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Different People, Different Supports: Using Latent Class Analysis and Behaviour Change Wheel Mapping to Inform Tailored Digital Health Implementation Strategies

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Abstract

Background

Digital health implementation efforts often focus on improving digital literacy and competence, yet digital health engagement is influenced by a broader range of behavioural, social, and contextual factors. While demographic disparities in digital health use are well documented, less is known about how different population groups prefer to receive support and how implementation strategies can be tailored to their needs. This study aimed to identify population segments with distinct sociodemographic characteristics and examine differences in digital competence, support preferences, learning preferences, and digital health engagement to inform implementation planning.

Methods

A cross-sectional survey was conducted among adults residing in the Fraser Health region of British Columbia, Canada (n = 617). Latent class analysis was used to identify population segments based on age, gender, income, and ethnicity. Structural equation modeling was used to compare digital competence across segments. Descriptive and bivariate analyses examined differences in support preferences, learning preferences, technology access, and virtual care use. Findings were subsequently mapped to the Behaviour Change Wheel to identify potential implementation implications.

Results

Three population segments were identified: Racially Diverse Younger Adults, Middle-Income White Seniors, and Affluent Midlife Adults. Population segments differed significantly in digital health competence ($p < 0.001$), with Middle-Income White Seniors showing the lowest competence and Affluent Midlife Adults the highest. Middle-Income White Seniors demonstrated significantly lower digital competence than Racially Diverse Younger Adults, while Affluent Middle-Aged Adults demonstrated significantly higher competence. Despite high competence and access, Racially Diverse Younger Adults were most likely to report no virtual care use. Support preferences differed significantly across segments, with Racially Diverse Younger Adults preferring online support, Middle-Income White Seniors preferring in-person support, and Affluent Midlife Adults preferring technical support. Behavioural mapping suggested that similar barriers often required different implementation approaches depending on the population segment experiencing them.

Conclusions

Digital competence alone does not fully explain engagement with digital health services. Population segments differed not only in competence, but also in support preferences, access, and patterns of

virtual care use. Combining behavioural frameworks with population segmentation may provide a practical approach for tailoring implementation strategies and improving the equity and reach of digital health interventions.

Contributions to the Literature

- Digital health implementation efforts often focus on improving digital literacy, but our findings suggest that competence alone does not explain engagement with virtual care services.
- This study demonstrates how population segmentation can complement behavioural frameworks by identifying not only what barriers exist, but how implementation strategies may need to differ across population groups.
- Similar behavioural barriers were observed across multiple population segments, yet preferred support mechanisms and communication channels differed substantially.
- Combining population segmentation with Behaviour Change Wheel analyses may provide a practical approach for designing more equitable and contextually appropriate implementation strategies.

Background

As health systems around the world expand to include virtual care and digital health technologies, concerns about *digital exclusion*, the inability to access, understand or effectively use digital tools for health, have taken on a greater urgency (1–3). While digital health promises to improve access and convenience, it can also reinforce existing barriers for people with limited digital skills, poor access to devices or connectivity, language barriers, or for those unfamiliar with health system technologies (4). These concerns were exacerbated during the COVID-19 pandemic, which catalyzed a rapid and widespread shift to delivery of care using digital technologies. While this shift increased convenience for some patients and healthcare-seekers, it simultaneously exposed substantial disparities in individuals' access and ability to engage with digital health services (1, 5, 6).

A growing body of research has demonstrated that digital health engagement is unevenly distributed across populations. Individuals from culturally and linguistically diverse backgrounds, older adults, low-income populations, and those with limited educational attainment are more likely to experience barriers to digital health participation (4, 7–12). Many of these barriers are rooted in differences in digital health competence (i.e., the skills and confidence required to engage with digital technologies for health-related needs) (13). Digital competence is consistently associated with factors such as age, income, education, employment, and gender, with higher levels of confidence and ability in using digital technologies reported among younger, more affluent, and more highly educated individuals (14–16).

Although these patterns are well established, they provide only a partial picture of digital health equity. Existing literature has largely focused on identifying demographic groups with lower digital competence or reduced engagement with digital health services, while devoting less attention to how these disparities can be addressed. Consequently, there is limited understanding of how different population

groups prefer to receive support, how they wish to learn about digital health services, and whether higher competence necessarily translates into greater use of digital healthcare. These questions are becoming increasingly important as health systems move beyond the adoption of digital technologies toward their large-scale implementation and sustained use.

Digital health engagement is influenced by more than technical skill alone. Even individuals who report high levels of digital competence may encounter barriers related to trust, awareness, language, system navigation, accessibility, or the perceived relevance of digital health services (13, 15, 17). Conversely, some individuals with lower confidence may successfully engage when appropriate supports are available. Understanding these differences is essential for designing implementation strategies that are responsive to the needs of diverse populations rather than relying on one-size-fits-all approaches to digital inclusion.

An additional challenge is that demographic characteristics rarely operate independently. Engagement with, and competence in, digital health are shaped by the intersection of age, gender, income, education, language, and racial or ethnic identity (18, 19). Populations historically marginalized within health care systems often face compounding challenges in accessing and effectively using digital health technologies (4, 18). While previous studies often examine these characteristics separately, health systems must ultimately design services for real-world populations whose experiences are shaped by multiple, overlapping social factors. Therefore, identifying commonly occurring population profiles may provide a more practical lens for understanding how different groups engage with digital health services and what types of support may be most beneficial.

Fraser Health, one of British Columbia, Canada's largest and most diverse health authorities, serves more than two million residents, including substantial immigrant, multilingual, and culturally diverse populations. As digital health services continue to expand across the region, there is a need to better understand how different population groups engage with these technologies and which implementation approaches may best support equitable uptake. Given the scale and diversity of the population served, insights from this context may also be relevant to other health systems facing similar challenges in equitably implementing digital health services.

Using latent class analysis (LCA) and structural equation modeling (SEM), this study identified population segments with distinct sociodemographic characteristics and examined whether they differed in digital health competence, support preferences, and preferred approaches for learning about digital health services. The goal of this work was to generate implementation-relevant population profiles that may inform tailored digital health engagement strategies. By examining how competence, support needs, and learning preferences cluster across different segments of the population, this study aims to provide actionable insights for designing more inclusive and equitable digital health services.

Methods

Study Design and Data Collection

A cross-sectional survey was conducted between June and August 2024 in the Fraser Health region of British Columbia, Canada. Eligible participants were adults aged 19 years or older living within the Fraser Health region. Ethics approval was obtained from both Fraser Health and the University of British Columbia Research Ethics Boards (#H24-01086) in accordance with the Declaration of Helsinki.

A combined stratified and purposive sampling strategy was used to ensure representation across age and ethnocultural groups. Stratified sampling was applied to reflect the proportion of older adults (65+) in the regional population. Purposive sampling engaged participants from diverse ethnocultural communities via in-person community events, clinical sites, and local organizations.

The survey was developed in English in collaboration with research partners, patient advisors, and a Plain Language Specialist. It was piloted with five patient partners and subsequently translated into six of the most widely spoken languages in the Fraser Health region: Traditional Chinese, Simplified Chinese, Arabic, Tigrigna, Panjabi, and Spanish. The final survey was administered using Qualtrics, with both online and paper-based options. The survey was shared online through Fraser Health's website, social media channels and via email through community organizations. In-person data collection was supported by trained data collectors who assisted participants in multiple languages using tablets. All data collectors were trained in the ethical administration of surveys.

Following informed consent, participants completed a structured questionnaire (full questionnaire can be found in the appendix) that assessed perceived digital health competence, current use of virtual health tools, preferred learning methods, support needs, and demographic characteristics. The survey was anonymous; participants who completed it in person received a $10 CAD coffee shop gift card, and all participants had the option to enter a draw for a tablet.. Contact information was collected separately and only from those who consented.

Variables and Measures

This study sought to identify population segments with distinct sociodemographic characteristics and examine differences in digital health competence, support preferences, learning preferences, and digital health engagement. Digital competence was assessed as one important implementation-related characteristic, alongside respondents' preferred sources of support and preferred methods for learning about digital health services.

Digital competence was measured using four items adapted from Yuen et al. (200, designed to assess perceived ability to use digital health technologies. The first three items employed a binary response format ("Yes" or "No"/"Not sure") and were derived from "I am capable of using digital health technologies" (20). These included:

- Computer competence = *Do you know how to use a desktop or laptop computer?*

- Tablet competence = *Do you know how to use a tablet?* and
- Smartphone competence = *Do you know how to use a smartphone (iPhone or Android)*?

The fourth item, Virtual Health competence, evaluated perceived knowledge to use digital technologies for health care, was adapted from "I have enough knowledge and skills to use digital health technologies" (20). This item utilized a Likert-type scale ranging from "Definitely not" to "Definitely" and asked: *Do you have enough knowledge and skills to use technology for health care?*

Support preferences were explored through a single-response question designed to identify preferred forms of assistance for increasing respondents' confidence in using digital health technologies. Participants were asked: "*What single thing would make you feel more confident using technology for health care*?" Response options included: Online support such as eLearning, support groups, how-to guides or videos; In-person support such as family or friends, health care provider, courses; and technical support via phone or live chat.

Learning preferences were investigated using a multiple-response question aimed at understanding how respondents prefer to learn about new digital health services. Participants who responded to "*How would you like to learn about new health care services you can use through technology*?" were able to select all that applies from the following options: Fraser Health websites and social media; Hospitals, clinics and other health care locations; Community groups such as community centres and events; and Local papers such as Surrey leader, Peace arch news, Vancouver Sun and The Province.

Demographic and socioeconomic characteristics collected include: age, gender, ethnicity, household income, and experiences of disabilities and chronic conditions. Respondents with missing values or who preferred not to answer any of the competency or demographic questions were excluded from the analysis.

Statistical Analysis

Latent class analysis (LCA) was used to identify commonly occurring sociodemographic profiles within the sample (21). Rather than examining age, income, gender, and ethnicity independently, LCA allows individuals who share similar demographic characteristics to be grouped into population segments that may have different implementation needs and engagement patterns. These segments were subsequently compared on digital competence, support preferences, learning preferences, and virtual health use.

LCA was performed using the *poLCA* package in R (22). The analysis included age, gender, income, and ethnicity as observed indicators. To determine the optimal number of latent classes, models specifying one to five classes were iteratively estimated. Model selection was based on a combination of fit statistics, including Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), along with likelihood-based criteria and entropy (21). The final model comprised three latent classes. Class

membership probabilities were estimated using the Expectation-Maximization (EM) algorithm, and individuals were assigned to classes for which they had the highest posterior probability.

Confirmatory factor analysis (CFA) was conducted to assess whether four observed indicators collectively (virtual health competence, desktop competence, tablet competence, and smartphone competence) adequately represented a latent construct of digital competence. Structural equation modeling (SEM) analysis was then conducted using the *lavaan* package in R (23) to examine differences across latent classes. Class membership derived from the LCA was treated as an observed grouping variable. The primary aim was to assess whether class assignment predicted differences in the latent digital competence construct, rather than to model all determinants of competence. Model fit for both CFA and SEM models was evaluated using the chi-square test, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR).

To explore the relationship between demographic latent class membership and perceived digital competence, we conducted SEM which allowed for estimation of class-specific mean competence scores and test for significant differences across the latent classes. The maximum-likelihood estimation was performed in the model. Model fit was assessed using chi-square test, CFI, RMSEA, and SRMR.

Finally, descriptive and bivariate analyses were conducted to characterize each latent class with respect to digital health engagement, support preferences, learning preferences, and access-related characteristics. These analyses were intended to identify practical considerations to inform tailored digital health implementation strategies.

Theory-Informed Behavioural Mapping

To support interpretation of findings and inform implementation strategies, a structured, theory-informed analysis was conducted using the Behaviour Change Wheel (BCW) framework (24). The BCW provides a systematic approach to understanding behaviour and identifying intervention strategies through the following stages: behavioural diagnosis using the COM-B model (Capability, Opportunity, Motivation), identification of intervention functions, and selection of policy categories to support implementation.

Behavioural Diagnosis Using COM-B

Survey measures were first deductively mapped onto COM-B domains, including capability (physical and psychological), opportunity (physical and social), and motivation (reflective and automatic). Mapping was conducted by one author (MM) and reviewed by all remaining authors to ensure conceptual alignment.

Following latent class analysis, COM-B mapping was conducted separately for each population segment to identify distinct behavioural profiles. This step was interpretive rather than statistical, and aimed to

identify actionable barriers and enablers influencing engagement in digital health. Particular attention was given to identifying mismatches between capability, opportunity, and motivation as potential targets for intervention.

Identification of Intervention Functions, Policy Categories, and Behaviour Change Techniques (BCTs)

The BCW identifies nine intervention functions that can be used to address behavioural determinants: education, persuasion, incentivization, coercion, training, restriction, environmental restructuring, modelling, and enablement (24). Intervention functions were selected based on their alignment with the identified COM-B barriers and facilitators within each population segment. Candidate intervention functions were then assessed using the APEASE criteria (Affordability, Practicability, Effectiveness, Acceptability, Side-effects/safety, and Equity) to determine their suitability within the context of a publicly funded health authority.

Selected intervention functions were mapped to corresponding policy categories (e.g., communication/marketing, service provision, environmental/social planning) and Behaviour Change Techniques (BCTs) (25). Policy categories and BCTs were evaluated using APEASE criteria to assess feasibility within a regional health authority context.

The BCW outlines seven policy categories that can support implementation of intervention functions: communication/marketing, guidelines, fiscal measures, regulation, legislation, environmental/social planning, and service provision (24). Policy categories were linked to the selected intervention functions using matrices within the BCW.

Behaviour Change Techniques (BCTs) are considered the smallest observable and replicable components of behaviour change interventions (25). The BCT Taxonomy version 1 (BCTTv1) includes 93 BCTs that can be used to operationalize intervention functions and support behaviour change. All 93 BCTs were considered for all intervention functions, and selection of appropriate BCTs was guided by the matrices within the BCW linking intervention functions to commonly used BCTs, as well as the theory and techniques tool (https://theoryandtechniquetool.humanbehaviourchange.org/tool).

Intervention functions, policy categories, and BCTs were translated into example implementation strategies tailored to each population segment to generate actionable, theory-informed recommendations for digital health implementation.

Results

Study Sample Characteristics

A total of 617 valid responses were collected, 322 (52%) of which were completed in-person and 295 completed online. A total of 188 respondents were excluded from the LCA and SEM analyses due to

missing data or because they opted not to answer any competency or demographic questions.

Respondents represented a broad age range: 36% were aged 19 to 34, 25% aged 35 to 54, 10% aged 55 to 64, 15% aged 65 to 74, and 14% aged 75 or older. The majority identified as women (69%), followed by men (27%), with 1.5% identifying as transgender, non-binary, gender-queer, or preferred not to disclose.

Household income varied, with 34% earning below $40,000; 18% earning between $40,000–$79,999; 9% earning between $80,000–$99,999; and 24% reporting household incomes over $100,000.

Respondents also represented a range of ethnic and cultural backgrounds, with the majority identifying as South Asian (30%), followed by White (28%), and East Asian (11%) (see Table 1 for full breakdown).

Table 1
Descriptive statistics of the sample: Respondents to the 2024 Virtual Health Preferences and Access Survey

Characteristics	n (%)
Age-group, years	
19–34	224 (36.3%)
35–54	152 (24.6%)
55–64	62 (10.1%)
65–74	90 (14.6%)
75 and older	89 (14.4%)
Ethnic/cultural background	
Black	44 (7.1%)
East Asian	70 (11.3%)
First Nations	4 (0.7%)
Indigenous - Inuk	1 (0.2%)
Indigenous - Metis	2 (0.3%)
Indigenous - Other	2 (0.3%)
Latino	27 (4.4%)
Middle Eastern	24 (3.9%)
Multiracial	26 (4.2%)
South Asian	184 (29.8%)
Southeast Asian	32 (5.2%)
White	174 (28.2%)
Preferred not to answer	27 (4.4%)
Gender	
Woman	425 (68.9%)
Man	168 (27.2%)
Trans-Man	1 (0.2%)
Trans-Woman	2 (0.3%)

Characteristics	n (%)
Age-group, years	
Two-Spirit	2 (0.3%)
Non-Binary or gender-queer	4 (0.7%)
Preferred not to answer	15 (2.4%)
Household income	
Less than $40k	210 (34%)
$40k to $79k	112 (18.2%)
$80k+	146 (23.7%)
Preferred not to answer	149 (24.1%)

This variation in age, gender, income, and cultural identity provided a strong foundation for examining differences in digital health competence and support needs across socio-demographic groups.

[Insert Table 1]

Latent Class Analysis

Table 2 summarizes model fit indices for LCA models ranging from one to five classes. The indices demonstrated a progressive improvement in the model fit from one to four classes. Despite the BIC for the 3-class model being slightly higher than the 2-class model, the AIC and likelihood ratio were lower, indicating an enhancement in fit from two to three classes. Furthermore, the 3-class model exhibited higher entropy, denoting better class separation (26). Although the 4-class model showed better fit indices, specifically with AIC and likelihood ratio, it failed to generate maximum likelihood, indicating potential issues with model convergence. Therefore, the 3-class model was selected as the optimal fit for our analysis, with the most balanced statistical fit and interpretability.

Table 2
Fit indices for LCA models

Model	AIC	BIC	Likelihood Ratio	Entropy
1	4587.234	4648.156	514.2223	5.311462
2	4457.912	4583.818	352.9003	5.130963
3	**4428.748**	**4619.637**	**291.7361**	**5.067635**
4	4422.503	4678.375	253.4911	5.017484
5	4424.477	4745.332	223.465	4.973044

Latent Class Profiles

Table 3 presents the demographic characteristics for each latent class. Class 1 comprises over half of the total population (52.5%) and is characterized as “Racially Diverse Younger Adults”. This class includes primarily adults aged 19–34 with low household incomes (most between $20,000–$39,999). A majority identified as South Asian (49.3%) or multiracial/other (21.3%), and 66.9% identified as women.

Class 2, with the smallest sample of the three classes (17.5%), is characterized as “Middle-Income White Seniors”. Comprising primarily individuals aged 65 and older, this class is predominantly White (85.8%) and middle-income (median income $40,000–$59,999). The gender distribution is relatively balanced, with 58% identifying as women.

Class 3, characterized as “Affluent Middle-Aged Adults”, makes up 30% of the population. This group includes individuals aged 35–54 with high household incomes (≥$100,000). Ethnic composition is more diverse: 46.5% identified as White, 16.5% as East Asian, and 15.2% as South Asian. Women comprised 82% of this group. From here-on, “classes” are referred to as “population segments”.

Table 3
Class demographics

n	Racially Diverse Younger Adults	Middle-Income White Seniors	Affluent Middle-Aged Adults
	225 (52.45%)	**75 (17.48%)**	**129 (30.07%)**
Age (median)	19–34	≥ 65	35–54
Gender (%)			
Man	30.44	39.93	17.97
Woman	66.88	58.77	82.03
Trans-Woman, Trans-Man, Two-spirit, non-binary or gender-queer	2.68	1.3	0
Ethnicity (%)			
White	0	85.08	46.53
Black	13.42	0	1.5
East Asian	11.34	14.92	16.5
South Asian	49.32	0	15.2
Southeast Asian	4.63	0	7.53
Multiracial or other (including Indigenous, Latino, and Middle Eastern)	21.29	0	12.74
Income (median)	$20,000 to $39,999	$40,000 to $59,999	$100,000 and over

Confirmatory Factor Analysis

CFA demonstrated that four observed indicators, virtual health competence, tablet competence, desktop competence, and smartphone competence, loaded strongly onto a latent construct of digital competence. Fit indices indicated good model fit: χ^2 ($p = 0.60$), CFI > 0.95, TLI > 0.95, RMSEA = 0.064 (90% CI: 0.00–0.13), and SRMR = 0.019. All factor loadings were statistically significant ($p < 0.001$) and greater than 0.50, supporting the construct validity of the competence measure.

Structural Equation Modeling

The SEM model fit indices (CFI = 0.976, SRMR = 0.031) indicated that the model fits the data well overall, supporting the validity of the model for comparative purposes. Although the RMSEA is considered moderate (0.059), this is acceptable given the model's low degrees of freedom and the exploratory nature of the group comparisons.

The measurement model demonstrated strong factor loadings, confirming that virtual health competence ($\beta = 0.802$, $p < 0.001$), tablet competence ($\beta = 0.742$, $p < 0.001$), desktop competence ($\beta = 0.598$, $p < 0.001$) and smartphone competence ($\beta = 0.579$, $p < 0.001$), reliably capture the latent construct of digital competency. Results based on SEM are shown in Fig. 1

* $p < 0.05$

** $p < 0.001$

The three population segments demonstrated significantly different levels of digital competence, suggesting that demographic segmentation may help identify groups requiring different approaches to digital health implementation and support. Specifically, individuals in population segment 2 (Middle-Income White Seniors) had significantly lower levels of digital competence (estimate = -0.53; standardized estimate = -0.26; $p < 0.001$) relative to those in population segment 1 (Racially Diverse Younger Adults). Conversely, those in population segment 3 (Affluent Middle-Aged Adults) demonstrated significantly higher digital competence (estimate = 0.27; standardized estimate = 0.16; $p = 0.003$).

Support and Learning Preferences Across Population Segments

Participants' preferences for receiving support in using technology for health care varied significantly across the three population segments ($p < 0.001$; see Table 4 (a for full breakdown). The most commonly selected option by Racially Diverse Younger Adults was online support (41.8% of respondents). In contrast, Middle-Income White Seniors had more diverse preferences; 44% preferred in-person support, 25.1% preferred online support, and 18.7% favored technical support. Finally, 31% of Affluent Middle-Aged Adults opted for technical support, 27.1% selected in-person support, and 21.7% for online support.

Table 4
Population segment preferences and other characteristics

Support preferences **(p < 0.001)**	**Racially Diverse Younger Adults**	**Middle-Income White Seniors**	**Affluent Middle-Aged Adults**
Online support	94 (41.8%)	19 (25.3%)	28 (21.7%)
In-person support	68 (30.2%)	33 (44%)	35 (27.1%)
Technical support	43 (19.1%)	14 (18.7%)	40 (31%)
Channel preferences for learning about new health care services[1]			
Online websites (p = 0.7)	160 (71.1%)	50 (66.7%)	88 (68.2%)
Health care settings (p = 0.1)	115 (51.1%)	41 (54.7%)	81 (62.8%)
Community centers (p = 0.95)	74 (32.9%)	26 (34.7%)	44 (34.1%)
Local newspapers (p = 0.001)	34 (15.1%)	26 (34.7%)	30 (23.3%)
Device ownership[1]			
Desktop/laptop computer (p < 0.001)	137 (60.9%)	55 (73.3%)	109 (84.5%)
Smartphone (p < 0.001)	205 (91.1%)	58 (77.3%)	125 (96.9%)
Tablet (p < 0.001)	55 (24.4%)	35 (46.7%)	68 (52.7%)
Landline (p < 0.001)	38 (16.9%)	46 (61.3%)	30 (23.3%)
None (p = 0.5)	6 (2.6%)	2 (2.7%)	1 (0.8%)
Device able to borrow[1,2]			
Desktop/laptop computer (p = 0.2)	37 (21.8%)	6 (13%)	9 (14.3%)
Smartphone (p = 0.3)	2 (1.2%)	2 (4.4%)	2 (3.2%)

[1] Multiple answers

[2] Among those who did not own any of the listed devices

[3] Among those who reported not having enough knowledge or skills to use technology for health care

[4] Among those who have enough support to use technology for health care

Support preferences **(p < 0.001)**	**Racially Diverse Younger Adults**	**Middle-Income White Seniors**	**Affluent Middle-Aged Adults**
Tablet (p = 0.06)	56 (32.9%)	7 (15.2%)	20 (31.8%)
None (p = 0.009)	83 (48.8%)	34 (73.9%)	35 (55.6%)
Have internet access (p = 0.005)	209 (92.9%)	67 (89.3%)	129 (100%)
Virtual Health Use[1]			
Phone calls (p = 0.001)	129 (57.3%)	53 (70.7%)	98 (76%)
Televideos (p = 0.5)	52 (23.1%)	16 (21.3%)	36 (27.9%)
Email (p = 0.2)	73 (32.4%)	29 (38.7%)	55 (42.6%)
Text messaging (p = 0.3)	55 (24.4%)	12 (16%)	31 (24%)
None (p = 0.045)	47 (20.9%)	11 (14.7%)	14 (10.9%)
Have enough support to use technology for health care[3] (p = 0.08)			
Definitely	13 (29.5%)	2 (6.1%)	2 (11.8%)
For the most part	7 (15.9%)	6 (18.2%)	6 (35.3%)
Somewhat	11 (25%)	8 (24.2%)	7 (41.2%)
Not at all/Does not have anyone to help	12 (27.3%)	16 (48.5%)	2 (11.8%)
Not applicable, does not need support	1 (2.3%)	1 (3%)	0
Who usually provides support when needed[1,3,4]			
Co-worker (p = 0.4)	0	1(6.3%)	1 (6.7%)
Family member (p = 0.09)	20 (64.5%)	8 (50%)	13 (86.7%)

[1] Multiple answers

[2] Among those who did not own any of the listed devices

[3] Among those who reported not having enough knowledge or skills to use technology for health care

[4] Among those who have enough support to use technology for health care

Support preferences **(p < 0.001)**	**Racially Diverse Younger Adults**	**Middle-Income White Seniors**	**Affluent Middle-Aged Adults**
Friend (p = 0.1)	5 (16.1%)	7 (43.8%)	4 (26.7%)
Health care provider (p = 0.4)	3 (9.7%)	2 (12.5%)	0
Community organization (p = 0.6)	5 (16.1%)	3 (18.8%)	1 (6.7%)
Other (p = 0.6)	2 (6.5%)	1 (6.3%)	0
Knows where to go for learning resources[3] (p = 0.97)			
Definitely	5 (11.6%)	2 (6.1%)	2 (11.8%)
For the most part	6 (14%)	6 (18.2%)	3 (17.6%)
Somewhat	9 (20.9%)	9 (27.3%)	4 (23.5%)
Not at all	23 (53.5%)	16(48.5%)	8 (47.1%)
[1] Multiple answers			
[2] Among those who did not own any of the listed devices			
[3] Among those who reported not having enough knowledge or skills to use technology for health care			
[4] Among those who have enough support to use technology for health care			

When it comes to the preferred channels for learning about health care services, online websites were the top pick across all population segments, with 71.1% of Racially Diverse Younger Adults, 66.7% of Middle-Income White Seniors, and 68.2% of Affluent Middle-Aged Adults selecting this option, with no significant differences. In contrast, there was a significant difference among the population segments in learning about health care services through local newspapers ($p < 0.001$), with a larger proportion of Middle-Income White Seniors (34.7%) choosing this option, compared to Racially Diverse Younger Adults (15.1%) and Affluent Middle-Aged Adults (23.3%).

Digital Health Engagement Across Population Segments

Despite demonstrating higher levels of digital competence than Older White Adults, Younger Diverse Adults were more likely to report no virtual interactions with healthcare providers in the previous year. Additionally, there were significant differences in device ownership across the three population

segments (see Table 4). Among respondents who did not own the listed devices, a significant difference was observed in the proportions of each population segment that were unable to borrow any device. Middle-Income White Seniors reported the largest proportion, with 74% of those who did not own a device reporting being unable to borrow any devices, compared to 56% of Affluent Middle-Aged Adults and 49% of Racially Diverse Younger Adults ($p = 0.01$).

A significant difference across all population segments was also seen in internet access ($p = 0.004$). All Affluent Middle-Aged Adults had access to the internet, in contrast to 93% of Racially Diverse Younger Adults and 89% of Middle-Income White Seniors.

There were no significant differences in the proportion of respondents who had used video, email or text messaging to connect with a health care provider in the previous 12 months ($p > 0.05$). The use of phone calls to connect with health care providers was more common among Affluent Middle-Aged Adults (76%) compared to 71% of Middle-Income White Seniors and 57% Racially Diverse Younger Adults ($p = 0.001$). Racially Diverse Younger Adults were more likely to not have any virtual interactions with their health care providers (21%) compared to 15% of Middle-Income White Seniors and 11% of Affluent Middle-Aged Adults ($p = 0.045$).

When it comes to receiving support for those who responded not having enough knowledge and skills to use technology for health care, there were no significant differences between each population segment ($p = 0.08$). Among all respondents, 38% “definitely” or “for the most part” have someone to support them. Support through family is the most common form, with 87% of Affluent Middle-Aged Adults, 65% of Racially Diverse Younger Adults, and 50% of Middle-Income White Seniors having this support. Additionally, roughly a quarter of each population segment “definitely” or “for the most part” know where to go to learn how to use technology for health care.

[Insert Table 4]

Theory-Informed Behavioural Mapping

Behavioural Diagnosis Using COM-B

Several survey measures mapped directly onto COM-B domains. Measures of digital competence were interpreted as indicators of physical and psychological capability, while device ownership, internet access, ability to borrow devices, and availability of support were interpreted as indicators of physical and social opportunity. No survey items directly assessed motivation. Consequently, reflective and automatic motivation were inferred from observed patterns of virtual care use relative to reported capability and opportunity. These interpretations should therefore be considered exploratory and hypothesis-generating rather than direct measures of motivational processes.

Theory-informed mapping of findings to the COM-B model revealed distinct behavioural profiles across population segments, suggesting that digital health engagement is shaped by different combinations of

capability, opportunity, and motivation (Table 5).

Table 5
COM-B analysis by population segment and implementation focused interpretation.

COM-B	Key Finding	Implementation Focused Interpretation
Racially Diverse Younger Adults		
Capability – Physical	High digital competence; high reported ability to use devices	Technical skills largely sufficient; focus should be on converting capability into virtual service uptake, not prioritize basic training
Capability – Psychological	*54% did not know where to find learning resources	Awareness and navigation supports are likely more relevant than device specific knowledge-building
Opportunity – Physical	High internet access and device ownership	Structural access barriers are minimal; infrastructure is not the main constraint
Opportunity – Social	*27% felt they did not have enough support. Preference for online support; moderate family support	Integrate peer/family reinforcement and use online channels as default outreach pathways
Motivation – Reflective	High rate of no virtual care use, despite high competence and access	Focus on bridging intention–behaviour gap: embed prompts and clinician-led introduction of virtual care during encounters
Motivation – Automatic	Low virtual care use may indicate lack of established habits	Consider habit formation strategies (e.g., repeated exposure in clinical workflows)
Middle Income White Seniors		
Capability – Physical	Low digital competence	Limited ability to use digital tools independently; prioritise assisted use rather than self-directed learning
Capability – Psychological	*49% did not know where to find learning resources	Develop clear, accessible, step-by-step guidance and structured onboarding pathways
Opportunity – Physical	Low smartphone ownership, low internet access, and low ability to borrow devices; high landline use	Structural access barriers persist; device lending programs and hybrid non-digital service options remain essential; maintain and strengthen telephone-based care options
Opportunity – Social	Preference for in-person supports; low support availability	Social isolation/limited support may reduce ability to engage; prioritise formal support structures and in-person facilitators
Motivation – Reflective	Moderate virtual care use despite low capability (may see value but lack confidence)	Prioritize confidence-building interventions and structured guided practice (e.g., supported use during care visits)
Motivation – Automatic	Reliance on phone and traditional media indicates established low-tech habits	Leverage low-tech modalities as entry points of engagement

* Of those who reporting not having the skills to use technology for virtual care

COM-B	Key Finding	Implementation Focused Interpretation
Racially Diverse Younger Adults		
Affluent Middle-Aged Adults		
Capability – Physical	Highest digital competence	Technical skills largely sufficient; focus should be on optimization and usability rather than education
Capability – Psychological	*47% did not know where to find learning resources	Targeted, efficient information delivery may still be beneficial
Opportunity – Physical	High device ownership and internet access	No major structural barriers to engagement; focus on advanced digital service delivery
Opportunity – Social	High family support; preference for technical support	Need for responsive technical assistance rather than relational support
Motivation – Reflective	High engagement in virtual care across modalities	Behaviour is already established; focus on maintaining engagement and reducing friction in service use
Motivation – Automatic	Consistent use of virtual care modalities indicates established habits and routine	Behaviour is already established; focus on maintaining engagement and reducing friction in service use
* Of those who reporting not having the skills to use technology for virtual care		

[Insert Table 5]

Identification of Intervention Functions, Policy Categories, and BCTs

Application of BCW matrices and the APEASE criteria resulted in a prioritized set of intervention functions, policy categories, and BCTs across population segments. Across all groups, environmental restructuring and enablement consistently met APEASE criteria as primary intervention functions. Education, modelling, and training were identified as context-specific supporting strategies, depending on the nature of the barrier. Among policy categories, service provision, environmental/social planning, and communication/marketing were consistently identified as feasible and appropriate mechanisms for implementation. In contrast, regulation and legislation were excluded, as they fall outside the scope of regional health authority control and present challenges related to acceptability and equity. Tailored implementation strategies derived from this analysis are presented in Table 6 and full BCW mapping can be found in Appendix.

Table 6
Implementation Strategies Based on BCW Mapping

COM-B	Intervention Functions	Example Implementation Strategy (BCTs)
Racially Diverse Younger Adults		
Capability: 54%* unaware of learning resources	Education	Develop a centralized virtual care resource webpage linked from health authority websites, appointment reminders, and patient portals. Include step-by-step guides, videos, FAQs, and information on where to obtain support. Promote resources through online channels, which are preferred by this group (Instruction on how to perform the behaviour; Information about antecedents; Credible source; Conserving mental resources; Prompts/Cues).
Opportunity: 27%* lacked support; online support preferred	Environmental restructuring, Enablement	Establish an online virtual care help desk offering live chat, email support, and scheduled video troubleshooting sessions. Provide easy access to support links within appointment booking and virtual care platforms (Social support, practical; Social support, emotional; Adding objects to the environment; Restructuring the social environment; Prompts/Cues).
Motivation: High non-use despite high capability; low habitual use	Persuasion, Modelling, Enablement, Environmental Restructuring	Implement a virtual care onboarding campaign featuring patient testimonials and short demonstration videos showing peers successfully using virtual care. Encourage first-time use through automated appointment reminders containing direct links and simple instructions (Demonstration of behaviour; Social comparison; Information about health consequences; Credible source; Habit formation; Prompts/Cues; Framing/Reframing).
Middle Income White Seniors		
Capability: Low competence; 49%* unaware of learning resources	Training, Education	Offer structured digital skills training through community centres, libraries, and healthcare settings using hands-on workshops with opportunities for repeated practice. Training should progress from basic device use to joining virtual appointments (Instruction on how to perform the behaviour; Demonstration of behaviour; Behavioural practice/rehearsal; Graded tasks; Feedback on behaviour; Verbal persuasion about capability).
Opportunity: Low device/internet access; in-person support preference	Environmental restructuring, Enablement, Modelling	Create community-based digital access hubs where older adults can borrow tablets, access internet-enabled devices, and receive in-person support from trained staff or volunteers. Printed resource guides should also be distributed through healthcare settings and local newspapers, which are more commonly used by this group (Adding objects to the environment; Restructuring the physical environment; Social support, practical; Conserving mental resources; Demonstration of behaviour).

* Of those who reporting not having the skills to use technology for virtual care

COM-B	Intervention Functions	Example Implementation Strategy (BCTs)
Racially Diverse Younger Adults		
Motivation: Moderate use despite low capability; low-tech habits	Persuasion, Modelling, Enablement, Environmental Restructuring	Build on existing phone-based care by introducing a graduated pathway from telephone appointments to video visits. For example, healthcare providers could first conduct telephone appointments while guiding patients through connecting to video for a brief portion of the visit (Generalisation of target behaviour; Graded tasks; Feedback on behaviour; Focus on past success; Verbal persuasion about capability; Demonstration of behaviour).
Affluent Middle-Aged Adults		
Capability: 47%* unaware of learning resources	Education	Develop targeted educational materials embedded within healthcare settings and online portals that clearly direct patients to available technical support services and learning resources. Resources should focus on troubleshooting and advanced virtual care skills rather than introductory content (Instruction on how to perform the behaviour; Information about antecedents; Credible source; Conserving mental resources).
Opportunity: technical support preference	Environmental restructuring, Enablement	Implement a family-supported virtual care model where caregivers or family members are invited to participate in technology onboarding sessions. Provide caregiver-focused technical support guides in multiple languages and dedicated support contacts to facilitate troubleshooting (Social support, practical; Social support, unspecified; Restructuring the social environment; Adding objects to the environment; Problem solving).
* Of those who reporting not having the skills to use technology for virtual care		

[Insert Table 6]

Discussion

Health systems are increasingly relying on digital and virtual care delivery to expand access, improve efficiency, and support continuity of care (27, 28). However, the success of these initiatives depends not only on whether individuals can use digital tools, but on whether they engage with them in the context of real-world health system interactions. Current approaches to improving digital health equity largely focus on improving individual-level digital competence or literacy (29). Yet this assumes that non-use or under-use of digital health services is primarily a skills problem (30, 31). Our findings challenge this assumption.

Using population segmentation, we identified distinct sociodemographic profiles that differ not only in digital health competence, but also in support preferences, learning channels, device access, and patterns of virtual healthcare use. Interestingly, higher competence did not consistently translate into

higher engagement with virtual care. Theory informed behavioural mapping using the BCW further highlights that barriers to digital health engagement differ across population segments, with some groups primarily constrained by capability and opportunity, and others by motivational factors, reinforcing the need for tailored implementation strategies. This has direct implications for how health systems design, deliver, and scale digital health interventions.

Health systems frequently design digital health interventions for broad populations despite evidence that different groups experience different barriers to engagement (32). By identifying clusters of demographic characteristics that commonly occur together and examining their support and learning preferences, segmentation approaches such as latent class analysis may help guide more targeted and efficient implementation planning (33, 34).

Racially Diverse Younger Adults

Racially diverse younger adults demonstrated strong digital access and competence, and tended to prefer online forms of support, consistent with broader trends in digital engagement among younger adults (35). Despite this digital readiness, they were also the group most likely to report no virtual care use. This suggests that barriers are less about skills and more about engagement and activation.

Potential Implementation Implications

Implementation efforts for this group should focus less on digital literacy and more on integrating digital health options into routine clinical encounters, increasing awareness of available virtual services, and ensuring outreach is culturally and linguistically appropriate. Strategies that leverage online communication channels and provider-driven introductions to digital care at the point of service may be particularly valuable because these approaches directly address the observed gap between capability and use.

Middle Income White Seniors

Middle Income White Seniors demonstrated lower levels of digital competence and device access (both ownership and ability to borrow devices). They showed a preference for in-person support and were more likely to rely on traditional information sources such as local newspapers, alongside continued high use of landlines.

Potential Implementation Implications

Implementation efforts for this group should prioritize improving both access and confidence through hands-on assistance and familiar communication methods, as these are consistent with identified preferences for this group and have also been shown to enhance engagement for older or less digitally confident users (20). These insights suggest the need for community-based, multi-modal outreach strategies such as one-on-one mentoring or support at health care sites to promote digital inclusion

among groups with lower competence (9, 36). Maintaining and strengthening telephone-based care options is also critical, as is supporting device access through loan programs or assisted setup. Outreach should rely on trusted, non-digital channels, including print media and provider recommendations, and emphasize guided, confidence-building experiences rather than self-directed digital learning.

Affluent Middle-Aged Adults

Affluent Middle-Aged Adults demonstrated the highest levels of digital access and competence, alongside high uptake of virtual care services. This group had a preference for technical support. Barriers for this group tended to be related more to service quality than access.

Potential Implementation Implications

Implementation efforts for this group should focus on optimizing usability and reliability, including streamlining digital interfaces, ensuring platform stability, and offering responsive, on-demand technical support such as chat functions or helplines.

Population Segmentation as a Tool for Tailored Implementation

A key contribution of this study is demonstrating the value of population segmentation as an implementation planning tool. Much of the existing digital health literature identifies demographic groups that are more likely to experience digital exclusion, often focusing on characteristics such as age, income, education, or ethnicity in isolation (4, 37, 38). While these approaches are useful for identifying disparities, they provide limited guidance regarding how implementation strategies should be designed and delivered to address those disparities. The population segments identified in this study reflected combinations of age, ethnicity, gender, and socioeconomic characteristics rather than any single demographic variable. This suggests that implementation planning based on a single characteristic may overlook important differences in support needs and engagement patterns that emerge through the intersection of multiple social factors. The goal of segmentation is not to create fixed categories of users, but rather to identify groups that may benefit from different implementation approaches.

An important finding from this dd is that the same behavioural barrier may require different implementation approaches depending on the population segment experiencing it. For example, lack of awareness regarding where to find digital health learning resources emerged across all three population segments and was classified as a psychological capability barrier. However, the most appropriate implementation response differed substantially between groups due to differences in support preferences, communication channels, and broader contextual factors.

Among Racially Diverse Younger Adults, awareness-building efforts may be most effective when delivered through digital channels, integrated into virtual care workflows, and provided in culturally and

linguistically relevant formats. In contrast, Middle-Income White Seniors may benefit more from printed materials, provider-led explanations, and community-based learning opportunities that incorporate in-person support. For Affluent Middle-Aged Adults, efficient, embedded guidance within existing digital platforms may be preferable to standalone educational resources.

These findings also demonstrate how behavioural frameworks and population segmentation can complement one another. The COM-B model (24) helped identify potential capability, opportunity, and motivational barriers to digital health engagement, while segmentation helped identify how those barriers manifest across different population groups and what implementation approaches may be most appropriate. Together, these approaches provide a practical method for translating population-level data into tailored implementation strategies.

Digital Exclusion is Multidimensional

Our findings reinforce the growing recognition that digital exclusion is multidimensional (31). Middle-Income White Seniors experienced multiple barriers simultaneously, including lower competence, reduced internet access, fewer opportunities to borrow devices, and lower levels of support. These findings are consistent with evidence suggesting that barriers to digital health often cluster together rather than occurring in isolation (31). At the same time, the experience of Racially Diverse Younger Adults illustrates that access and competence do not necessarily translate into engagement. Participants in this group reported generally high access to devices and internet connectivity and high competence, yet they were more likely to report no virtual healthcare use.

These findings suggest that digital inclusion should be conceptualized not as a single continuum of competence, but as a dynamic interaction among skills, access, support structures, and healthcare system engagement. Consequently, implementation efforts that focus exclusively on improving digital literacy risk overlooking other critical determinants of digital health participation.

Collectively, these findings suggest that digital health equity cannot be achieved through a single intervention or universal digital literacy strategy. Rather, implementation efforts must recognize that different population segments encounter different combinations of capability, opportunity, and motivational barriers. Population segmentation may therefore provide a practical mechanism for designing implementation strategies that are both more equitable and more responsive to the needs of diverse communities.

Strengths and Limitations

This study has several strengths, including a large and diverse sample, multilingual data collection, and the use of LCA to identify implementation-relevant population segments rather than examining demographic characteristics in isolation. However, several limitations should also be acknowledged.

First, digital competence was self-reported and may not reflect actual ability; however, perceived competence remains an important predictor of health behaviors and digital tool uptake (39, 40). Second, the cross-sectional design prevents causal inference and does not capture how digital competence or virtual care engagement may change over time. Third, while LCA identifies useful population segments, these groups should be interpreted as implementation-oriented profiles rather than definitive or naturally occurring categories.

Forth, despite our efforts to recruit diverse participants, some voices remained underrepresented in our sample, specifically individuals with disabilities and gender-diverse individuals. As these groups may experience unique barriers to digital health engagement (41–44), future research should prioritize more inclusive recruitment strategies and co-design approaches to better understand their experiences.

Finally, the BCW analysis was conducted retrospectively and was not incorporated into the original survey design. Survey measures were not explicitly developed to assess COM-B constructs, and motivation was not directly measured. Consequently, conclusions regarding reflective and automatic motivation were inferred from patterns of virtual care use and should be interpreted cautiously. Future research should prospectively assess COM-B domains, particularly motivation, to better understand behavioural determinants of digital health engagement across population segments.

Conclusion

Efforts to improve digital health equity should move beyond universal digital literacy interventions. While some population segments may benefit from skills training and in-person support, others may require strategies that address awareness, trust, engagement, and relevance. Our findings suggest that digital competence alone does not guarantee participation in digital health services, and that implementation strategies should be tailored to the needs of specific population segments. Segmenting populations according to commonly occurring demographic characteristics and implementation needs may provide health systems with a practical approach for designing more equitable and effective digital health programs.

Abbreviations

AIC
Akaike Information Criterion
BCT
Behaviour Change Techniques
BCW
Behaviour Change Wheel
BIC
Bayesian Information Criterion
CFA

Confirmatory Factor Analysis
CFI
Comparative Fit Index
CI
Confidence Interval
COM
B—Capability, Opportunity, Motivation, Behaviour Model
COVID
19—Coronavirus Disease 2019
EM
Expectation—Maximization
LCA
Latent Class Analysis
RMSEA
Root Mean Square Error of Approximation
SEM
Structural Equation Modeling
SRMR
Standardized Root Mean Square Residual
TLI
Tucker—Lewis Index

Declarations

Ethics Approval and Consent to Participate: Ethics approval was obtained from both Fraser Health and the University of British Columbia Research Ethics Boards (#H24-01086).

Consent for Publication: Not applicable.

Availability of Data and Materials: The datasets generated and analyzed during the current study are not publicly available due to confidentiality agreements and privacy concerns involving study participants, but are available from the corresponding author on reasonable request.

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Authors Contributions: JR, MMon, and MMac contributed to the conception and design of the study and led the development of the survey instrument. QH and MMon conducted the data analysis and contributed to interpretation of the findings. QH, JR, MMH and ONE contributed to data collection. QH,

MMon, and MMac drafted the first version of the manuscript, with substantive input and revisions from all authors. LH, JS, VC, MMac, and MMon provided methodological guidance, oversight of the study, and contributed to interpretation of the data. All authors read and approved the final manuscript and any substantially modified versions involving their contributions. All authors agree to be personally accountable for their own contributions and to ensure that questions related to the accuracy or integrity of any part of the work are appropriately investigated, resolved, and documented in the literature.

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Figures

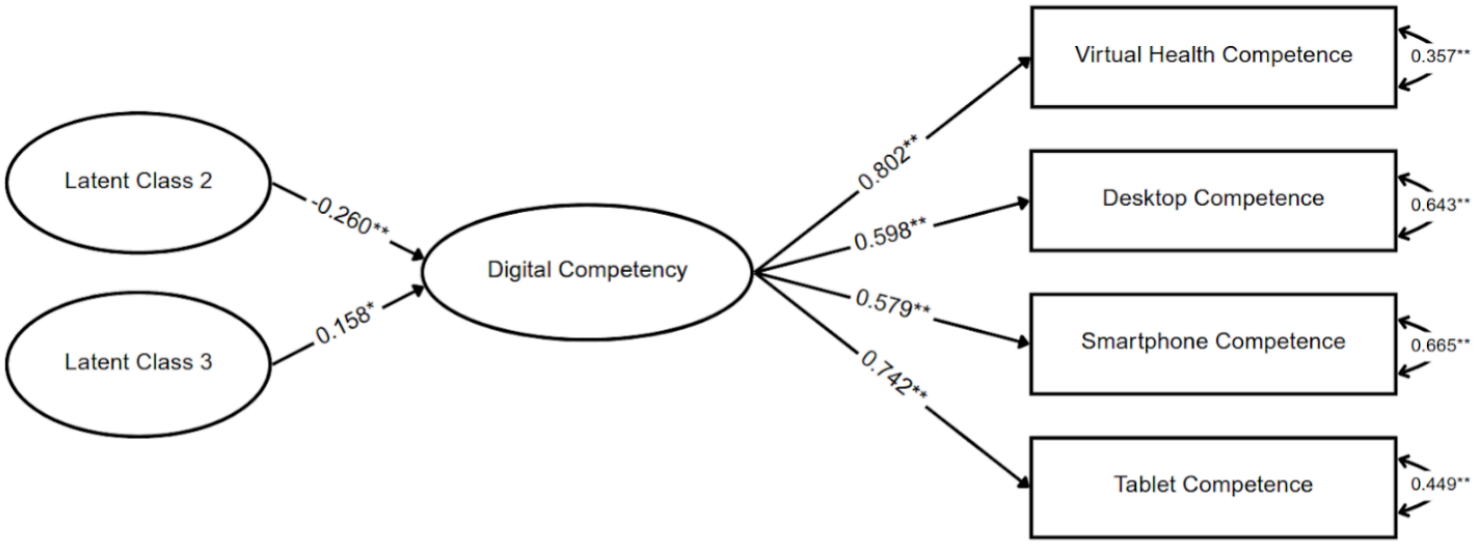


Figure 1

Structural Equation Model Path Diagram

* $p < 0.05$

** p < 0.001

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- BCWmapping.xlsx
- Appendix.docx