centric economy, housing type absorbs much of the variance attributable to current income.

While the aggregate DHC score above reveals the overall distribution of digital health capital, the dimensional analysis below identifies specific bottlenecks within the sequential process of usage, literacy, and transformative capacity. As shown below, the effects of SES indicators on each dimension are not uniform but present cross-cutting impact patterns.

Digital health usage: Once controlling for everything else, age, education, type of housing, employment and marital status all present a significant and positive association with the score of digital health usage, as shown in Table 7. In brief, the distribution pattern of this dimension has been consistent with the overall DHC and with the previous studies (Friemel, 2016; Robinson et al., 2015).

Digital health literacy: Similar to the usage, after controlling everything else, digital health literacy is positively associated with education: compared to individuals with

Table 6. Correlation matrix between three DHC dimensions.

Dimension	Digital health usage	Digital health literacy	Digital health transformative capacity
Digital health usage	1.00		
Digital health literacy	.52*	1.00	
Digital health Transformative capacity	.64*	.31*	1.00

*$p < .05$.

Table 7. Weighted OLS regression on DHC and its three dimensions.

Predictors	DHC	Usage	Literacy	Transformative capacity
	β	β	β	β
Gender *(ref. Male)*				
-Female	.03	.04	−.05	.01
Age group *(ref. Sandwiched Group (45-65))*				
-Young (under 45)	.20 ***	.20 ***	.03	.15 *
-Ederly (above 65)	.23 ***	.20 ***	.42 ***	.17 **
Educational Level *(ref. Secondary or below)*				
-Tertiary	.27 ***	.27 ***	.28 ***	.13 *
-Graduate or above	.32 ***	.30 ***	.27 ***	.24 ***
Marital Status (*ref. Not Married*)				
-Married	.20 ***	.22 ***	−.02	.13 *
Employment (*ref. Not Employed*)				
-Employed	.19 ***	.17 ***	.18 *	.15 *
Domestic Monthly Income (ref. *Under 30,000 HKD*)				
−30,000-60,000 HKD	−.03	−.01	−.07	−.03
-Above 60,000 HKD	.02	.02	−.07	.03
House type (ref. Public Rental)				
Subsidized House	−.01	.01	−.05	−.04
Private Owned	.15 ***	.16 ***	.002	.06
Immigration *(ref. Hong Kong)*				
-Mainland China & Overseas	−.16 ***	−.14 ***	−.31 ***	−.12 **
Chronic Illness Record *(ref. No chronic illness record)*				
-Has chronic illness record	−.04	.002	.14 **	−.18 ***
Constant	–	–	–	–
N	1233	1233	1233	1233
$\mathcal{X}^2$	27.15 (13, 1219)	30.50 (12, 1219)	10.25 (13, 1219)	7.36 (13, 1219)
$\mathcal{R}^2$	.3289	.3328	.3038	.1580

Note: β refers to the standardized coefficient
#$p < .1$*$p < .05$. **$p < .01$.***$p < .001$.

secondary education or below, those with tertiary education (β = .28, $p < .001$) and graduate education (β = .27, $p < .001$) report significantly higher scores. Age presents a surprising pattern: while the middle-aged generation does not have a significant difference from the young generation, the elderly show a higher score than the middle-aged (β = .42, $p < .001$).

Digital Health Transformative Capacity, reflecting the capacity to convert digital health knowledge into actionable health improvements, is positively associated with education: tertiary (β = .13, $p < .05$) and graduate education (β = .24, $p < .001$) all show significant effects. Gender remains non-significant (see Table 7). In terms of age, the middle-aged generation consistently score lower than the young generation (β = .15, $p < .05$) and the elderly counterpart (β = .24, $p < .001$).

4.5 Rethinking the impacts of age – The dilemma of the sandwiched generation

While digital aging discourse often centers on the elderly, our findings highlight the overlooked vulnerability of the sandwiched generation. This group lags behind the young generation across all dimensions. More notably, they also consistently score lower than the elderly in literacy and transformative capacity (see Table 5). Even after controlling for other conditions, the middle-aged group demonstrates significantly lower overall

DHC, usage and transformative scores compared to the young, with significant disadvantages against the elderly, particularly in literary (see in Table 8).

As Table 8 illustrates, higher education significantly boosts outcomes for the elderly (β = .19, $p < .001$) but offers limited benefits for the middle-aged. Similarly, private housing is associated with better outcomes for older adults (β = .20, $p < .01$) and steady engagement for the young, yet the middle-aged group fails to benefit from better housing levels. In contrast, older adults with higher SES show most pronounced gains from education and housing, suggesting that their health capacity is strongly resource-contigent (see Table 8).

5. Conclusion and discussion

5.1 Reconceptualizing digital health capital

This study develops and validates the DHC as an integrated multidimensional tool to identify the pattern of digital divide in the health arena in Post-COVID Hong Kong.

Table 8. Moderating interaction terms with robust standard errors on DHC.

Predictors	DHC	DHC
	β	β
Gender *(ref. male)*		
-Female	.02	.03
Age group *(ref. sandwiched group (45-65))*		
-Young (under 45)	.23 **	.19 *
-Ederly (above 65)	.12	.12
Educational level *(ref. secondary or below)*		
-Tertiary	.16 *	.26 ***
-Graduate or above	.26 *	.30 ***
Marital status (*ref. not married*)		
-Married	.20 ***	.22 ***
Employment (*ref. not employed*)		
-Employed	.18 ***	.18 ***
Domestic monthly income (ref. *under 30,000 HKD*)		
−30,000-60,000 HKD	−.02	−.06
-Above 60,000 HKD	.03	−.01
House type (ref. Public Rental)		
Subsidized house	−.01	−.02
Private owned	.13 *	.03
Immigration *(ref. Hong Kong)*		
-Mainland China & overseas	−.14 **	−.15 ***
Chronic illness record *(ref. No chronic illness record)*		
-Has chronic illness record	−.03	−.05
Age*education		
-Young*tertiary	.05	
– Young*graduate	−.09	
-Elderly*tertiary	.10	
-Elderly*graduate	.19 ***	
Age*house type		
- Young*subsidized house		.007
- Young* private owned		.03
- Elderly*subsidized house		−.05
- Elderly* private owned		.20 **
Constant	–	–
N	1233	1233
$\mathcal{X}^2$	40.49 (17,1215)	24.17 (17,1215)
$\mathcal{R}^2$	.3664	.3485

Note: β refers to the standardized coefficient
#$p < .1$*$p < .05$. **$p < .01$.***$p < .001$.

The proposed DHC consists of measurements in three dimensions: digital health usage, digital health literacy, and digital health transformative capacity. The DHC contributes to existing digital health and digital divide literature in two aspects.

First, as the ongoing widespread adoption of AI technologies has been reshaping how individuals' access and utilize health services (Siala & Wang, 2022), the DHC adapts to the shifting socio-technical environment by adding the measurements on how individuals use newly emerged digital health technology. Second, the DHC framework bridges the gap between digital capability and consequence. While existing digital health literacy effectively gauge the potential to use health information (the second-level divide), but the current literacy scale was not always led to capture the actualization of that potential (Ji et al., 2024). By integrating transformative capacity as a consequential dimension, the DHC framework allows us to empirically observe the capability to convert digital resources into offline capital.

5.2 Digital health capital divide in post-COVID HK

We used the proposed DHC to gauge the digital health equality in the post-COVID Hong Kong. Our data suggests three empirical findings. First, the DHC exhibits substantial variation in Hong Kong, and the digital health capital divide aligns with socioeconomic stratification: individuals with higher education, better housing, and greater household income consistently score higher across usage, literacy, and transformative capacity, while those from lower SES backgrounds remain digitally marginalized. These results echo a long-standing consensus in digital divide research: digital inequalities often mirror broader social inequalities (Saeed & Masters, 2021; Scheerder et al., 2017).

Second, the divides across the three DHC dimensions are not uniform. Usage and literacy largely follow a resource-based logic: individuals with higher SES status consistently score higher, reflecting the well-documented hierarchy of digital access and skills (e.g., van Dijk, 2006). Transformative capacity, however, does not simply mirror this linear pattern. Several predictors lose their explanatory power. For instance, private home ownership, despite being a strong predictor of digital usage, shows no comparable advantage in transformative capacity, indicating that material conditions facilitating digital access do not automatically convert into tangible health gains.

Third, the findings also caution a stereotype of the elderly generation and reveal the often-overlooked disadvantage faced by the middle-aged 'sandwiched generation.' For instance, while age is positively associated with usage and literacy, its relationship with transformative capacity follows a curvilinear pattern, with the middle-aged cohort scoring lower than both younger and older groups. Such nuanced findings are further analyzed in the next sections and call for more refined policy responses to address health inequalities in the digital age.

5.3 Cross-cutting impacts of SES on different dimensions of DHC

While overall digital capital inequalities aligned with SES disparities, our findings reveal cross-cutting impacts across SES on different dimensions of DHC: usage, literacy, and transformative capacity. Among the SES indicators, education exerts the most consistent and powerful effect across all three dimensions. Housing type also shows a stable positive association, particularly pronounced for transformative capacity, where private housing residents substantially outscore public rental tenants even after controlling for income. This finding suggests that housing serves a more robust SES indicator than income, especially for elderly participants who may lack formal employment but possess long-term accumulated assets.

From policy perspective, this may imply that resources should be channeled specifically through public housing estates to provide the necessary infrastructure and peer support that private housing residents already possess. These divergent patterns do not weaken the rationale for a unified DHC, rather, the difference highlight the inherent complexity of the digital divide. The aggregate score reflects an individual's net capacity, whereas the distinct dimensions allow for rapid identification of specific bottlenecks within the sequential process. Consequently, interpreting the DHC alongside its three dimensions ensures that the composite score does not obscure the nuanced mechanisms of inequality.

5.4 Multi-level implications for tailored interventions

Our results identify the sandwiched generation and low-SES older adults are two structurally vulnerable groups whose disadvantages stem from distinct mechanisms and multi-level interventions. The 45–65 group is structurally excluded from both age-based and class-based digital health advantages, likely reflecting time poverty driving by the competing work and family obligations (Wu et al., 2024). Therefore, at the structural level, support for the sandwiched group should move beyond basic skills training to focus on occupational health policies that integrate digital health management into the workplace. At the individual level, interventions should prioritize low-friction, time-efficient digital health tools suited to their fragmented schedules. Secondly, the finding that high-SES older adults can match younger cohorts in digital capacity disputes the stereotype of uniform digital exclusion among the elderly, suggesting that age-based disadvantage is conditional, not absolute. This cautions against one-size-fits-all elderly assistance. At the community level, interventions should encourage capable high-SES seniors to act as peer digital health mentors. At the structural level, resources should be channeled through public housing estates to target low-SES seniors who lack support.

5.5 Limitations and further directions

Several limitations of this study warrant acknowlegement. First, although our data reveals the dilemma of the middle-aged 'sandwiched generation', this study has not fully unpacked the underlying mechanisms driving their digital health vulnerabilities. Understanding these structural and psychological factors remains a priority for further research. Second, while this study establishes the DHC framework, it does not empirically test the causal pathways or interaction effects among the three dimensions. Future research should examine how usage and literacy translate into transformative capacity, clarifying whether these conversions are sequential or contingent on other enabling conditions. Third, two measurement limitations warrant attention. Our scale includes only limited items directly addressing AI technologies, given the accelerating role of

Generative AI in personal health management, the digital divide is evolving into an algorithmic divide (Wang et al., 2024), and future research should expand the DHC to measure algorithmic health literacy and users' interactions with automated decision-making systems. Additionally, while the two-item measure of transformative capacity demonstrates strong inter-item correlation and composite reliability (CR = .98; see Section 3.2), its content coverage remains constrained. Future research should incorporate items on health decision-making quality and the sustainability of health behaviors to further develop this dimension. More broadly, we recommend a dual-level analytical approach when applying the DHC framework. The composite DHC score captures an individual's overall digital health capital, while separate dimension-level analysis can complement the aggregate score by identifying which specific components drive observed patterns. As the measurement of each dimension matures, future work may also explore separate indices for each dimension to improve analytical precision. Finally, the generalizability of our findings is bounded by Hong Kong's specific socio-cultural context. As a 'high-tech and high-aging' society, the DHC patterns observed here may differ in regions with younger demographic structures, lower digital penetration, or distinct cultural attitudes toward technology and health. Moreover, because the DHC framework was developed in a context where basic access is near-univeral, it does not incorporate the first-level digital divide. Thus, applying DHC in Global South settings where connectivity remains a significant barrier would require integrating access-related measures. Future comparative studies are needed to validate the cross-cultural applicability of the DHC framework.

Notes

1. Deailed weighted method is introduced in Appendix A.
2. We utilized "ChatGPT" as a recognizable generic term for generative AI tools to ensure respondent comprehension. Despite direct access restrictions by OpenAI, Hong Kong residents widely access these models via legitimate third-party platforms, such as Poe.com or Copilot.
3. This classification is based on the median monthly domestic household income in Hong Kong, ranging from 29,600 to 30,000 HKD in 2024 Census. Therefore, 30,000 HKD was used as the threshold to distinguish lower-income groups.
4. Employment is treated as a control rather than an SES because a substantial portion of our sample comprises older adults for whom non-employment reflects retirement rather than economic disadvantage; housing type serves as a more robust proxy for material circumstances in this population.

Author contributions

CRediT: **Fen Lin:** Conceptualization, Formal analysis, Funding acquisition, Project administration, Supervision, Writing – original draft, Writing – review & editing; **Pei Zhi:** Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Writing – original draft, Writing – review & editing; **Yulu Ouyang:** Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing; **Xiaohui Wang:** Funding acquisition, Project administration, Supervision, Writing – review & editing; **Bo Wen:** Funding acquisition, Project administration, Supervision; **Yi-Hui Christine Huang:** Funding acquisition, Project administration, Supervision.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by City University of Hong Kong: [Grant Number 7020080].

Data availability statement

Data are available upon request from the author.

Notes on contribuors

LIN Fen is a professor in the Department of Media and Communication at City University of Hong Kong. She gained her Ph.D. in sociology and M.S. in statistics at the University of Chicago and her B.A. in economics at Peking University. Her research interests include media and social change, technology and ICT innovation, information governance, professionalism, and political communication.

ZHI Pei is a Postdoc researcher in the Department of Media and Communication at City University of Hong Kong. His research interests include political communication, electoral politics, digital media and inequality, communication technology and privacy, and social media participation. He obtained his Ph.D. in communication in City University of Hong Kong. .

OUYANG Yulu is PhD candidate in Department of Media and Communication at City University of Hong Kong. She earned her Master's degree at Peking University and her research focuses on digital inequality and digital governance.

WANG Xiaohui Vincent is an assistant professor in the Department of Media and Communication at City University of Hong Kong. His research converges at the intersection of information, communication, and new technologies, with special focuses on social media, computational social science, and informetrics. He obtained his Ph.D. in Nanyang Technological University.

WEN Bo is an associate professor in the Faculty of Social Sciences at University of Macau. His primary areas of study are public management, organization theory and behavior, institutional analysis, and policy implementation.

HUANG Yi-Hui Christine is a chair professor in the Department of Media and Communication at City University of Hong Kong. She is a Fellow of the International Communication. She is an expert in strategic communication with extensive experience in cross-regional longitudinal surveys.

ORCID

Pei Zhi http://orcid.org/0000-0003-4727-2647

References

Abel, T. (2008). Cultural capital and social inequality in health. *Journal of Epidemiology and Community Health*, *62*(7), e13. https://doi.org/10.1136/jech.2007.066159

Abernethy, A., Adams, L., Barrett, M., Bechtel, C., Brennan, P., Butte, A., Faulkner, J., Fontaine, E., Friedhoff, S., Halamka, J., Howell, M., Johnson, K., Long, P., McGraw, D., Miller, R., Lee, P., Perlin, J., Rucker, D., Sandy, L., … Valdes, K. (2022). The promise of digital health: Then, Now, and the future. *NAM Perspectives*, *2022*, 10.31478/202206e. https://doi.org/10.31478/202206e

Alvarez-Galvez, J., Salinas-Perez, J. A., Montagni, I., & Salvador-Carulla, L. (2020). The persistence of digital divides in the use of health information: A comparative study in 28 European countries. *International Journal of Public Health*, *65*(3), 325–333. https://doi.org/10.1007/s00038-020-01363-w

Bashshur, R., Shannon, G., Krupinski, E., & Grigsby, J. (2011). The taxonomy of telemedicine. *Telemedicine and e-Health*, *17*(6), 484–494. https://doi.org/10.1089/tmj.2011.0103

Benis, A., Barkan, R. B., Sela, T., & Harel, N. (2020). Communication behavior changes between patients With diabetes and healthcare providers over 9 years: Retrospective cohort study. *Journal of Medical Internet Research*, *22*(8), e17186. https://doi.org/10.2196/17186

Bennett, A. M. (1978). *Telehealth handbook. U.S. Department of health, education, and welfare, public health service, national center for health services research : available from*. NCHSR Publications and Information Branch.

Bokolo, A. J. (2021). Application of telemedicine and eHealth technology for clinical services in response to COVID-19 pandemic. *Health and Technology*, *11*(2), 359–366. https://doi.org/10.1007/s12553-020-00516-4

Bourdieu, P. (1986). The forms of capital. In J. Richardson (Ed.), *Handbook of theory and research for the sociology of education* (pp. 241–258). Greenwood.

Büchi, M., Festic, N., & Latzer, M. (2018). How social well-being Is affected by digital inequalities. *International Journal of Communication*, *12*(2018), 3686–3706.

Budd, J., Miller, B. S., Manning, E. M., Lampos, V., Zhuang, M., Edelstein, M., Rees, G., Emery, V. C., Stevens, M. M., Keegan, N., Short, M. J., Pillay, D., Manley, E., Cox, I. J., Heymann, D., Johnson, A. M., & McKendry, R. A. (2020). Digital technologies in the public-health response to COVID-19. *Nature Medicine*, *26*(8), 1183–1192. https://doi.org/10.1038/s41591-020-1011-4

Calderón Gómez, D. (2021). The third digital divide and bourdieu: Bidirectional conversion of economic, cultural, and social capital to (and from) digital capital among young people in Madrid. *New Media & Society*, *23*(9), 2534–2553. https://doi.org/10.1177/1461444820933252

Census and Statistics Department. (2025, June 12). Thematic Household Survey Report No. 82 published. The Government of the Hong Kong Special Administrative Region. https://www.info.gov.hk/gia/general/202506/12/P2025061200354.htm.

Chang, B. L., Bakken, S., Brown, S. S., Houston, T. K., Kreps, G. L., Kukafka, R., Safran, C., & Stavri, P. Z. (2004). Bridging the digital divide: Reaching vulnerable populations. *Journal of the American Medical Informatics Association*, *11*(6), 448–457. https://doi.org/10.1197/jamia.M1535

Das, M. (2023). From crisis to insight: Navigating public health challenges in an aging society—lessons from Hong Kong's COVID-19 experience. *Journal of Urban Health*, *100*(4), 852–859. https://doi.org/10.1007/s11524-023-00760-9

Diamantopoulos, A., & Winklhofer, H. M. (2001). Index construction with formative indicators: An alternative to scale development. *Journal of Marketing Research*, *38*(2), 269–277. https://doi.org/10.1509/jmkr.38.2.269.18845

Dobransky, K., & Hargittai, E. (2012). Inquiring minds acquiring wellness: Uses of online and offline sources for health information. *Health Communication*, *27*(4), 331–343. https://doi.org/10.1080/10410236.2011.585451

Eisinga, R., Grotenhuis, M. t., & Pelzer, B. (2013). The reliability of a two-item scale: Pearson, cronbach, or spearman-brown? *International Journal of Public Health*, *58*(4), 637–642. https://doi.org/10.1007/s00038-012-0416-3

Friemel, T. N. (2016). The digital divide has grown old: Determinants of a digital divide among seniors. *New Media & Society*, *18*(2), 313–331. https://doi.org/10.1177/1461444814538648

Frishammar, J., Essén, A., Bergström, F., & Ekman, T. (2023). Digital health platforms for the elderly? Key adoption and usage barriers and ways to address them. *Technological Forecasting and Social Change*, *189*, 122319. https://doi.org/10.1016/j.techfore.2023.122319

Fu, S., Chen, X., Zheng, H., & Ou, M. (2021). Understanding health information literacy of mHealth app users from digital wellbeing perspective: Evidence from regression analysis and fsQCA. *Library & Information Science Research*, *43*(3), 101108. https://doi.org/10.1016/j.lisr.2021.101108

Gershon-Cohen, J., & Cooley, A. G. (1950). Telognosis. *Radiology*, *55*(4), 582–587. https://doi.org/10.1148/55.4.582

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy*, *80*(2), 223–255. https://doi.org/10.1086/259880

Hadjiat, Y. (2023). Healthcare inequity and digital health–A bridge for the divide, or further erosion of the chasm? *PLOS Digital Health*, *2*(6), e0000268. https://doi.org/10.1371/journal.pdig.0000268

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hargittai, E. (2010). Digital Na(t)ives? Variation in internet skills and uses among members of the "Net generation". *Sociological Inquiry*, *80*(1), 92–113. https://doi.org/10.1111/j.1475-682X.2009.00317.x

Harris, A., Jain, A., Dhanjani, S. A., Wu, C. A., Helliwell, L., Mesfin, A., Menga, E., Aggarwal, S., Pusic, A., & Ranganathan, K. (2023). Disparities in telemedicine literacy and access in the United States. *Plastic & Reconstructive Surgery*, *151*(3), 677–685. https://doi.org/10.1097/PRS.0000000000009939

Hospital Authority. (2025, October 27). *HA holds "smart health made easy—HA Go at your fingertips" launch ceremony (with photos)*. HKSAR Government Information Services Department. https://www.info.gov.hk/gia/general/202510/27/P2025102700426.htm.

Hua, Y., Shujuan, W., & Fucheng, W. (2023). Online health community—An empirical analysis based on grounded theory and entropy weight TOPSIS method to evaluate the service quality. *DIGITAL HEALTH*, *9*, 20552076231207201. https://doi.org/10.1177/20552076231207201

Istepanian, R. s. H., Laxminarayn, S., & Pattichis, C. (2006). *M-Health: Emerging mobile health systems*. Springer.

Ji, H., Dong, J., Pan, W., & Yu, Y. (2024). Associations between digital literacy, health literacy, and digital health behaviors among rural residents: Evidence from zhejiang, China. *International Journal for Equity in Health*, *23*(1), 68. https://doi.org/10.1186/s12939-024-02150-2

Jin, L., Chen, X., Lin, F., Zou, Y., & Gao, H. (2022). Does education matter for psychological recovery amidst the COVID-19 pandemic? Evidence from a panel survey in Hubei, China. *Anxiety, Stress, & Coping*, *35*(1), 101–110. https://doi.org/10.1080/10615806.2021.1978431

Kaihlanen, A.-M., Virtanen, L., Buchert, U., Safarov, N., Valkonen, P., Hietapakka, L., Hörhammer, I., Kujala, S., Kouvonen, A., & Heponiemi, T. (2022). 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 Services Research*, *22*(1), 188. https://doi.org/10.1186/s12913-022-07584-4

Karnoe, A., Furstrand, D., Christensen, K. B., Norgaard, O., & Kayser, L. (2018). Assessing competencies needed to engage With digital health services: Development of the eHealth literacy assessment toolkit. *Journal of Medical Internet Research*, *20*(5), e178. https://doi.org/10.2196/jmir.8347

Lin, F., Jin, L., & Chen, X. (2025). Digitalization, psychological well-being, and the third-level digital divide: Survey study during the COVID-19 pandemic in China. *Journal of Medical Internet Research*, *27*(1), e48195. https://doi.org/10.2196/48195

Lin, T. T. C., & Bautista, J. R. (2017). Understanding the relationships between mHealth apps' characteristics, trialability, and mHealth literacy. *Journal of Health Communication*, *22*(4), 346–354. https://doi.org/10.1080/10810730.2017.1296508

Magsamen-Conrad, K., Dillon, J. M., Billotte Verhoff, C., & Joa, C. Y. (2020). Toward a theory of HealthIT adoption across the lifespan: Findings from five years in the community. *Health Communication*, *35*(3), 308–321. https://doi.org/10.1080/10410236.2018.1563027

Meskó, B., Drobni, Z., Bényei, É, Gergely, B., & Győrffy, Z. (2017). Digital health is a cultural transformation of traditional healthcare. *mHealth*, *3*, 38. https://doi.org/10.21037/mhealth.2017.08.07

Murphy, R. L., & Bird, K. T. (1974). Telediagnosis: A new community health resource. Observations on the feasibility of telediagnosis based on 1000 patient transactions. *American Journal of Public Health*, *64*(2), 113–119. doi:10.2105/AJPH.64.2.113

Norman, C. D., & Skinner, H. A. (2006). eHEALS: The eHealth literacy scale. *Journal of Medical Internet Research*, *8*(4), e27. https://doi.org/10.2196/jmir.8.4.e27

Paige, S. R., Stellefson, M., Krieger, J. L., Miller, M. D., Cheong, J., & Anderson-Lewis, C. (2019). Transactional eHealth literacy: Developing and testing a multi-dimensional instrument. *Journal of Health Communication*, *24*(10), 737–748. https://doi.org/10.1080/10810730.2019.1666940

Rachmani, E., Haikal, H., & Rimawati, E. (2022). Development and validation of digital health literacy competencies for citizens (DHLC), an instrument for measuring digital health literacy in the community. *Computer Methods and Programs in Biomedicine Update*, *2*, 100082. https://doi.org/10.1016/j.cmpbup.2022.100082

Ragnedda, M. (2017). *The third digital divide: A weberian approach to digital inequalities*. Taylor & Francis.

Ragnedda, M., Ruiu, M. L., & Addeo, F. (2020). Measuring digital capital: An empirical investigation. *New Media & Society*, *22*(5), 793–816. https://doi.org/10.1177/1461444819869604

Ramsetty, A., & Adams, C. (2020). Impact of the digital divide in the age of COVID-19. *Journal of the American Medical Informatics Association*, *27*(7), 1147–1148. https://doi.org/10.1093/jamia/ocaa078

Robinson, L., Cotten, S. R., Ono, H., Quan-Haase, A., Mesch, G., Chen, W., Schulz, J., Hale, T. M., & Stern, M. J. (2015). Digital inequalities and why they matter. *Information, Communication & Society*, *18*(5), 569–582. https://doi.org/10.1080/1369118X.2015.1012532

Saeed, S. A., & Masters, R. M. (2021). Disparities in health care and the digital divide. *Current Psychiatry Reports*, *23*(9), 61. https://doi.org/10.1007/s11920-021-01274-4

Sakumoto, M. D., & Krug, M. S. (2023). Reframing equity: A multi-perspective analysis of telehealth screening tools through the lens of patients and clinicians. *Telehealth and Medicine Today*, *8*(5). https://doi.org/10.30953/thmt.v8.439

Scheerder, A., van Deursen, A., & van Dijk, J. (2017). Determinants of internet skills, uses and outcomes. A systematic review of the second- and third-level digital divide. *Telematics and Informatics*, *34*(8), 1607–1624. https://doi.org/10.1016/j.tele.2017.07.007

Shim, J. K. (2010). Cultural health capital. *Journal of Health and Social Behavior*, *51*(1), 1–15. https://doi.org/10.1177/0022146509361185

Siala, H., & Wang, Y. (2022). SHIFTing artificial intelligence to be responsible in healthcare: A systematic review. *Social Science & Medicine*, *296*, 114782. https://doi.org/10.1016/j.socscimed.2022.114782

Stern, M., Adams, A., & Elsasser, S. (2009). Digital inequality and place: The effects of technological diffusion on internet proficiency and usage across rural, suburban, and urban counties*. *Sociological Inquiry*, *79*(4), 391–417. https://doi.org/10.1111/j.1475-682X.2009.00302.x

Uzun, B., Taiwo, M., Syidanova, A., & Uzun Ozsahin, D. (2021). The technique For order of preference by similarity to ideal solution (TOPSIS). In D. Uzun Ozsahin, H. Gökçekuş, B. Uzun, & J. LaMoreaux (Eds.), *Application of multi-criteria decision analysis in environmental and civil engineering* (pp. 25–30). Springer International Publishing. https://doi.org/10.1007/978-3-030-64765-0_4.

Vaart, R. v. d., & Drossaert, C. (2017). Development of the digital health literacy instrument: Measuring a broad spectrum of health 1.0 and health 2.0 skills. *Journal of Medical Internet Research*, *19*(1), e27. https://doi.org/10.2196/jmir.6709

van, D. A. J. A. M., & Helsper, E. J. (2015). The third-level digital divide: Who benefits most from being online?. In L. Robinson, S. R. Cotten, J. Schulz, T. M. Hale, & A. Williams (Eds.), *Communication and information technologies annual: Digital distinctions and inequalities* (Vol. 10, pp. 29–52). Emerald Group Publishing Limited. https://doi.org/10.1108S2050-206020150000010002

van Deursen, A. J., & van Dijk, J. A. (2014). The digital divide shifts to differences in usage. *New Media & Society*, *16*(3), 507–526. https://doi.org/10.1177/1461444813487959 van Dijk, J. A. G. M. (2006). Digital divide research, achievements and shortcomings. *Poetics*, *34*(4-5), 221–235. https://doi.org/10.1016/j.poetic.2006.05.004

Virlée, J., van Riel, A. C. R., & Hammedi, W. (2020). Health literacy and its effects on well-being: How vulnerable healthcare service users integrate online resources. *Journal of Services Marketing*, *34*(5), 697–715. https://doi.org/10.1108/JSM-02-2019-0057

Wang, Y., Li, J., Zhang, G., Li, Y., & Asare, M. H. (2017). Fuzzy evaluation of comprehensive benefit in urban renewal based on the perspective of core stakeholders. *Habitat International*, *66*, 163–170. https://doi.org/10.1016/j.habitatint.2017.06.003

Wang, L., Wang, X., & Lin, F. (2024). Algorithmic divide among elderly and sandwich generation in Hong Kong: Development and validation an algorithm literacy scale. Paper presented at International Association for Media and Communication Research Conference 2024, Christchurch, New Zealand.

World Health Organization. (2006). Electronic health records: Manual for developing countries. https://iris.who.int/server/api/core/bitstreams/8663e0dc-075e-443a-8334-c344e7818652/content

Wu, J., Tian, B., Gao, Y., & Wang, L. (2024). Extinguishing the fire at both ends: The dual family-caregiving stress of the sandwich generation of China's "4-2-2" families. *Families in Society: The Journal of Contemporary Social Services*, *105*(4), 604–620. https://doi.org/10.1177/10443894231183406

Yoon, J., Lee, M., Ahn, J. S., Oh, D., Shin, S.-Y., Chang, Y. J., & Cho, J. (2022). Development and validation of digital health technology literacy assessment questionnaire. *Journal of Medical Systems*, *46*(2), 13. https://doi.org/10.1007/s10916-022-01800-8

Zhang, L., & Li, P. (2022). Problem-Based mHealth literacy scale (PB-mHLS): Development and validation. *JMIR MHealth and UHealth*, *10*(4), e31459. https://doi.org/10.2196/31459