Digital Divide: Evidence from the 2020 Canadian Internet Use Survey*

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Abstract

This paper studies inequality in digital participation across socioeconomic and demographic groups using the 2020 Canadian Internet Use Survey (CIUS). We combine survey-weighted logistic Lasso, an exact Shapley decomposition of age–education gaps, a sequential logit, and a bifactor item response theory (IRT) measure of digital literacy to identify who is excluded, why gaps persist, and where along the adoption path they arise.

Education is the only determinant that remains significant at every rung of the digital ladder. Income inequality is most pronounced for virtual-wallet adoption; for online banking, employment and education together account for nearly half of the pro-rich concentration, indicating a broad socioeconomic gradient rather than a purely income-based divide. Persons with disabilities face the largest penalty at the digital-payments stage rather than at online banking, pointing to accessibility gaps in retail payment interfaces. Conditioning on digital literacy eliminates the education gradient at internet entry and reduces it by 61% at the online banking rung, but a substantial residual persists, pointing to behavioral and institutional frictions beyond measurable competence. The youngest cohort records the lowest information-seeking score despite high digital engagement, and security deficits are concentrated among landed immigrants and visible minorities.

Keywords: Digital inequality, income concentration, logistic Lasso, survey microdata, sequential logit, item response theory.

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1 Introduction

What we know about the Canadian digital divide. There is broad agreement that digital participation in Canada is unequally distributed along familiar socioeconomic lines. Haight et al. (2014), using the 2010 CIUS, show that age, income, and education are the primary predictors of internet use and that the digital divide extends well beyond infrastructure access to encompass the skills and willingness needed for meaningful engagement. Wavrock et al. (2022) document significant differences in the breadth and depth of digital engagement across age, education, and income groups in the 2018 CIUS, while administrative sources show that the urban–rural gap in broadband access remains substantial despite federal investments under the Universal Broadband Fund (Canadian Radio-television and Telecommunications Commission, 2023; Innovation, Science and Economic Development Canada, 2024). The resulting picture is one of layered disadvantage: low-income households, older adults, and individuals with limited educational attainment are less likely to access the internet and, conditional on access, less likely to use it for financially or socially consequential activities (Van Deursen and Van Dijk, 2019; The Dais, 2024).

What distinguishes Canada. Canada's digital inequality challenge has features that set it apart from other developed economies. The central issue is not absent infrastructure: by 2020, 92.2% of CIUS respondents reported using the internet. Instead, inequality reflects differences in the cost, reliability, and quality of connections across geographic areas; the absence of a coordinated national digital literacy strategy (Canada remains one of the few OECD countries without one); and the concentration of exclusion among specific populations — Indigenous communities, persons with disabilities, low-income seniors, and recent immigrants (The Dais, 2024; Employment and Social Development Canada, 2024; Kwok and Korpela, 2024) — who are also among those most reliant on digital services to access health information, government benefits, and financial services as physical alternatives continue to decline.

Four gaps this paper addresses. Despite a growing descriptive literature, four questions remain unanswered or only partially answered.

Q.1. Which characteristics predict digital financial service adoption once the full covariate space is taken into account? Most existing studies rely on a small, fixed set of regressors. In CIUS 2020, the set of plausible predictors is broad, including age, education, income, employment, language, household composition, immigration status, Indigenous identity, visible minority status, disability, health, and province. Because these variables are categorical, dummy expansion yields a relatively large candidate regressor set, making standard stepwise selection ad hoc and uncorrected post-selection inference invalid.

Q.2. How much of the age–education gap in digital financial service use is explained by observable mediators? Most studies identify *who* is excluded but say little about *why*. Differences in online banking or digital payment use may reflect income constraints, health and disability limitations, or personal preferences rather than digital skill or access barriers per se. Distinguishing among these channels is essential for targeting policy effectively.

Q.3. At which stage of the adoption process do different groups fall behind? The CIUS routes respondents sequentially: internet users are asked about online banking, and those who shop online are asked about payment methods. A lower unconditional digital payment rate may therefore arise from barriers at internet access, basic online communication, banking adoption, or payment adoption. Identifying where disadvantage emerges is directly relevant for policy design.

Q.4. How is digital competence distributed, and which dimension explains the gaps that income and health do not? Any residual gap in digital service use after accounting for income, health, and preferences must reflect structural barriers — such as connection quality or interface inaccessibility — or differences in digital skill. A principled latent measure of digital literacy is needed to assess which component matters more and where skill deficits are most concentrated.

Contributions. The four research questions map directly onto four empirical contributions using the 2020 CIUS, a nationally representative cross-sectional survey of 17,409 Canadians aged 15 and older across the ten provinces.

(i) We apply the `svy LLasso` of Jasiak et al. (2026), a survey-weighted logistic Lasso designed for variable selection in complex survey data, together with debiased post-selection inference (Javanmard and Montanari, 2014; Zhang and Zhang, 2014), to identify predictors of online banking and digital payment adoption from a broad candidate set of sociodemographic characteristics, and to measure how these services are concentrated across the income distribution.

(ii) We decompose age $\times$ education gaps in unconditional online banking and health-information use into contributions from income, disability, health, and preferences using an exact Shapley decomposition (Shorrocks, 2013).

(iii) We estimate a continuation-ratio (sequential) logit that models digital adoption as a four-rung ladder: internet use, email use, online banking, and digital payments.

(iv) We construct a bifactor IRT measure of digital literacy (Birnbaum, 1968; Chalmers, 2012) and embed it in the sequential framework to assess how much of the residual education gradient reflects measurable competence.

Main findings. The `svy LLasso` identifies age, education, and employment as the most consistent predictors of digital financial service adoption, with education the only covariate that remains significant at every rung of the digital ladder. Income-related inequality is significant across all digital financial services and is especially pronounced for virtual-wallet adoption; for online banking, employment and education together account for nearly half of the pro-rich concentration, indicating a broad socioeconomic gradient rather than a purely income-based divide.

The age–education decomposition shows that income, disability, health, and preferences together explain a substantial but incomplete share of the observed gaps, with preferences the dominant mediator and large residual gaps persisting across all cells. The sequential logit shows that disadvantage emerges at different stages for different groups: education generates significant barriers throughout the ladder, disability produces its largest penalty at the digital-payments stage, and the most excluded profiles — older, less-educated respondents with low income or non-employment — face compounding barriers at multiple rungs.

The IRT analysis shows that digital literacy eliminates the education gradient at internet entry and substantially reduces it at the online banking rung, but a residual persists, pointing to behavioral and institutional frictions beyond measurable competence. The IRT analysis also reveals counterintuitive patterns: a Gen Z deficit in structured information-seeking and a security-behavior gap concentrated among recent immigrants and visible minorities rather than among seniors.

Paper organization. Section 2 describes the CIUS 2020 data, and Section 3 sets out the analytical frameworks. Section 4 presents the `svy LLasso` results and concentration-index analysis (Q.1), while Section 5 reports the age–education decomposition (Q.2). Section 6 presents the sequential logit analysis (Q.3), and Section 7 reports the IRT-based digital literacy measure and mediator analysis (Q.4). Section 8 concludes. Additional technical details, supplementary results, and robustness checks are provided in the appendix.

2 Data

We use the publicly available 2020 Canadian Internet Use Survey public-use microdata file (PUMF).[1] The PUMF is close in scope to the Statistics Canada Research Data Centre version, although some variables are available only in more aggregated form. CIUS 2020 comprises 17,409 observations on Canadians aged 15 and older living in one of the ten provinces. First Nations persons living on reserve are excluded by the sampling frame. The survey uses a stratified sampling design at the province/census-metropolitan-area/census-agglomeration level and combines landline and cellular telephone frames; the overall response rate is 41.6%. All estimates use the person weight `WTPG`, which reflects the adjusted selection probability, non-response adjustment, and calibration to independent population totals.[2]

The three main outcomes used in Sections 4–6 are internet use, online banking, and digital payments. Internet use is defined on the full sample. Online banking is defined for internet users. The digital payments outcome indicates whether the respondent used a virtual wallet or credit card for online purchases; this outcome is defined for respondents who ordered goods or services online. The `svy LLasso` analysis also considers virtual wallet and credit card use as separate outcomes; the corresponding results are reported in Appendix A.2.[3]

The Q.2 decomposition uses two unconditional outcomes: online banking and online health-information search. For these outcomes, non-internet users are coded as zero. Wavrock et al. (2022) highlight these measures as especially policy-relevant and well suited to the survey's sequential routing structure.

The explanatory variables include household income quintile, educational attainment, employment status, age group, gender, Indigenous identity, visible minority status, immigration status, language, household composition, disability status, self-reported health, preference for non-use, and province. This covariate set is used across all empirical analyses, with the `svy LLasso` specification allowing for a flexible variable-selection step.

[1] The dataset is available at `https://abacus.library.ubc.ca/dataset.xhtml?persistentId=hdl:11272.1/AB2/NUVBX2`.

[2] Precise variable definitions, item codes, and further information on sampling and weighting correspond to the publicly available CIUS 2020 codebook and User Guide.

[3] Email use is not reported as a standalone outcome because it is nearly universal among internet users; it enters the analysis as the second rung of the sequential logit in Section 6.

3 Analytical framework

3.1 Survey-weighted logistic Lasso

To address Q.1, we adopt the `svy LLasso` of Jasiak et al. (2026), which obtains the survey-weighted logistic Lasso estimator $\hat{\theta}$ by minimizing the penalized weighted negative log-likelihood:

$$\hat{\theta} := \arg \min_{\theta=(\alpha,\beta')' \in \mathbb{R}^{p+1}} \left(-L(\theta) + \lambda \sum_{j=1}^{p} |\beta_j| \right), \tag{3.1}$$

where $\beta = (\beta_1, \ldots, \beta_p)'$,

$$L(\theta) := n^{-1} \sum_{i=1}^{n} w_i \left(y_i x_i' \theta - \log(1 + \exp(x_i' \theta)) \right) \tag{3.2}$$

is the weighted log-likelihood of the logit model, and w_i is the survey weight. The intercept α is left unpenalized, and the ℓ_1 penalty shrinks weak predictors toward zero. The tuning parameter λ is chosen by ten-fold cross-validation using the AUC criterion, implemented in the `R` package `glmnet`; person weights are rescaled to mean one within the estimation sample. In Appendix A.3, we consider two alternative tuning rules: a design-aware weighted cross-validation procedure (Iparragirre et al., 2023) and the bootstrap-after-cross-validation rule of Chetverikov and Sørensen (2025). Both yield very similar empirical patterns.

Following Jasiak et al. (2026), we apply the debiased Lasso correction to conduct valid post-selection inference:

$$\tilde{\theta}^{\mathsf{DB}} = \hat{\theta} + H(\hat{\theta})^{-1} S(\hat{\theta}), \tag{3.3}$$

where $H(\cdot)$ and $S(\cdot)$ denote the sample Hessian and score of the full weighted logistic log-likelihood in (3.2). This one-step estimator removes regularization bias and is asymptotically normal, facilitating standard t-ratio inference on coefficients and AMEs. Throughout, we report $\tilde{\theta}^{\mathsf{DB}}$ together with the debiased estimates of the AMEs, denoted by $\widetilde{\mathrm{AME}}^{\mathsf{DB}}$; technical details are given in Appendix A.1.

3.2 Age–education decomposition framework

To address Q.2, we estimate two nested survey-weighted logit models for each outcome y_i:

$$y_i = \alpha + \theta_g + u_i, \tag{3.4}$$

$$y_i = \alpha + \theta_g + x_i' \beta + u_i, \tag{3.5}$$

where θ_g denotes the coefficient for the age $\times$ education cell g relative to the omitted reference cell of adults aged 65 and older with high school or less education. The control vector x_i

includes household-size-adjusted income quintile, a disability indicator, indicators for self-reported health, and a preference indicator for non-use due to lack of interest or time.

Let

$$m_g(x) := \Lambda(\alpha + \theta_g + x'\beta), \qquad \Lambda(z) = \frac{e^z}{1+e^z},$$

denote the conditional probability for cell g. We partition the covariate vector into four explanatory blocks,

$$x = \left(x^{(\text{inc})}, x^{(\text{dis})}, x^{(\text{health})}, x^{(\text{pref})}\right),$$

corresponding to income, disability, health, and preferences. We define the characteristics-explained component of the age–education gap as

$$E_g := m_g(x_g) - m_g(x_r), \tag{3.6}$$

where x_g denotes the observed covariate values for respondents in cell g, and x_r denotes the corresponding values for respondents in the reference cell. Thus, $m_g(x_g)$ is the average fitted probability evaluated at the observed characteristics of group g, whereas $m_g(x_r)$ evaluates the same fitted probability after replacing those characteristics with the reference-group values.

To allocate E_g across the four explanatory blocks, we implement the exact simulation-based Shapley decomposition of Shorrocks (2013), which adapts the Shapley value (Shapley, 1953) to regression decomposition. Let K denote the set of blocks. For any subset $S \subseteq K$, let $m_g(x_r^{(-S)}, x_g^{(S)})$ denote the fitted probability obtained by assigning the blocks in S their group-g values and all remaining blocks their reference-group values. Then the contribution of block k to the explained component for cell g is

$$C_{gk} := \sum_{S \subseteq K \setminus \{k\}} \frac{|S|!\,(|K| - |S| - 1)!}{|K|!} \left[m_g\left(x_r^{(-S \cup \{k\})}, x_g^{(S \cup \{k\})}\right) - m_g\left(x_r^{(-S)}, x_g^{(S)}\right) \right], \tag{3.7}$$

where the bracketed term is the marginal contribution of block k when it is added after the blocks in S have already been switched from reference-group values to group-g values. By construction, the decomposition is exact,

$$E_g = \sum_{k \in K} C_{gk},$$

and invariant to the ordering of the blocks because it averages marginal contributions over all possible permutations. These properties make it especially attractive in the present nonlinear logit setting, where first-order linearization can perform poorly when fitted probabilities lie near the boundaries of the unit interval.

We estimate the decomposition on three nested samples — urban non-disabled respondents, all urban respondents, and the full sample — to distinguish connectivity constraints from disability-related barriers. The underlying logit models are estimated using `svyglm` in the `R` package `survey`, and the Shapley decomposition is then applied to the fitted values.

3.3 Sequential logit

The CIUS routing structure described in Section 2 implies a natural four-rung adoption ladder: internet use, email use, online banking, and digital payments. We exploit this structure by estimating a continuation-ratio logit in which each stage is modelled as a binary logit on the subsample that has cleared the previous gate.

Let $p_{g,1}$ denote the probability that group g clears Stage 1, and let $c_{g,j}$ denote the conditional probability of clearing Stage j given clearance of Stage $j-1$. The unconditional probability of reaching the digital-payments rung is $\pi_{g,4} = p_{g,1}c_{g,2}c_{g,3}c_{g,4}$. The gap relative to a benchmark group $\bar{g}$ admits the exact sequential decomposition

$$\Delta_g^{S4} = (\bar{p}_1 - p_{g,1})\bar{c}_2\bar{c}_3\bar{c}_4 + p_{g,1}(\bar{c}_2 - c_{g,2})\bar{c}_3\bar{c}_4 + p_{g,1}c_{g,2}(\bar{c}_3 - c_{g,3})\bar{c}_4 + p_{g,1}c_{g,2}c_{g,3}(\bar{c}_4 - c_{g,4}), \quad (3.8)$$

obtained by sequentially replacing the benchmark-stage probabilities with those of group g from Stage 1 onward. The weighting terms reflect the sequential nature of the process: gaps at later stages matter only for the subset that clears the earlier rungs. The same covariate vector is used at each stage, and each stage is estimated using `svyglm`.

3.4 IRT digital literacy score

To measure digital competence, we estimate a weighted bifactor two-parameter logistic (2PL) item-response model (Birnbaum, 1968) on 20 binary CIUS items covering information-seeking, software and file management, and security and privacy tasks. Let $y_{ij} \in \{0, 1\}$ denote the response of individual i to item j, where $y_{ij} = 1$ if the respondent reports performing the corresponding digital task and $y_{ij} = 0$ otherwise. The model includes one latent general factor, interpreted as overall digital literacy, and three latent domain-specific factors that capture residual covariance within the information-seeking, software/file-management, and security/privacy domains. The response probability is specified as

$$P(y_{ij} = 1 \mid \theta_i^{(G)}, \theta_i^{(D_j)}) = \Lambda\Big(a_j^{(G)}\theta_i^{(G)} + a_j^{(D_j)}\theta_i^{(D_j)} - b_j\Big),$$

where $\Lambda(\cdot)$ is the logistic CDF, $\theta_i^{(G)}$ is the latent general factor for individual i, $\theta_i^{(D_j)}$ is the latent domain-specific factor for the domain to which item j belongs, $a_j^{(G)}$ and $a_j^{(D_j)}$ are item discrimination parameters, and b_j is an item difficulty parameter. The latent factors are assumed to be mutually orthogonal and normalized to unit variance for identification. The bifactor structure is identified without rotation because the general factor loads on all items and each domain-specific factor loads only on items within its domain (Reise, 2012).

Our digital literacy score is the estimated general-factor score $\hat{\theta}_i^{(G)}$, which summarizes each respondent's overall digital competence net of domain-specific residual variation. Given the estimated item parameters $\hat{\psi} = \{\hat{a}_j^{(G)}, \hat{a}_j^{(D_j)}, \hat{b}_j\}_{j=1}^{20}$, this score is computed as the expected a posteriori (EAP) estimate (see Appendix D.2 for the formal definition), obtained using the EM or quasi-Monte Carlo EM algorithm implemented in the `R` package `mirt` (Chalmers, 2012), with survey weights normalized within the estimation sample. For use in the concentration-index and sequential-logit analyses, we rescale the estimated general-factor score $\hat{\theta}_i^{(G)}$ to the unit interval and denote the resulting literacy index by $\hat{L}_i \in [0, 1]$.

The standardized loadings reported in Appendix D.3 are obtained via the Schmid–Leiman orthogonalization (Schmid and Leiman, 1957), which decomposes the factor solution into a general factor and orthogonal domain-specific residual factors, ensuring that $\hat{a}_j^{(G)}$ reflects the unique contribution of the general factor to item j net of domain-specific variance.

Item selection and dimensionality diagnostics are reported in Appendix D. Reliability is assessed using McDonald's hierarchical omega (McDonald, 1999), which measures the proportion of composite-score variance attributable to the general factor net of domain-specific variance; values above 0.70 are generally taken as evidence that a single general factor dominates reliable variation.

3.5 Income-ranked and literacy-ranked concentration indices

To complement the regression analysis with a distributional perspective, we use concentration indices to measure whether digital outcomes are disproportionately concentrated among respondents higher in the income or digital-literacy distribution.

Income-ranked concentration index. Let R_i denote respondent i's fractional rank in the household-income distribution, and let $\mu_y = \mathrm{E}[y_i]$ denote the population mean of outcome y_i. The population concentration index is

$$\mathcal{C}_y := \frac{2}{\mu_y} \operatorname{Cov}(y_i, R_i).$$

A positive value indicates that the outcome is concentrated among higher-income respondents. In the data, we estimate $\mathcal{C}_y$ using survey weights. With $w_i > 0$ denoting the person weight, let $W := \sum_{i=1}^{n} w_i$ be the total survey weight, and let

$$\bar{y} = \frac{1}{W} \sum_{i=1}^{n} w_i y_i$$

and $\hat{r}_i$ denote the weighted sample mean of y_i and the weighted midpoint fractional rank in the income distribution, respectively. The survey-weighted sample analogue is

$$\widehat{\mathcal{C}}_y := \frac{2}{\bar{y}\, W} \sum_{i=1}^{n} w_i \Big(y_i - \bar{y}\Big)\Big(\hat{r}_i - \tfrac{1}{2}\Big). \tag{3.9}$$

Because y_i is directly observed, the influence function of $\widehat{\mathcal{C}}_y$ admits a closed-form linearization and inference is based on the resulting first-order variance estimator (Kakwani et al., 1997).[4]

Since the outcomes of interest are binary, the standard concentration index is bounded by $[-(1-\mu_y),\, 1-\mu_y]$ rather than $[-1, 1]$, which complicates comparisons across outcomes with different means (Wagstaff, 2005). We therefore also report two normalized versions. Following Wagstaff (2005), the Wagstaff-normalized index is

$$\widehat{\mathcal{C}}_y^{\text{Wag}} = \frac{\widehat{\mathcal{C}}_y}{1 - \bar{y}},$$

and, following Erreygers (2009), the Erreygers index is

$$\widehat{\mathcal{C}}_y^{\text{E}} = 4\bar{y}\, \widehat{\mathcal{C}}_y.$$

The income-ranked decomposition in Section 4.3 uses the standard index, which admits the standard linear decomposition of Wagstaff et al. (2003).

Literacy-ranked concentration index. To study how digital activities are distributed across the competence distribution, we define a literacy-ranked concentration index by replacing the income rank with the weighted rank of the estimated general-factor digital literacy score. Let r_i^L denote respondent i's weighted midpoint fractional rank in that literacy distribution. The corresponding population index is

$$\mathcal{C}_y^L := \frac{2}{\mu_y} \operatorname{Cov}(y_i, r_i^L),$$

with survey-weighted sample analogue

$$\widehat{\mathcal{C}}_y^L := \frac{2}{\bar{y}\, W} \sum_{i=1}^{n} w_i \Big(y_i - \bar{y}\Big)\Big(\hat{r}_i^L - \tfrac{1}{2}\Big).$$

[4] In the implementation, we use the equivalent three-moment representation $\widehat{\mathcal{C}}_y = 2\bar{y}^{-1} W^{-1} \sum_i w_i y_i \hat{r}_i - 1 - 2(W^{-1} \sum_i w_i \hat{r}_i - \frac{1}{2})$, which reduces to the formula (3.9) when $W^{-1} \sum_i w_i \hat{r}_i = \frac{1}{2}$ exactly. After excluding observations with missing outcome values, the weighted mean rank in the estimation sample need not equal $\frac{1}{2}$, so the three-moment form is used throughout.

A positive value indicates that the outcome is concentrated among the more digitally literate.

Because the literacy rank is constructed from an estimated bifactor IRT model, $\widehat{\mathcal{C}}_y^L$ is a two-step estimator. Inference therefore uses Murphy–Topel-type standard errors (Murphy and Topel, 1985) that account for both second-stage sampling variation and first-stage IRT estimation uncertainty; details are in Appendix D.6.

4 Q.1: Who is excluded? Predictors of digital engagement

4.1 Online banking

Table 1 presents the `svy LLasso` results for the online banking model. Age is the strongest predictor: relative to the reference group aged 45–54, respondents aged 25–34 and 35–44 are 7 and 6 percentage points more likely to use online banking, while those aged 55–64 and 65 and older are 3 and 9 percentage points less likely. Employment status is also important: employed respondents are about 9 percentage points more likely to use online banking ($\widetilde{\text{AME}}^{\mathsf{DB}} = 0.09$, $p < 0.001$), consistent with payroll direct deposit and employer-linked financial access. Educational attainment generates a clear gradient: high school (HS) or less reduces the probability of online banking by 7 percentage points, while a university degree raises it by 5 percentage points relative to some post-secondary. Visible minority status is associated with a 5 percentage point lower probability ($p = 0.003$). Among provinces, Manitoba is associated with a 5 percentage point lower probability ($p = 0.010$) and Quebec with a 5 percentage point higher probability ($p = 0.021$). Gender, rural residence, Aboriginal identity, immigration status, and disability are not statistically significant after conditioning on the full covariate set.

Language of use is also a notable predictor. Relative to respondents reporting neither English nor French, English speakers and English-French speakers are 17 and 13 percentage points more likely to use online banking, respectively. These are among the largest AMEs in the model, though their magnitude partly reflects the small and linguistically heterogeneous reference category rather than a uniform language penalty. Within the Canadian financial system, online banking interfaces have historically been designed around English and French, and some platforms impose official language requirements for digital enrollment. The language gradient is therefore consistent with a combination of interface accessibility barriers and the occupational and socioeconomic sorting that correlates with language of use. The French-speaker coefficient is positive but falls short of conventional significance ($p = 0.178$), consistent with Quebec's above-average online banking rate.

4.2 Digital payments

Table 2 presents the `svy LLasso` results for virtual wallet and credit card use. For virtual wallet adoption, age remains the dominant predictor: those aged 15–24, 25–34, and 35–44 are 11, 8, and 4 percentage points more likely to adopt relative to the reference group, while those aged 55–64 and 65 and older are 6 and 8 points less likely. Rural residence reduces adoption by 5 points. Unlike in the online-banking model, visible minority status has a positive association ($\widetilde{\text{AME}}^{\text{DB}} \approx 0.04$, $p < 0.01$), pointing to a distinct adoption pattern rather than a general financial-inclusion gradient. University education and top-quintile income are also positively associated, with AMEs of about 2 and 8 percentage points.

For credit card use, the youngest group (15–24) is about 9 percentage points less likely to use a credit card online. Education generates the sharpest gradient: high school or less reduces the probability by 7 percentage points, while a university degree raises it by 7 points. Family households without children and Ontario residence are positively associated, while disability is associated with a 7 percentage point reduction and Quebec with a 6 point reduction. Visible minority status is weakly negative for credit card use, in contrast to its positive association with virtual wallet adoption. This sign reversal is consistent with substitution between payment instruments and differential access barriers across socioeconomic groups.

4.3 Concentration of digital banking access across income

Table 3 reports the standard concentration index together with the Wagstaff-normalized and Erreygers versions for online banking, virtual wallet use, credit card use, and the composite digital-payments outcome. Inference for the standard concentration index is based on a first-order linearization estimator.

Online banking is significantly concentrated among higher-income respondents: $\widehat{\mathcal{C}}_y = 0.027$ (SE = 0.003; 95% CI [0.020, 0.034]; $p < 0.001$). Panel B shows that the Wagstaff et al. (2003) decomposition associates 33.1% of this concentration with income, 26.6% with employment, 22.3% with education, and 14.4% with age. Employment and education together account for 48.9% — nearly one half — while income, although the single largest component, does not dominate the decomposition on its own. Inequality in digital banking access therefore reflects a broad socioeconomic gradient rather than a purely income-based divide.

The comparison across digital-finance outcomes in Panel A reveals a much sharper income gradient for newer payment technologies. Virtual-wallet use is far more concentrated among

Table 1: Lasso Logistic Regression Results: Online Banking

Variables	Categories	`svy LLasso`	$\tilde{\theta}^{\mathsf{DB}}$	p-value	$\widetilde{\mathrm{AME}}^{\mathsf{DB}}$	p-value
Intercept		1.09	-0.15	0.757	-	-
Location	Rural	-	-0.04	0.583	-0.01	0.591
Age	15–24	-0.00	-0.21	0.132	-0.03	0.129
	25–34	0.42	0.58***	< 0.001	0.07***	< 0.001
	35–44	0.32	0.51***	< 0.001	0.06***	< 0.001
	55–64	-	-0.23**	0.024	-0.03**	0.023
	65 and older	-0.34	-0.60***	< 0.001	-0.09***	< 0.001
Gender	Female	-	0.09	0.162	0.01	0.173
Aboriginal identity	Aboriginal	-	-0.16	0.381	-0.02	0.377
Language	English	-	1.13**	0.014	0.17**	0.010
	French	-	0.80*	0.095	0.09	0.178
	Eng and Fr	0.02	1.14**	0.015	0.13**	0.045
Employment	Employed	0.68	0.62***	< 0.001	0.09***	< 0.001
Education	HS or less	-0.50	-0.47***	< 0.001	-0.07***	< 0.001
	University degree	0.29	0.35***	< 0.001	0.05***	< 0.001
Minority	Visible minority	-0.16	-0.32***	0.002	-0.05***	0.003
Household type	Family w/o child	0.13	0.35***	< 0.001	0.05***	< 0.001
	Single	-	0.08	0.414	0.01	0.434
	Other household	-	0.38*	0.067	0.05	0.105
Income	Income Q1	-	-0.01	0.949	0.00	0.951
	Income Q3	-	0.15	0.134	0.02	0.154
	Income Q4	-	0.24**	0.019	0.03**	0.028
	Income Q5	-	0.26**	0.015	0.03**	0.023
Immigration	Non-landed	-	-0.03	0.828	0.00	0.833
Disability	Disabled	-	-0.16	0.190	-0.02	0.188
General health	Excellent	-	-0.10	0.279	-0.01	0.286
	Very good	0.13	0.21***	0.008	0.03***	0.009
	Fair	-	0.21*	0.076	0.03*	0.099
	Poor	-	0.11	0.595	0.01	0.615
Province	NL	-	0.05	0.752	0.01	0.761
	PEI	-	-0.01	0.956	0.00	0.957
	NS	-	-0.03	0.815	0.00	0.819
	NB	-	-0.03	0.822	0.00	0.826
	QC	0.11	0.36**	0.015	0.05**	0.021
	ON	-	-0.05	0.650	-0.01	0.658
	MB	-	-0.36**	0.015	-0.05**	0.010
	SK	-	-0.05	0.756	-0.01	0.760
	BC	-	-0.03	0.810	0.00	0.814

Notes: $n = 15,020$. $\tilde{\theta}^{\mathsf{DB}}$ and $\widetilde{\mathrm{AME}}^{\mathsf{DB}}$ denote debiased Lasso estimates of the logit parameter and AME respectively. "-" denotes variables not selected by `svy LLasso`. Comparison categories and not-stated responses are omitted for brevity. Reference: urban, age 45–54, male, non-Aboriginal, neither English nor French, not employed, some post-secondary, non-visible minority, family with child, income Q2, landed immigrant, not disabled, omitted health category, Alberta. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Exact p-values are reported; values below 0.001 are shown as < 0.001.

Table 2: Lasso Logistic Regression Results: Digital Payments

Variables	Categories	Virtual wallet			Credit card		
		svy LLasso	$\tilde{\theta}^{\mathsf{DB}}$	$\widetilde{\text{AME}}^{\mathsf{DB}}$	svy LLasso	$\tilde{\theta}^{\mathsf{DB}}$	$\widetilde{\text{AME}}^{\mathsf{DB}}$
Location	Rural	−0.16	−0.56***	−0.05***	–	0.07	0.01
Age	15–24	0.30	0.83***	0.11***	−0.41	−0.54***	−0.09***
	25–34	0.22	0.63***	0.08***	–	0.04	0.01
	35–44	–	0.36***	0.04***	–	0.12	0.02
	55–64	−0.31	−0.59***	−0.06***	–	−0.03	0.00
	65 and older	−0.54	−0.96***	−0.08***	–	−0.09	−0.01
Education	HS or less	–	−0.04	0.00	−0.42	−0.43***	−0.07***
	Univ. degree	0.03	0.21**	0.02**	0.39	0.49***	0.07***
Minority	Visible min.	0.18	0.37***	0.04***	−0.02	−0.19*	−0.03*
Household	Fam. w/o child	–	0.08	0.01	0.09	0.34***	0.05***
Income	Income Q1	–	0.19	0.02	−0.08	−0.21*	−0.03*
	Income Q4	–	0.23*	0.03*	–	0.19*	0.03*
	Income Q5	0.25	0.68***	0.08***	–	0.13	0.02
Immigration	Non-landed	–	0.26*	0.03*	–	0.16	0.02
Disability	Disabled	–	−0.01	0.00	–	−0.44***	−0.07***
General health	Excellent	–	0.22*	0.03*	–	−0.21**	−0.03**
Province	MB	–	−0.44**	−0.04**	–	0.03	0.00
	ON	–	0.01	0.00	0.06	0.24**	0.04**
	QC	–	−0.11	−0.01	−0.42	−0.38**	−0.06**

Notes: $n = 12{,}124$ for both models. Condensed PUMF version based on the full virtual-wallet and credit-card tables. Comparison categories and not-stated responses are omitted for brevity. Reference: urban, age 45–54, male, non-Aboriginal, neither English nor French, not employed, some post-secondary, non-visible minority, family with child, income Q2, landed immigrant, not disabled, health category 3, Alberta. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

higher-income respondents ($\widehat{\mathcal{C}}_y = 0.106$, SE $= 0.023$, 95% CI [0.061, 0.152]; $p < 0.001$) than online banking (0.027), credit card use (0.023), or the broader digital-payments measure (0.024). The grouped decompositions in Panel B show that income accounts for 93.0% of the measured concentration in virtual-wallet use, compared with 51.6% for credit card use and 57.8% for the composite digital-payments measure. The role of income therefore becomes much more prominent as one moves from general digital banking toward newer payment instruments.

5 Q.2: Why do age–education gaps persist?

This section focuses on *unconditional* digital use. Unlike conditional measures, unconditional outcomes assign zero to those who do not reach a given stage, thereby capturing cumulative

Table 3: Income-Related Concentration of Digital Financial Services

Panel A. Concentration Indices

Outcome	Mean	$\widehat{\mathcal{C}}_y$	$\widehat{\mathcal{C}}_y^{\mathrm{Wag}}$	$\widehat{\mathcal{C}}_y^{\mathrm{E}}$
Online banking	0.817	0.027	0.147	0.088
Virtual wallet	0.123	0.106	0.121	0.053
Credit card	0.793	0.023	0.110	0.072
Digital payments (composite)	0.812	0.024	0.129	0.079

Panel B. Grouped Decomposition Shares (%)

Outcome	Income	Employment	Education	Age
Online banking	33.1	26.6	22.3	14.4
Virtual wallet	93.0	-1.3	8.0	-1.3
Credit card	51.6	4.0	30.5	3.0
Digital payments (composite)	57.8	2.5	24.9	2.4

Notes: Panel A reports the standard concentration index, $\widehat{\mathcal{C}}_y$, together with the Wagstaff-normalized and Erreygers versions for each digital financial service. Positive values indicate a pro-rich gradient. Panel B reports grouped percentage contributions from the Wagstaff-type decomposition of the standard concentration index. Positive values indicate that the covariate group contributes to the pro-rich gradient; negative values indicate an offsetting contribution. Smaller grouped contributions are omitted for brevity.

barriers along the full pathway to digital participation. Unadjusted rates and gaps relative to the reference cell are reported in Appendix B.2; for online banking, rates range from 0.381 for the reference cell to 0.977 for the 15–24 × University cell, an unadjusted gap of 0.596.

5.1 Adjusted gaps and decomposition

Table 4 reports the exact Shapley decomposition of age–education gaps after conditioning on income, disability, health, and preferences; results for health-information search are included alongside online banking as a cross-outcome robustness check and show qualitatively similar patterns throughout. Adjustment reduces the gaps but does not eliminate them. In the full sample, the adjusted gap in online banking remains 0.379 for the 15–24 × University cell, 0.261 for the 25–44 × University cell, and 0.225 for the 45–64 × University cell.

Among the mediators, preferences account for the largest explained share in most cells. Income contributes a meaningful but smaller portion. Disability and health effects are generally modest; health contributions are sometimes slightly negative, indicating that differences in self-reported health do not reinforce the age–education gradient once other covariates are held fixed.

The total explained component is substantial but incomplete: it is 0.202 for the 15–24 × University cell and 0.247 for the 25–44 × University cell in online banking, leaving sizable residual gaps. These persistent adjusted gaps point to digital skills, confidence, interface familiarity, and other unobserved barriers. Subsample results for urban and urban non-disabled respondents are qualitatively similar and are reported in Appendix B.2. Section 7 uses the IRT literacy score to assess how much of the residual is accounted for by measurable digital competence.

6 Q.3: Where do groups fall off the digital ladder?

6.1 Stage-specific marginal effects and model fit

Figure 1 reports average marginal effects (AMEs) from the four sequential logit models. The sequential logit is estimated as a continuation-ratio model with one binary logit at each rung of the adoption ladder. Model fit declines monotonically across stages: McFadden's pseudo-R^2 falls from 0.29 at internet entry to 0.12 for email use, 0.09 for online banking, and 0.06 for digital payments. Sociodemographic characteristics therefore explain a substantial share of variation in *who gets online*, but progressively less of the variation in higher-order activities. This pattern is consistent with early barriers reflecting structural constraints, while later stages depend more on trust, preferences, and transaction-specific behavior. Full goodness-of-fit statistics are reported in Appendix C.1.

The ladder is characterized by different barriers at different stages. Low educational attainment is the only disadvantage that remains significant throughout the entire sequence, from internet access to digital payment adoption, suggesting that education captures not only access differences but also the skills and confidence needed for progressively more demanding digital tasks.

Income-related gaps become sharper at later stages, with the role of financial capacity most pronounced for digital-payment adoption. Rural disadvantage shows the opposite pattern: it is concentrated at the early stages — especially internet and email use — and largely disappears once earlier access barriers are cleared. Gender is largely neutral across the ladder, with one exception: female respondents are 1.6 percentage points more likely to use email conditional on internet access ($p = 0.022$), consistent with occupational sorting toward communication-intensive roles.

Age-related gaps are largest at initial entry and narrow at later stages, suggesting that older adults face stronger barriers to getting online than to using digital transactions condi-

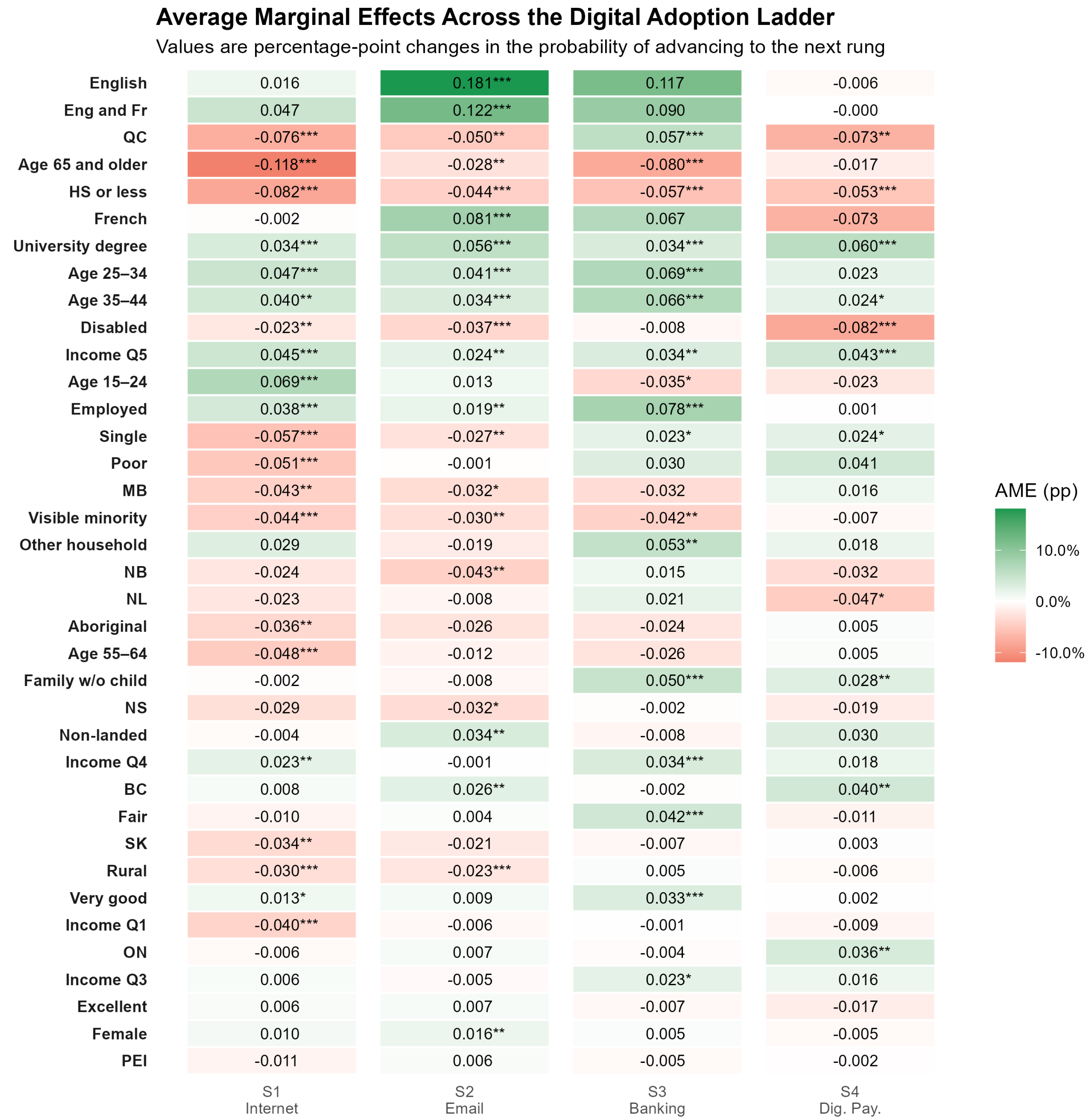
Table 4: Exact Shapley Decomposition of Age–Education Gaps in Unconditional Digital Use

Cell	Obs. gap	Adj. gap	Income	Disability	Health	Preferences	Total expl.
Online banking							
15–24 × HS or less	0.257	0.054	0.000	-0.001	0.002	0.189	0.190
15–24 × Some PSE	0.436	0.189	0.014	0.002	-0.003	0.232	0.247
15–24 × University	0.596	0.379	0.011	0.001	0.000	0.190	0.202
25–44 × HS or less	0.448	0.222	0.001	-0.002	0.004	0.226	0.231
25–44 × Some PSE	0.521	0.277	0.003	0.001	0.000	0.239	0.242
25–44 × University	0.535	0.261	0.011	0.002	0.003	0.231	0.247
45–64 × HS or less	0.260	0.100	0.013	-0.008	-0.001	0.146	0.152
45–64 × Some PSE	0.424	0.175	0.013	0.007	0.008	0.219	0.247
45–64 × University	0.491	0.225	0.015	0.001	-0.003	0.240	0.254
65-plus × Some PSE	0.203	0.046	0.016	0.005	-0.001	0.144	0.163
65-plus × University	0.329	0.099	0.024	-0.004	-0.005	0.181	0.196
Health-information search							
15–24 × HS or less	0.345	0.119	0.038	0.000	-0.013	0.198	0.223
15–24 × Some PSE	0.330	0.110	0.033	-0.002	-0.016	0.198	0.213
15–24 × University	0.506	0.246	0.014	-0.002	-0.011	0.241	0.243
25–44 × HS or less	0.370	0.150	0.022	-0.001	-0.004	0.203	0.218
25–44 × Some PSE	0.447	0.191	0.028	0.002	-0.006	0.224	0.248
25–44 × University	0.531	0.281	0.018	-0.003	-0.006	0.224	0.233
45–64 × HS or less	0.186	0.034	0.030	0.000	-0.002	0.123	0.151
45–64 × Some PSE	0.347	0.116	0.030	0.003	-0.008	0.196	0.220
45–64 × University	0.475	0.212	0.034	0.001	-0.008	0.230	0.257
65-plus × Some PSE	0.242	0.079	0.015	0.005	-0.003	0.148	0.166
65-plus × University	0.379	0.174	0.023	-0.001	-0.010	0.191	0.204

Notes: The reference cell is individuals aged 65 and older with high school education or less. "Obs. gap" is the weighted difference in the unconditional probability relative to the reference cell. "Adj. gap" is the remaining gap after replacing the mediator distribution with that of the reference cell. Mediator columns report exact Shapley contributions. "Total expl." is the exact explained component; mediator contributions sum to this value up to machine precision.

tional on access. Disability, by contrast, is associated with negative effects across multiple stages, consistent with barriers that persist beyond entry. Figure 6 in Appendix C translates these stage-specific marginal effects into predicted adoption trajectories for six representative profiles, illustrating how multiple disadvantages compound across the ladder.

Figure 1: Stage-Specific Average Marginal Effects from the Sequential Logit

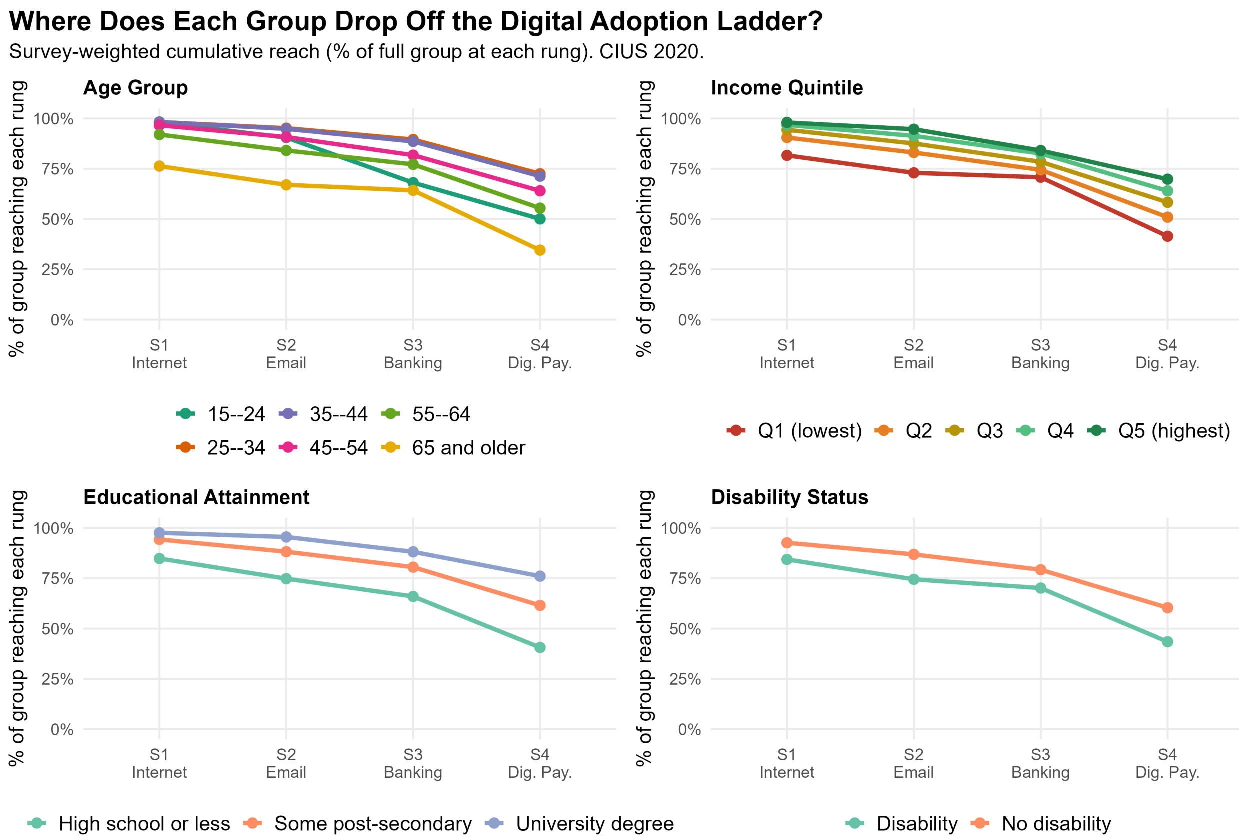


Notes: Cells report AMEs from the four sequential survey-weighted logit models. Values are expressed in percentage-point changes in the probability of advancing to the next rung. Categories corresponding to "not stated" responses are not shown. Reference categories: urban residence, age 45–54, male, non-Indigenous, neither English nor French, not employed, some post-secondary education, non-visible minority, family household with children under 18, income quintile 2, landed immigrant, no disability, health category 3, Alberta. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

6.2 Cumulative reach and drop-off patterns

Figure 2 traces the cumulative share of each demographic group reaching each rung.

Figure 2: Survival Curves: Cumulative Reach at Each Rung



Notes: Survey-weighted cumulative reach at each rung by demographic group. The panels report cumulative reach for visible minority status, income quintile, educational attainment, and disability status.

Income inequality becomes most visible at the digital payments rung. Income quintile groups remain close through Stages 1–3 but diverge sharply at Stage 4: roughly 42% of respondents in Income Q1 reach digital payments, compared with about 70% in Income Q5. This gap reflects accumulated advantages rather than a single transition: Income Q5 raises the probability of internet use by 4.5 points, email by 2.4, online banking by 3.4, and digital payments by 4.3. Income Q1, by contrast, reduces internet adoption by 4.0 points while showing little additional conditional disadvantage at later stages.

Education is the one disadvantage that persists at every rung. High school or less generates a significant negative AME at all four stages: -0.082, -0.044, -0.057, and -0.053.

A university degree produces significant positive increments at every rung: 0.034, 0.056, 0.034, and 0.060. No other covariate produces significant effects uniformly across all four stages. The persistence of education — even after controlling for income, age, employment, disability, and health — motivates the IRT mediator analysis in Section 7.

Disability generates compounding but non-monotonic disadvantage. The AMEs are -0.023 at Stage 1, -0.037 at Stage 2, -0.008 at Stage 3 (not significant), and -0.082 at Stage 4. The pattern is cumulative but not monotonic. Online banking interfaces appear relatively more standardized for persons with disabilities, whereas retail payment checkout flows remain difficult to navigate. This points to the importance of accessibility enforcement beyond core banking platforms.

Employment is specific to the banking rung. Employment shows its largest AME at Stage 3 (0.078, $p < 0.01$), while its effect at Stage 4 is essentially zero. The mechanisms connecting employment to banking — payroll direct deposit, benefits management, employer-provided financial portals — appear specific to the banking rung and do not carry through to retail payment adoption.

Age effects and geographic heterogeneity. Respondents aged 65 and older are 11.8 percentage points less likely to use the internet, 2.8 points less likely to use email, and 8.0 points less likely to use online banking, with no significant difference at digital payments. The 15–24 group shows a distinct profile: substantially more likely to use the internet (0.069) but less likely to use online banking (-0.035). Age therefore operates primarily through entry and banking barriers rather than a uniform resistance to all digital activities.

Rural residence reduces internet use by 3.0 points and email use by 2.3 points but has no meaningful effect at later stages, indicating that rural disadvantage in the PUMF data operates mainly through initial connectivity. Quebec displays a distinctive profile: negative effects at Stages 1–2, a positive banking effect (0.057), and a negative digital payments effect (-0.073), consistent with strong banking-platform penetration alongside lower adoption of newer payment methods.

6.3 Empirically grounded disadvantaged profiles

To identify which combinations of characteristics jointly characterize the bottom tail of predicted digital payment adoption, we examine the modal characteristics among respondents in the bottom decile of the predicted adoption distribution, retaining those whose weighted modal share exceeds 0.80 (0.75 for virtual wallet). Appendix C.2 reports the corresponding profile summaries and predicted probabilities.

The virtual wallet exclusion profile is especially stark: respondents aged 65 and older, with high school or less education, in the lowest income quintile, and with non-visible minority status have a predicted adoption probability of only 0.010, against a weighted national average of 0.097 ($n = 244$). For credit card and composite digital payment outcomes, the most excluded profile converges on older, non-employed, less-educated respondents, with predicted adoption probabilities of 0.315 and 0.316 against national averages of 0.595 ($n = 671$) and 0.608 ($n = 693$) respectively.

Across technologies, digital payment exclusion operates through overlapping socioeconomic disadvantages (especially age, education, and weak economic attachment) rather than any single barrier, while the most excluded subpopulations differ meaningfully across payment instruments.

7 Q.4: Digital literacy and mechanisms

This section uses the digital literacy score from Section 3.4 to assess whether gaps in digital adoption reflect broad differences in digital competence or more specific domain-level deficits. The score is constructed from 20 binary CIUS items spanning information-seeking, software and file management, and security and privacy tasks.

The diagnostics support the use of the general-factor score as our main summary measure: the ratio of the first to second tetrachoric eigenvalue is 5.18 and McDonald's $\omega_h = 0.76$, indicating a dominant general factor. The loading pattern is also substantively coherent: software and file-management items load most strongly on the general factor, while security and privacy items retain an additional domain-specific component. A scree plot, full loading estimates, and additional dimensionality diagnostics are reported in Appendix D.

7.1 Distributional patterns in digital literacy

Figure 3 plots survey-weighted domain scores by age group. The general score exhibits a pronounced age gradient: the 25–34 group records the highest mean (0.275), while the 65-plus group records the lowest (-0.509), a gap of 0.784 standard deviations. The decline is modest through middle age but steepens markedly after age 55, driven largely by the software and file-management dimension, where scores fall below zero for the 55–64 group (-0.104) and decline further for the 65-plus group (-0.207).

The information-seeking dimension tells a different story. The youngest cohort (15–24) records the *lowest* information-seeking score (-0.206), while the 35–44 group records the highest (0.135). This suggests that younger Canadians may be highly engaged digitally without being equally proficient in structured information-search tasks — locating services, comparing options, or navigating institutional websites — at which middle-aged respondents perform better.

Security behavior exhibits a weaker age gradient. Most age groups cluster near the population average, but the 55–64 cohort scores significantly above zero on the security subscore (0.050, 95% CI [0.016, 0.084]), possibly reflecting workplace exposure to formal IT security practices during the organizational expansion of the late 1990s and early 2000s. Figure 4 shows that the security dimension does not follow a simple socioeconomic gradient: visible minorities and landed immigrants score significantly lower, whereas rural residents score significantly higher. These patterns suggest that digital-inclusion policies should address privacy-risk awareness and protective practices, not only access and general skills.

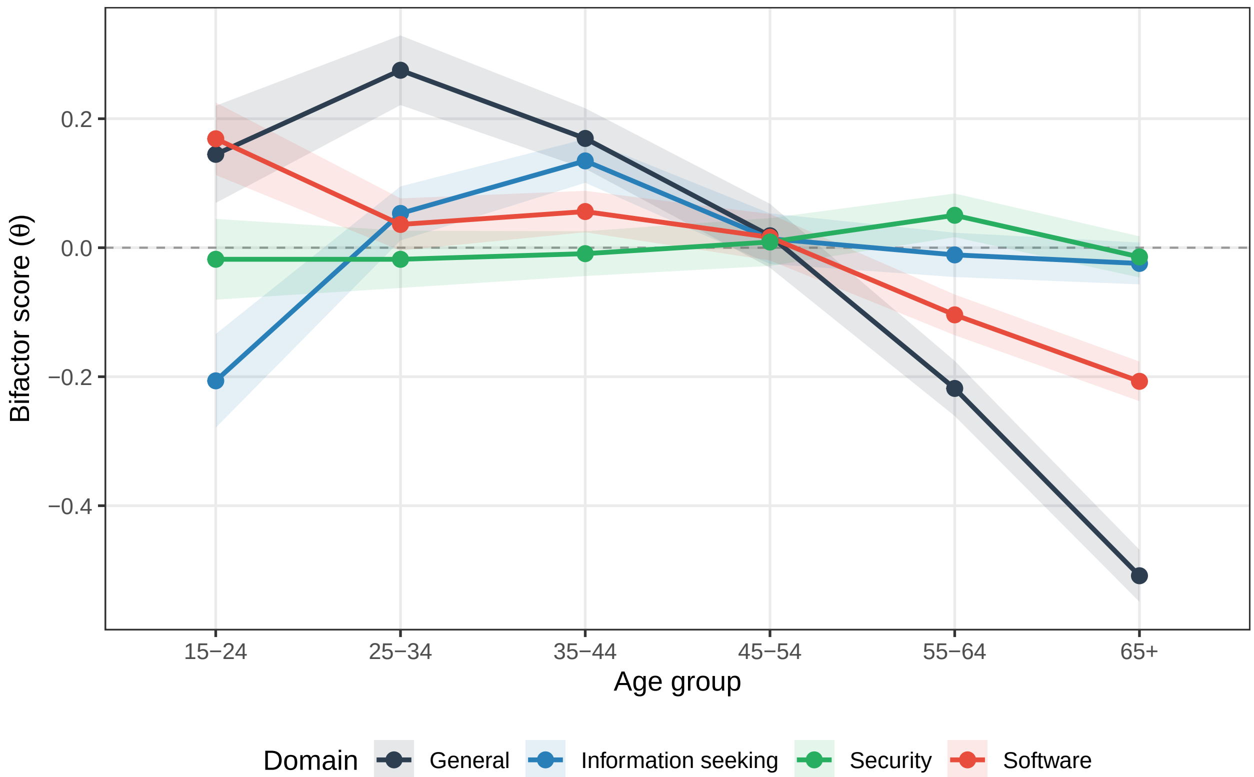
Digital literacy itself is also unequally distributed across income. Applying the income-ranked concentration index of Section 3.5 to the rescaled literacy score $\hat{L}_i$ (Panel A of Table 6) yields $\widehat{\mathcal{C}}_L = 0.029$ (SE $= 0.003$, $p < 0.001$), confirming a statistically significant pro-rich gradient in digital competence and motivating the literacy-ranked analysis below.

7.2 Digital literacy, the education gradient, and literacy-ranked concentration

The persistent education gradient in the sequential logit may reflect differences in digital capability, connectivity quality, or behavioral preferences. To assess the capability channel, we augment the sequential logit with the general digital literacy score and compare the AME of the high-school-or-less indicator before and after conditioning.

Table 5 reports results for Stages 1 and 3. At Stage 1 (internet use), the baseline education gap is about 5.5 percentage points; after conditioning on literacy, the effect becomes statistically indistinguishable from zero, indicating that the initial education gradient largely reflects differences in digital capability. At Stage 3 (online banking), conditioning on literacy reduces the gap by 61%, but the effect remains significant at the 5% level, pointing to behavioral and institutional mechanisms — trust, financial interface familiarity, and perceived risk — that continue to shape adoption beyond basic skill. The literacy score itself raises the probability of online banking by 7.2 percentage points per standard deviation.

Figure 3: Digital Literacy Domain Scores by Age Group



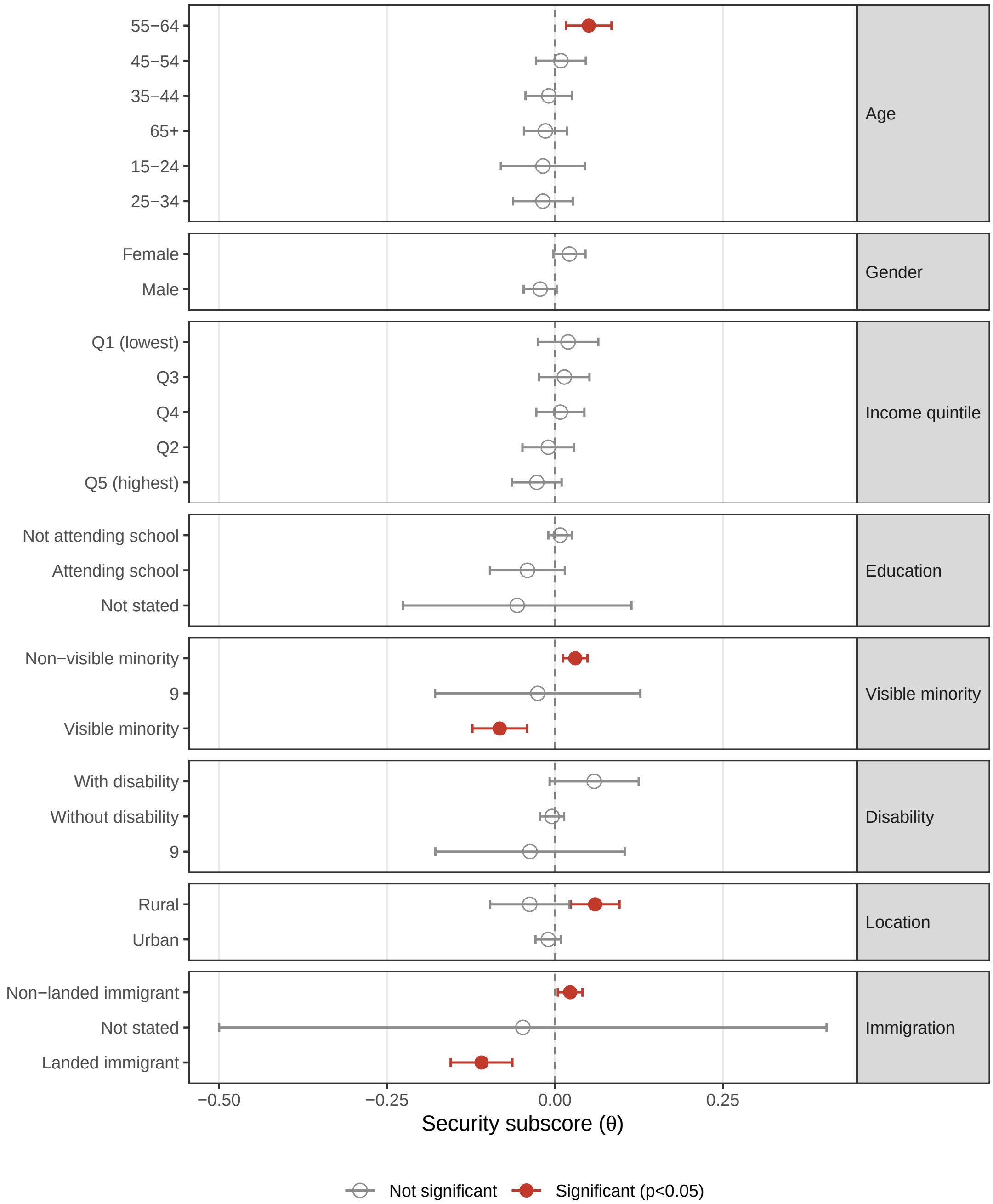
Notes: Survey-weighted bifactor domain scores by age group. Points are weighted means and bands denote 95% confidence intervals. The dashed line at zero denotes the population average.

These are descriptive conditioning effects rather than causal mediation estimates, since digital literacy is jointly determined with education and other socioeconomic characteristics. Even so, the attenuation pattern is informative: capability accounts for most of the education gradient at entry, while behavioral and institutional frictions dominate at higher rungs.

Table 6 reports the literacy-ranked concentration indices defined in Section 3.5 for six digital activities. All six indices are positive, indicating that digital participation is systematically tilted toward the more digitally literate. Near-universal activities show the smallest gradients: email use ($\widehat{\mathcal{C}}_y^L = 0.026$) and smartphone use (0.030) are only mildly concentrated at the upper end of the literacy distribution. By contrast, routine transactional activities display moderate and tightly clustered gradients: online banking (0.066), credit-card use (0.062), and government online services (0.067) have very similar concentration indices, suggesting a common competence threshold for mainstream digital transactions.

Virtual-wallet adoption stands apart. Its literacy-ranked concentration index is $\widehat{\mathcal{C}}_y^L = 0.344$, with a Murphy–Topel standard error of 0.023 and a 95% confidence interval of $[0.298,\ 0.389]$,

Figure 4: Security Subscore by Demographic Group



Notes: Survey-weighted bifactor security subscore. Filled circles denote estimates significant at $p < 0.05$; open circles denote non-significant estimates.

against a base rate of only 12.3%. Part of this larger value reflects the $1/\bar{y}$ scaling of the concentration index for relatively rare outcomes, but the contrast with credit-card use — a similarly payment-oriented activity with a much higher base rate and an index of only 0.062 — still points to a substantially stronger literacy gradient for newer payment instruments.

Taken together, these results place digital competence as a distributional link between economic resources and digital financial inclusion, complementing the income-ranked indices in Section 4.3 and the conditioning evidence above.

Table 5: Education gradient before and after conditioning on digital literacy

Stage	Model	AME (HS or less)	Reduction
Internet use (Stage 1)	Baseline	-0.0545^{***}	—
Internet use (Stage 1)	+ Literacy	0.0000	100%
Online banking (Stage 3)	Baseline	-0.0548^{***}	—
Online banking (Stage 3)	+ Literacy	-0.0213^{**}	61%

Notes: Entries report average marginal effects from survey-weighted sequential logit models. The literacy score is standardized to mean zero and unit variance. Reduction is the percentage change in the AME of HS or less after conditioning on literacy. $^{***}p < 0.01$, $^{**}p < 0.05$.

Table 6: Digital Literacy and Literacy-Ranked Concentration Indices

Panel A. Income-Ranked Concentration of Digital Literacy				
Outcome	Mean	$\widehat{\mathcal{C}}_L$	SE	95% CI
Digital literacy score	0.601	0.029	0.003	[0.023, 0.034]
Panel B. Literacy-Ranked Concentration of Digital Activities				
Outcome	Mean	$\widehat{\mathcal{C}}_y^L$	SE	95% CI
Email use	0.957	0.026	0.002	[0.022, 0.030]
Online banking	0.862	0.066	0.004	[0.059, 0.074]
Virtual wallet	0.123	0.344	0.023	[0.298, 0.389]
Credit card	0.793	0.062	0.005	[0.053, 0.071]
Government online services	0.851	0.067	0.004	[0.059, 0.074]
Smartphone use	0.945	0.030	0.002	[0.026, 0.033]

Notes: Panel A reports the income-ranked concentration index $\widehat{\mathcal{C}}_L$ applied to the rescaled digital literacy score $\hat{L}_i$, measuring the extent to which digital competence is concentrated among higher-income respondents; its standard error uses the closed-form linearization variance estimator (Kakwani et al., 1997), treating the estimated literacy scores as fixed. Panel B reports literacy-ranked concentration indices for selected digital activities, where $\widehat{\mathcal{C}}_y^L = \frac{2}{\bar{y}W}\sum_i w_i(y_i - \bar{y})(\hat{r}_i^L - \frac{1}{2})$ and $\hat{r}_i^L$ is the weighted midpoint fractional rank in the distribution of $\hat{L}_i$. Standard errors in Panel B account for both second-stage sampling variation and first-stage IRT estimation uncertainty via a Murphy–Topel-type correction (Murphy and Topel, 1985); see Appendix D.6 for details. All estimates use person weights `WTPG`.

8 Conclusion

This paper studies digital inequality in Canada using four complementary empirical approaches: survey-weighted logistic Lasso for digital financial adoption, an exact Shapley decomposition of age–education gaps, a sequential logit tracing where disadvantage emerges along the adoption path, and a bifactor IRT measure of digital literacy. The results show that digital inequality is multidimensional: income, education, disability, age, and digital capability matter in different ways and at different stages of participation.

Three conclusions stand out. First, education is the only determinant that remains significant throughout the full adoption ladder; this effect is only partly accounted for by income, health, disability, preferences, and measured digital literacy, pointing to behavioral and institutional frictions that persist beyond measurable competence. Second, income-based inequality is most pronounced for virtual-wallet adoption, where both the income and literacy gradients are especially steep, and for online banking the concentration reflects a broad socioeconomic gradient in which employment and education are nearly as important as income itself. Third, the disability penalty is stage-specific rather than uniform: it disappears at online banking but reappears with the largest penalty at the digital-payments stage, pointing to accessibility gaps in retail payment interfaces that banking platforms have largely addressed. The digital literacy analysis further reveals that general capability and security behavior follow different social patterns, with security deficits concentrated among recent immigrants and visible minorities rather than among seniors — a finding with direct implications for digital-inclusion policy.

Limitations. Three limitations warrant acknowledgment. The CIUS 2020 covers only the ten provinces, excluding the territories and First Nations reserves, so the findings do not generalize to those populations. The digital literacy score is estimated on the routed subsample of internet users, which may introduce selection into capability measurement and limits the comparability of literacy-conditioned results with the full-population analyses. The decomposition and literacy-conditioning exercises are associational rather than causal; they identify plausible mechanisms but cannot rule out confounding. Future work using the CIUS 2022 wave could assess whether the stage-specific barriers documented here have persisted or shifted in the post-pandemic period.

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A Supplementary results for survey-weighted logistic Lasso (Q.1)

A.1 Debiased Lasso inference

From the weighted log-likelihood defined in (3.2), the score, information matrix, and negative Hessian are

$$\begin{aligned} S(\theta) &= n^{-1}\sum_{i=1}^{n} w_i x_i (y_i - \Lambda(x_i'\theta))\,, \\ I(\theta) &= n^{-1}\sum_{i=1}^{n} w_i^2 x_i x_i' \Lambda(x_i'\theta)\Big(1-\Lambda(x_i'\theta)\Big), \\ H(\theta) &= n^{-1}\sum_{i=1}^{n} w_i x_i x_i' \Lambda(x_i'\theta)\Big(1-\Lambda(x_i'\theta)\Big). \end{aligned}$$

To conduct inference on individual components of θ, we rely on the following result: under regularity conditions and for any fixed unit vector τ, the debiased estimator $\tilde{\theta}^{\mathsf{DB}}$ in (3.3) satisfies

$$n^{1/2}\left(\tau' H(\hat{\theta})^{-1} I(\hat{\theta}) H(\hat{\theta})^{-1}\tau\right)^{-1/2}\tau'\left(\tilde{\theta}^{\mathsf{DB}}-\theta_0\right) \xrightarrow{d} \mathcal{N}(0,1);$$

see Jasiak et al. (2026) for formal arguments. We also report debiased estimators of average marginal effects (AMEs). For the binary regressor x_{ij}, the individual marginal effect is defined as

$$\mathrm{ME}_{ij}(\theta) := \Lambda(x_i'\theta)\Big|_{x_{ij}=1} - \Lambda(x_i'\theta)\Big|_{x_{ij}=0}.$$

The corresponding weighted sample AME is

$$\widehat{\mathrm{AME}}_j(\theta) := \frac{1}{\sum_{i=1}^n w_i} \sum_{i=1}^n w_i \, \mathrm{ME}_{ij}(\theta).$$

The debiased estimator of the AME_j, the average marginal effect of regressor j, is obtained by a one-step correction:

$$\widetilde{\mathrm{AME}}_j^{\mathsf{DB}} = \widehat{\mathrm{AME}}_j(\hat{\theta}) + \nabla_\theta \widehat{\mathrm{AME}}_j(\hat{\theta})' H(\hat{\theta})^{-1} S(\hat{\theta}),$$

where

$$\nabla_\theta \widehat{\mathrm{AME}}_j(\hat{\theta}) = \frac{1}{\sum_{i=1}^n w_i} \sum_{i=1}^n w_i \Big(x_i \, \Lambda(x_i'\hat{\theta}) \Big(1 - \Lambda(x_i'\hat{\theta})\Big)\Big|_{x_{ij}=1} - x_i \, \Lambda(x_i'\hat{\theta}) \Big(1 - \Lambda(x_i'\hat{\theta})\Big)\Big|_{x_{ij}=0} \Big).$$

An asymptotic confidence interval for AME_j is based on

$$n^{1/2} \left(\nabla_\theta \widehat{\mathrm{AME}}_j(\hat{\theta})' H(\hat{\theta})^{-1} I(\hat{\theta}) H(\hat{\theta})^{-1} \nabla_\theta \widehat{\mathrm{AME}}_j(\hat{\theta}) \right)^{-1/2} \left(\widetilde{\mathrm{AME}}_j^{\mathsf{DB}} - \mathrm{AME}_j \right) \xrightarrow{d} \mathcal{N}(0, 1).$$

A.2 Additional regression tables

This appendix contains the full `svy LLasso` results for internet use (Table 7), email use (Table 8), and separate virtual wallet and credit card results (Tables 9 and 10).

A.3 Robustness to alternative tuning rules

In the main text, λ is selected by standard 10-fold cross-validation with the AUC criterion via `glmnet`. Because unequal selection probabilities raise a potential non-i.i.d. concern, we consider two alternative tuning rules.

First, following Iparragirre et al. (2023), we implement a design-aware stratified cross-validation procedure in a PUMF-feasible form, using weighted direct cross-validation (`dCV`) with rescaled person weights. The full survey-design inputs required for an exact implementation are not available in the PUMF analytical file; we therefore use the final person weight rescaled to mean one, as recommended by the CIUS User Guide (Statistics Canada, 2022).

Second, we implement the bootstrap-after-cross-validation (BCV) rule of Chetverikov and Sørensen (2025). Non-constant regressors are standardized using weighted means and standard deviations, and the BCV penalty uses 1,000 bootstrap replications.

Both alternatives yield very similar results to the baseline. After removing zero-variance, duplicate, and linearly dependent columns, each model contains 46 candidate first-order regressors. Under `dCV`, selected nonzero covariates number 41 (internet use), 29 (online banking),

Table 7: Lasso Logistic Regression Results: Internet Use

Variables	Categories	`svy LLasso`	$\tilde{\theta}^{\mathsf{DB}}$	p-value	$\widetilde{\text{AME}}^{\mathsf{DB}}$	p-value
Intercept		3.77	3.33***	< 0.001	-	-
Location	Rural	−0.23	−0.36***	< 0.001	−0.02***	< 0.001
Age	15–24	0.37	1.01***	< 0.001	0.05***	0.001
	25–34	-	0.57**	0.018	0.03**	0.043
	35–44	-	0.49**	0.028	0.03*	0.057
	55–64	−0.64	−0.51***	0.004	−0.03**	0.017
	65 and older	−1.61	−1.30***	< 0.001	−0.09***	< 0.001
Gender	Female	-	0.12	0.141	0.01	0.153
Aboriginal identity	Aboriginal	-	−0.41*	0.055	−0.03**	0.038
Language	English	-	0.24	0.612	0.01	0.615
	French	−0.49	−0.04	0.936	0.00	0.951
	Eng and Fr	0.07	0.60	0.220	0.03	0.269
Employment	Employed	0.44	0.49***	< 0.001	0.03***	< 0.001
Education	HS or less	−0.89	−0.93***	< 0.001	−0.06***	< 0.001
	University degree	0.32	0.42***	< 0.001	0.02***	< 0.001
Minority	Visible minority	−0.03	−0.47***	0.003	−0.03***	0.002
Household type	Family w/o child	-	−0.03	0.860	0.00	0.865
	Single	−0.54	−0.64***	< 0.001	−0.04***	0.001
	Other household	-	0.30	0.345	0.02	0.397
Income	Income Q1	−0.55	−0.45***	< 0.001	−0.03***	< 0.001
	Income Q3	-	0.07	0.576	0.00	0.592
	Income Q4	0.01	0.27*	0.060	0.01*	0.081
	Income Q5	0.18	0.51***	0.003	0.03***	0.005
Immigration	Non-landed	-	−0.05	0.797	0.00	0.805
Disability	Disabled	−0.19	−0.26**	0.037	−0.02*	0.050
General health	Excellent	-	0.09	0.476	0.01	0.496
	Very good	0.08	0.17*	0.083	0.01*	0.093
	Fair	-	−0.11	0.387	−0.01	0.391
	Poor	−0.02	−0.63***	0.003	−0.04***	< 0.001
Province	NL	-	−0.27	0.162	−0.02	0.145
	PEI	-	−0.11	0.586	−0.01	0.586
	NS	-	−0.32*	0.098	−0.02*	0.081
	NB	-	−0.24	0.205	−0.01	0.190
	QC	−0.32	−0.73***	< 0.001	−0.05***	< 0.001
	ON	-	−0.06	0.686	0.00	0.694
	MB	-	−0.48**	0.016	−0.03***	0.008
	SK	-	−0.37*	0.058	−0.02**	0.043
	BC	-	0.09	0.623	0.00	0.640

Notes: $n = 17,409$. "-" denotes variables not selected by `svy LLasso`. Reference: urban, age 45–54, male, non-Aboriginal, neither English nor French, not employed, some post-secondary, non-visible minority, family with child, income Q2, landed immigrant, not disabled, omitted health category, Alberta. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 8: Lasso Logistic Regression Results: Email Use

Variables	Categories	`svy LLasso`	$\tilde{\theta}^{\mathsf{DB}}$	p-value	$\widetilde{\text{AME}}^{\mathsf{DB}}$	p-value
Intercept		2.14	-0.35	0.579	-	-
Location	Rural	-0.16	-0.32^{***}	0.003	-0.02^{***}	0.003
Age	15–24	-	0.20	0.349	0.01	0.374
	25–34	0.26	0.67^{***}	< 0.001	0.03^{***}	0.001
	35–44	0.17	0.53^{***}	0.003	0.03^{***}	0.004
	55–64	-0.19	-0.16	0.299	-0.01	0.333
	65 and older	-0.44	-0.36^{**}	0.026	-0.02^{*}	0.051
Gender	Female	0.10	0.22^{**}	0.021	0.01^{**}	0.022
Aboriginal identity	Aboriginal	-	-0.34	0.205	-0.02	0.156
Language	English	0.19	2.66^{***}	< 0.001	0.26^{***}	< 0.001
	French	-	2.45^{***}	< 0.001	0.09^{**}	0.021
	Eng and Fr	0.42	3.07^{***}	< 0.001	0.15^{***}	< 0.001
Employment	Employed	0.30	0.27^{**}	0.025	0.02^{**}	0.026
Education	HS or less	-0.50	-0.57^{***}	< 0.001	-0.04^{***}	< 0.001
	University degree	0.84	0.94^{***}	< 0.001	0.05^{***}	< 0.001
Minority	Visible minority	-0.11	-0.36^{**}	0.030	-0.02^{**}	0.027
Household type	Family w/o child	-	-0.10	0.502	-0.01	0.505
	Single	-0.05	-0.34^{**}	0.026	-0.02^{**}	0.019
	Other household	-	-0.22	0.480	-0.01	0.449
Income	Income Q1	-0.09	-0.08	0.543	-0.01	0.555
	Income Q3	-	-0.06	0.666	0.00	0.664
	Income Q4	-	-0.01	0.935	0.00	0.935
	Income Q5	0.27	0.35^{**}	0.047	0.02^{**}	0.036
Immigration	Non-landed	0.27	0.41^{**}	0.022	0.03^{**}	0.029
Disability	Disabled	-0.15	-0.47^{***}	0.006	-0.03^{***}	0.004
General health	Excellent	-	0.10	0.497	0.01	0.509
	Very good	0.04	0.13	0.270	0.01	0.276
	Fair	-	0.05	0.758	0.00	0.763
	Poor	-	-0.03	0.926	0.00	0.926
Province	NL	-	-0.10	0.635	-0.01	0.625
	PEI	-	0.09	0.677	0.01	0.689
	NS	-	-0.42^{*}	0.051	-0.03^{**}	0.025
	NB	-	-0.56^{**}	0.010	-0.04^{***}	0.002
	QC	-0.33	-0.59^{***}	0.009	-0.04^{**}	0.012
	ON	0.07	0.10	0.556	0.01	0.556
	MB	-	-0.43^{*}	0.057	-0.03^{**}	0.029
	SK	-	-0.27	0.219	-0.02	0.180
	BC	0.13	0.36^{*}	0.074	0.02^{*}	0.084

Notes: $n = 15,153$. Reference: urban, age 45–54, male, non-Aboriginal, neither English nor French, not employed, some post-secondary, non-visible minority, family with child, income Q2, landed immigrant, not disabled, omitted health category, Alberta. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9: Lasso Logistic Regression Results: Virtual Wallet

Variables	Categories	`svy LLasso`	$\tilde{\theta}^{\mathsf{DB}}$	p-value	$\widetilde{\text{AME}}^{\mathsf{DB}}$	p-value
Intercept		-2.05	-3.62^{***}	< 0.001	-	-
Location	Rural	-0.16	-0.56^{***}	< 0.001	-0.05^{***}	< 0.001
Age	15–24	0.30	0.83^{***}	< 0.001	0.11^{***}	< 0.001
	25–34	0.22	0.63^{***}	< 0.001	0.08^{***}	< 0.001
	35–44	-	0.36^{***}	0.003	0.04^{***}	0.001
	55–64	-0.31	-0.59^{***}	< 0.001	-0.06^{***}	< 0.001
	65 and older	-0.54	-0.96^{***}	< 0.001	-0.08^{***}	< 0.001
Gender	Female	-	-0.05	0.521	-0.01	0.516
Aboriginal identity	Aboriginal	-	0.08	0.740	0.01	0.731
Language	English	-	0.76	0.447	0.08	0.472
	French	-	0.32	0.750	0.04	0.723
	Eng and Fr	-	0.88	0.382	0.11	0.310
Employment	Employed	-	0.03	0.786	0.00	0.784
Education	HS or less	-	-0.04	0.717	0.00	0.715
	University degree	0.03	0.21^{**}	0.030	0.02^{**}	0.027
Minority	Visible minority	0.18	0.37^{***}	0.003	0.04^{***}	0.003
Household type	Family w/o child	-	0.08	0.463	0.01	0.456
	Single	-	0.07	0.566	0.01	0.554
	Other household	-	0.22	0.388	0.02	0.353
Income	Income Q1	-	0.19	0.211	0.02	0.187
	Income Q3	-	0.21	0.130	0.02	0.111
	Income Q4	-	0.23^{*}	0.099	0.03^{*}	0.082
	Income Q5	0.25	0.68^{***}	< 0.001	0.08^{***}	< 0.001
Immigration	Non-landed	-	0.26^{*}	0.059	0.03^{*}	0.070
Disability	Disabled	-	-0.01	0.945	0.00	0.944
General health	Excellent	-	0.22^{*}	0.065	0.03^{*}	0.053
	Very good	-	0.05	0.624	0.01	0.618
	Fair	-	0.00	0.993	0.00	0.993
	Poor	-	0.39	0.240	0.05	0.182
Province	NL	-	-0.24	0.234	-0.02	0.265
	PEI	-	-0.11	0.621	-0.01	0.629
	NS	-	-0.33	0.102	-0.03	0.136
	NB	-	-0.26	0.222	-0.03	0.255
	QC	-	-0.11	0.574	-0.01	0.578
	ON	-	0.01	0.940	0.00	0.939
	MB	-	-0.44^{**}	0.025	-0.04^{**}	0.048
	SK	-	-0.18	0.370	-0.02	0.391
	BC	-	0.06	0.730	0.01	0.724

Notes: $n = 12,124$. Reference: urban, age 45–54, male, non-Aboriginal, neither English nor French, not employed, some post-secondary, non-visible minority, family with child, income Q2, landed immigrant, not disabled, omitted health category, Alberta. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 10: Lasso Logistic Regression Results: Credit Card

Variables	Categories	`svy LLasso`	$\tilde{\theta}^{\mathsf{DB}}$	p-value	$\widetilde{\text{AME}}^{\mathsf{DB}}$	p-value
Intercept		1.41	0.53	0.485	-	-
Location	Rural	-	0.07	0.368	0.01	0.390
Age	15–24	-0.41	-0.54^{***}	< 0.001	-0.09^{***}	< 0.001
	25–34	-	0.04	0.738	0.01	0.747
	35–44	-	0.12	0.240	0.02	0.264
	55–64	-	-0.03	0.808	0.00	0.813
	65 and older	-	-0.09	0.445	-0.01	0.453
Gender	Female	-	0.01	0.888	0.00	0.892
Aboriginal identity	Aboriginal	-	0.18	0.361	0.03	0.396
Language	English	0.05	0.58	0.436	0.09	0.432
	French	-0.00	-0.02	0.979	0.00	0.979
	Eng and Fr	-	0.49	0.513	0.07	0.553
Employment	Employed	0.05	0.12	0.155	0.02	0.168
Education	HS or less	-0.42	-0.43^{***}	< 0.001	-0.07^{***}	< 0.001
	University degree	0.39	0.49^{***}	< 0.001	0.07^{***}	< 0.001
Minority	Visible minority	-0.02	-0.19^{*}	0.080	-0.03^{*}	0.085
Household type	Family w/o child	0.09	0.34^{***}	< 0.001	0.05^{***}	< 0.001
	Single	-	0.33^{***}	0.001	0.05^{***}	0.004
	Other household	-	0.16	0.443	0.02	0.474
Income	Income Q1	-0.08	-0.21^{*}	0.065	-0.03^{*}	0.072
	Income Q3	-	0.06	0.596	0.01	0.610
	Income Q4	-	0.19^{*}	0.076	0.03^{*}	0.095
	Income Q5	-	0.13	0.250	0.02	0.274
Immigration	Non-landed	-	0.16	0.195	0.02	0.198
Disability	Disabled	-	-0.44^{***}	0.002	-0.07^{***}	0.001
General health	Excellent	-	-0.21^{**}	0.029	-0.03^{**}	0.029
	Very good	0.00	0.01	0.876	0.00	0.880
	Fair	-	-0.07	0.587	-0.01	0.593
	Poor	-	0.36	0.154	0.05	0.206
Province	NL	-	-0.33^{**}	0.045	-0.05^{**}	0.036
	PEI	-	-0.04	0.797	-0.01	0.801
	NS	-	-0.09	0.592	-0.01	0.597
	NB	-	-0.16	0.335	-0.03	0.332
	QC	-0.42	-0.38^{**}	0.014	-0.06^{**}	0.026
	ON	0.06	0.24^{**}	0.041	0.04^{**}	0.049
	MB	-	0.03	0.876	0.00	0.881
	SK	-	0.01	0.964	0.00	0.966
	BC	-	0.23	0.107	0.03	0.134

Notes: $n = 12,124$. Reference: urban, age 45–54, male, non-Aboriginal, neither English nor French, not employed, some post-secondary, non-visible minority, family with child, income Q2, landed immigrant, not disabled, omitted health category, Alberta. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

42 (email), 19 (virtual wallet), and 33 (credit card). Under BCV the corresponding numbers are 13, 6, 5, 7, and 6. Despite these differences in sparsity, the substantive conclusions are unchanged: strong age and education gradients, a positive employment effect at online banking, a positive visible-minority effect for virtual wallets, and a negative disability effect for credit cards all persist across all three tuning approaches, and the debiased AMEs remain very similar in magnitude.

A.4 IIA tests

We assessed whether the "Not stated" response should be retained as a separate alternative using weighted Hausman–McFadden-type multinomial logit tests comparing the full {Yes, No, Not stated} specification with the restricted {Yes, No} specification. For internet use, the test is not applicable (no observed "Not stated" responses in the PUMF estimation sample). For online banking, email, and credit card use, the tests yield negative Hausman–McFadden statistics; virtual wallet use produces a small positive statistic (2.95). In all cases the IIA assumption is not rejected, supporting the exclusion of "Not stated" responses from the binary `svy LLasso` analysis.

B Supplementary decomposition results (Q.2)

B.1 Connectivity quality as an additional mediator

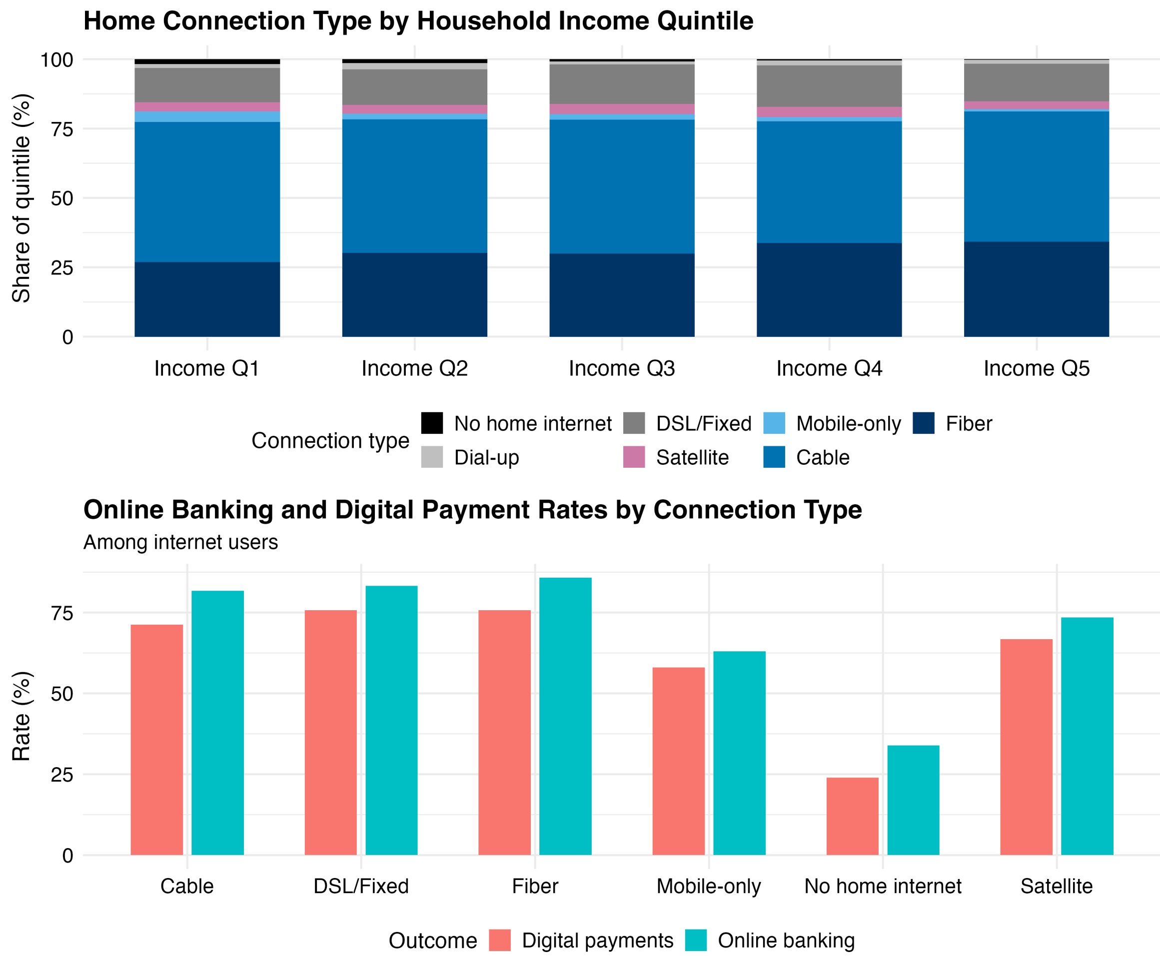
To examine the infrastructure channel in the age–education gap, we augment the Q.2 decomposition with three mediators derived from the CIUS: a *mobile-only* access indicator, a below-CRTC-benchmark speed indicator (50 Mbps), and a no-home-internet indicator.

Figure 5 shows clear differences in digital engagement across connection types: online banking is highest for fiber and cable users and substantially lower for mobile-only and no-home-connection respondents. Connection quality varies across the income distribution, but the gradient is modest relative to the underlying income and education differences, and the decomposition shows that connectivity quality explains only a limited additional share of the residual education gradient. Digital inequality reflects layered barriers, with infrastructure quality mattering at the margin but not accounting for most of the remaining gap.

B.2 Robustness of the decomposition across subsamples

Table 12 reports the adjusted decomposition results for the urban non-disabled and urban samples. The qualitative patterns closely match those in the full sample: adjustment reduces the observed gaps, but substantial residual differences remain.

Figure 5: Connectivity Quality as a Dimension of the Digital Divide



Notes: The upper panel shows the distribution of home connection types by household income quintile; the lower panel shows online banking and digital payment rates by connection type among internet users.

Table 11: Unconditional Use by Age and Education: Raw Rates and Unadjusted Gaps

Panel A: Unconditional rates

	Online banking			Health-information search		
Age group	HS or less	Some PSE	University	HS or less	Some PSE	University
15–24	0.638	0.817	0.977	0.726	0.711	0.887
25–44	0.829	0.901	0.915	0.751	0.828	0.912
45–64	0.640	0.805	0.872	0.567	0.728	0.856
65-plus	0.381	0.584	0.710	0.381	0.623	0.760

Panel B: Unadjusted differences relative to reference cell

	Online banking			Health-information search		
Age group	HS or less	Some PSE	University	HS or less	Some PSE	University
15–24	0.257	0.436	0.596	0.345	0.330	0.506
25–44	0.448	0.521	0.535	0.370	0.447	0.531
45–64	0.260	0.424	0.491	0.186	0.347	0.475
65-plus	0.000	0.203	0.329	0.000	0.242	0.379

Notes: Panel A reports weighted unconditional probabilities of using online banking and searching for health information on the internet by age and education group. Panel B reports unadjusted differences relative to the reference cell (individuals aged 65 and older with high school education or less), corresponding to equation (3.4). All estimates use survey weights.

Table 12: Exact Shapley Decomposition of Age–Education Gaps Across Urban Subsamples

Panel A. Urban Non-Disabled Sample

Cell	Obs. gap	Adj. gap	Income	Disability	Health	Preferences	Total expl.
15–24 × HS or less	0.257	0.055	0.001	0.000	0.002	0.187	0.190
15–24 × Some PSE	0.436	0.191	0.014	0.000	-0.003	0.231	0.244
15–24 × University	0.596	0.380	0.011	0.000	0.000	0.189	0.200
25–44 × HS or less	0.448	0.223	0.001	0.000	0.004	0.224	0.229
25–44 × Some PSE	0.521	0.278	0.003	0.000	0.000	0.237	0.243
25–44 × University	0.535	0.262	0.011	0.000	0.003	0.230	0.244
45–64 × HS or less	0.260	0.101	0.013	0.000	-0.001	0.145	0.152
45–64 × Some PSE	0.424	0.176	0.013	0.000	0.008	0.218	0.241
45–64 × University	0.491	0.226	0.015	0.000	-0.003	0.239	0.253
65-plus × Some PSE	0.203	0.047	0.016	0.000	-0.001	0.143	0.159
65-plus × University	0.329	0.100	0.024	0.000	-0.005	0.180	0.195

Panel B. Urban Sample

Cell	Obs. gap	Adj. gap	Income	Disability	Health	Preferences	Total expl.
15–24 × HS or less	0.257	0.056	0.001	-0.001	0.002	0.185	0.187
15–24 × Some PSE	0.436	0.192	0.014	0.002	-0.003	0.229	0.242
15–24 × University	0.596	0.381	0.011	0.001	0.000	0.187	0.199
25–44 × HS or less	0.448	0.224	0.001	-0.002	0.004	0.223	0.226
25–44 × Some PSE	0.521	0.279	0.003	0.001	0.000	0.236	0.240
25–44 × University	0.535	0.263	0.011	0.002	0.003	0.229	0.244
45–64 × HS or less	0.260	0.102	0.013	-0.008	-0.001	0.144	0.148
45–64 × Some PSE	0.424	0.177	0.013	0.007	0.008	0.216	0.244
45–64 × University	0.491	0.227	0.015	0.001	-0.003	0.238	0.251
65-plus × Some PSE	0.203	0.048	0.016	0.005	-0.001	0.142	0.160
65-plus × University	0.329	0.101	0.024	-0.004	-0.005	0.179	0.194

Notes: Reference cell is individuals aged 65 and older with high school or less education. Entries report exact simulation-based Shapley contributions from income, disability, health, and preference-related non-use. In Panel A, disability is excluded by sample restriction, so the disability contribution is zero by construction.

C Supplementary sequential logit results (Q.3)

C.1 Goodness-of-fit statistics

Table 13 reports the full goodness-of-fit statistics for the four sequential logit stages.

Table 13: Sequential Logit: Goodness-of-Fit Statistics

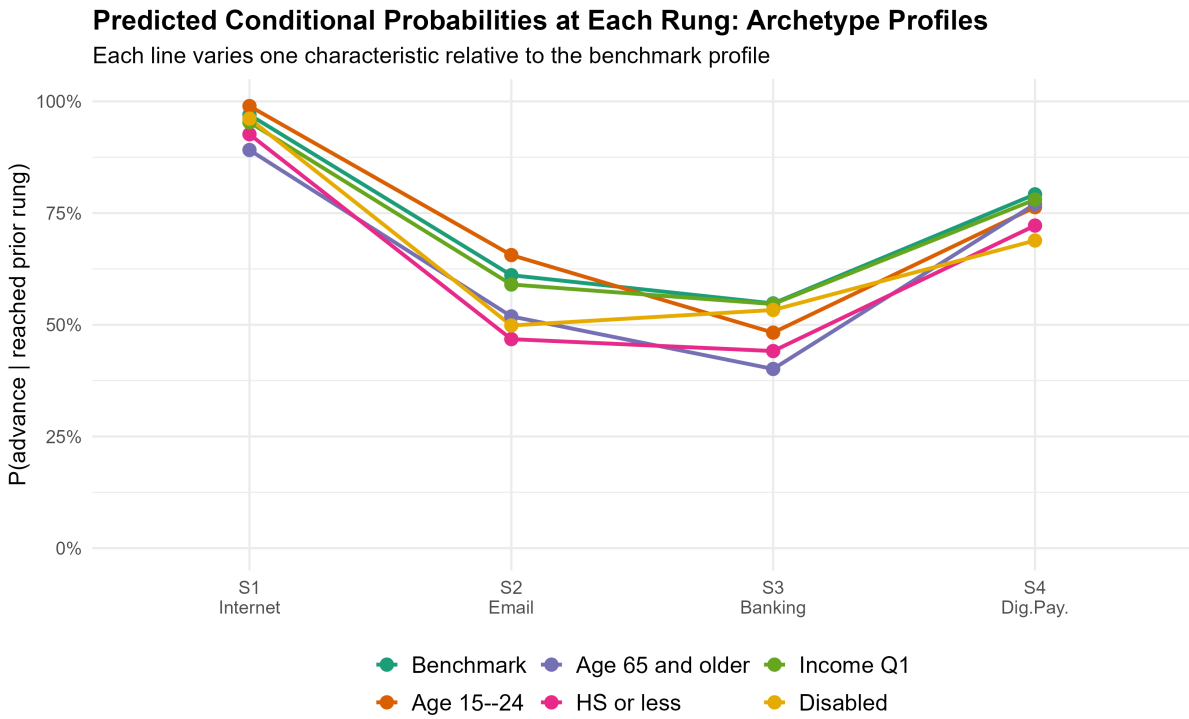
Stage	n	McFadden R^2	Dispersion	Resid. df	Null dev.	Resid. dev.
S1: Internet use	17,409	0.29	1.08	17,362	9,495.9	6,713.9
S2: Email use	15,153	0.12	0.95	15,106	7,523.0	6,630.5
S3: Online banking	13,794	0.09	1.01	13,747	12,067.4	10,928.0
S4: Digital payments	10,559	0.06	0.99	10,512	9,241.9	8,676.8

Notes: The covariates correspond to the baseline specification used in Table 1. Models are estimated using survey-weighted logit with person weights (`WTPG`). McFadden's pseudo-R^2 is defined as 1-Residual deviance/Null deviance.

C.2 Archetype and disadvantaged profiles

Figure 6 reports the predicted conditional probability of advancing at each rung for six representative demographic archetypes constructed from the estimated sequential logit models. The benchmark profile — a middle-aged, employed, English-speaking individual living in an urban family household with children, holding some post-secondary education, and without a disability — exhibits high advancement probabilities at all rungs. Profiles combining multiple sources of disadvantage show substantial attrition, especially at the early access stage and at the transition into online banking and digital payments.

Figure 6: Predicted Conditional Probabilities: Archetype Profiles



Notes: Lines report predicted conditional probabilities $P(\text{advance} \mid \text{reached prior rung})$ from the four survey-weighted sequential logit models. Each archetype varies one characteristic relative to the benchmark profile; all other covariates are held at their reference categories.

Table 14: Characteristics of the Most Disadvantaged Profiles and Predicted Adoption Probabilities

Outcome	Key disadvantaged characteristics	Prob.	National average	n
Virtual wallet	Age 65+, HS or less, income Q1, non-visible minority	0.010	0.097	244
Credit card	Age 65+, not employed, HS or less, non-visible minority	0.315	0.595	671
Digital payments	Age 65+, not employed, HS or less	0.316	0.608	693

Notes: Key characteristics are the weighted modal characteristics among respondents in the bottom decile of predicted adoption probabilities, retaining those with modal share exceeding 0.80 (0.75 for virtual wallet). Predicted probabilities are evaluated at the corresponding profile-specific covariate vector using the survey-weighted sequential logit model; remaining covariates are set to their weighted sample modes. National averages are weighted sample-average predictions. For virtual wallet and credit card outcomes, non-visible minority status appears because visible minorities are over-represented in the upper tail of the virtual-wallet distribution (see Section 4.2). *Digital payments* denotes adoption of either a virtual wallet or a credit card for online purchases.

D IRT model details (Q.4)

D.1 Item list

The digital literacy score is constructed from 20 binary indicators from the 2020 CIUS, grouped into three conceptual domains.

Information-seeking activities

- Using social networking services
- Making voice or video calls over the Internet
- Searching for community events
- Reading news or current affairs online
- Looking up locations or directions
- Searching for health information
- Researching goods or services before purchase

Software and file management

- Copying or moving files or folders
- Using word processing software
- Creating presentations
- Using spreadsheet software
- Editing photos or videos
- Deleting browser history
- Downloading files
- Uploading files to cloud storage
- Updating operating system software

Security and privacy

- Checking whether a website connection is secure
- Restricting location data sharing
- Refusing or limiting advertising tracking
- Changing privacy settings on online accounts

D.2 EAP estimator

The expected a posteriori (EAP) estimate (the general-factor score for individual i) is given by

$$\hat{\theta}_i^{(G)} = \frac{\int \theta^{(G)}\, p\left(\boldsymbol{y}_i \mid \theta^{(G)}, \theta^{(D)}, \hat{\psi}\right) \phi\left(\theta^{(G)}\right)\, d\theta^{(G)}\, d\theta^{(D)}}{\int p\left(\boldsymbol{y}_i \mid \theta^{(G)}, \theta^{(D)}, \hat{\psi}\right) \phi(\theta^{(G)})\, d\theta^{(G)}\, d\theta^{(D)}},$$

where $\boldsymbol{y}_i = (y_{i1}, \ldots, y_{i,20})'$, $\hat{\psi} = \{\hat{a}_j^{(G)}, \hat{a}_j^{(D_j)}, \hat{b}_j\}_{j=1}^{20}$,

$$p\left(\boldsymbol{y}_i \mid \theta^{(G)}, \theta^{(D)}, \hat{\psi}\right) = \prod_{j=1}^{20} P\left(y_{ij} = 1 \mid \theta^{(G)}, \theta_i^{(D_j)}, \hat{\psi}\right)^{y_{ij}} \left[1 - P\left(y_{ij} = 1 \mid \theta^{(G)}, \theta_i^{(D_j)}, \hat{\psi}\right)\right]^{1-y_{ij}}$$

is the conditional likelihood of $\boldsymbol{y}_i$ given both latent factors, $\phi(\cdot)$ is the standard normal prior, and $\theta^{(D)}$ collects the domain-specific factors integrated out jointly with $\theta^{(G)}$. The integrals are evaluated numerically via EM or quasi-Monte Carlo EM algorithms.

D.3 Bifactor loadings for the digital literacy score

Table 15: Bifactor Loadings for the Digital Literacy Score

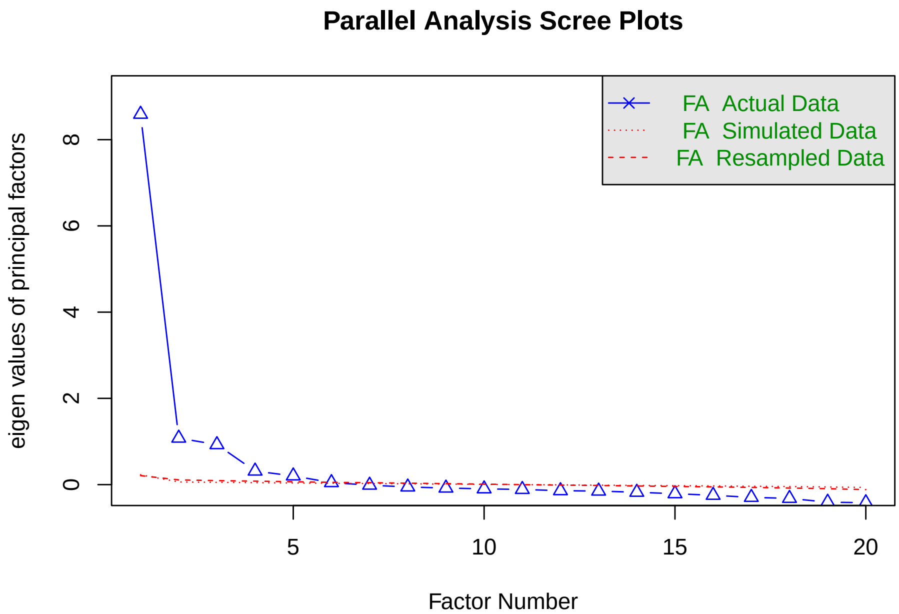
Item	General	InfoSeek	Software	Security
Information-seeking				
Social networking	0.382	0.058	0.284	0.032
Voice/video calls	0.465	0.127	0.284	0.010
Community events	0.455	-0.046	0.633	-0.051
News	0.483	0.062	0.405	0.016
Locations/directions	0.562	0.074	0.441	0.043
Health information	0.473	-0.030	0.556	0.010
Goods/services research	0.579	0.048	0.476	0.066
Software and file management				
Copy/move files	0.765	0.440	0.002	0.082
Word processing	0.783	0.530	-0.009	-0.022
Presentations	0.687	0.465	0.020	-0.043
Spreadsheet basics	0.717	0.503	-0.027	-0.028
Edit photo/video	0.635	0.315	0.069	0.083
Delete browser history	0.470	0.111	0.041	0.247
Download files	0.714	0.309	0.090	0.148
Upload to cloud	0.608	0.214	0.169	0.118
Update OS	0.569	0.132	0.097	0.262
Security and privacy				
Check HTTPS	0.512	0.010	0.022	0.450
Restrict location data	0.589	-0.005	-0.008	0.572
Refuse ad tracking	0.610	-0.021	-0.023	0.627
Change privacy settings	0.596	0.047	0.064	0.441

Notes: Schmid–Leiman standardized loadings from the weighted bifactor 2PL model estimated using normalized survey weights ($n = 12{,}065$). McDonald's $\omega_h = 0.760$ and $\omega_{\text{total}} = 0.782$.

D.4 Dimensionality diagnostics

The ratio of the first to the second eigenvalue of the tetrachoric correlation matrix is 5.18, indicating a strong dominant general factor. McDonald's $\omega_h = 0.760$ indicates that approximately three-quarters of the composite-score variance is attributable to the general factor ($\omega_{\text{total}} = 0.782$). Figure 7 reports the scree plot.

Figure 7: Scree Plot of the Tetrachoric Correlation Matrix

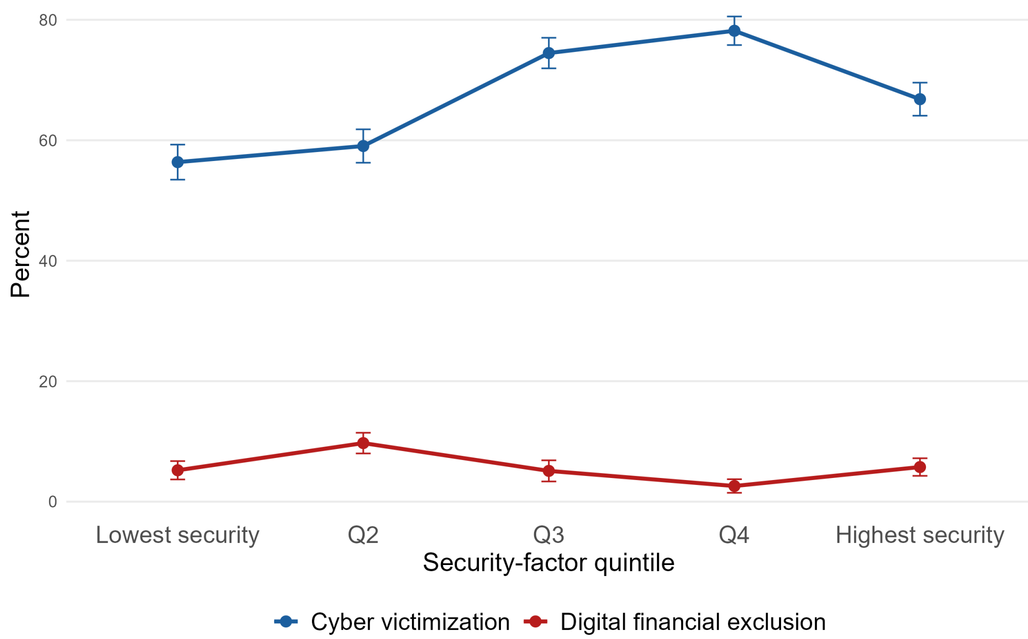


Notes: Eigenvalues of the tetrachoric correlation matrix for the 20 CIUS digital-skill items. The dashed reference lines correspond to parallel analysis based on factor analysis (FA), comparing eigenvalues from the observed data with those from simulated and resampled datasets. The ratio of the first to the second eigenvalue is 5.18, indicating a dominant general factor.

D.5 Cyber victimization and digital exclusion

Figure 8 compares cyber victimization and digital financial exclusion across quintiles of the bifactor security score. Cyber victimization is higher in the middle and upper part of the security distribution, whereas digital financial exclusion remains low throughout and reaches its minimum in the upper-security quintiles. This indicates that victimization is concentrated among digitally active and exposed users rather than among the most excluded. Higher general digital capability is associated with both a greater probability of reporting a cyber incident and a lower probability of digital financial exclusion; the security-specific factor is positively associated with victimization but has no meaningful association with exclusion. The inverse pattern thus operates mainly through overall digital engagement rather than security behavior alone.

Figure 8: Cyber Victimization and Digital Financial Exclusion by Quintile of the Bifactor Security Score



Notes: Points show survey-weighted percentages; vertical bars indicate 95% confidence intervals. Cyber victimization is measured among internet users. Digital financial exclusion is defined as non-use of online banking and digital payment methods. Quintiles are from the standardized security factor derived from the bifactor IRT model.

D.6 Variance estimation for literacy-ranked concentration indices

This appendix describes the variance estimator for the literacy-ranked concentration indices in Table 6. Because the literacy rank $\hat{r}_i^L$ is constructed from an estimated bifactor IRT model, $\widehat{\mathcal{C}}_y^L$ is a two-step estimator and its sampling variance must account for first-stage estimation uncertainty. We use a Murphy–Topel-style correction (Murphy and Topel, 1985) to account for IRT parameter uncertainty in the second-stage variance.

Let ψ_0 denote the true IRT parameter vector and $\hat{\psi} = \{\hat{a}_j^{(G)}, \hat{a}_j^{(D_j)}, \hat{b}_j\}_{j=1}^{20}$ be its first-stage estimate from the weighted bifactor 2PL model. Let $\boldsymbol{y}_i = (y_{i1}, \ldots, y_{i,20})'$ denote respondent i's vector of binary IRT item responses. Let $\hat{\theta}_i^{(G)}$ be respondent i's EAP general-factor score and $\hat{r}_i^L$ the corresponding weighted midpoint fractional rank, satisfying $\sum_{i=1}^n w_i \hat{r}_i^L / W = \frac{1}{2}$ by construction, where $W = \sum_{i=1}^n w_i$. The survey-weighted concentration index estimator is

$$\widehat{\mathcal{C}}_y^L = \frac{2}{\bar{y}\, W} \sum_{i=1}^n w_i (y_i - \bar{y}) \left(\hat{r}_i^L - \tfrac{1}{2}\right), \qquad \bar{y} = \sum_{i=1}^n w_i y_i / W. \tag{D.1}$$

Let $\mu_y = \mathrm{E}[y_i]$ denote the population mean.

Asymptotic linear representation. Let $U_i(\psi)$ denote the score contribution of observation i from the weighted bifactor 2PL likelihood, and let

$$A := -\mathrm{E}\left[\frac{\partial U_i(\psi_0)}{\partial \psi'}\right] \text{ and } B := \frac{\partial \mathcal{C}_y^L}{\partial \psi'}$$

denote the expected information matrix, and the gradient of the population concentration index w.r.t. the first-stage parameters, respectively. Under standard regularity conditions for two-step M-estimation, the first-stage estimator satisfies

$$n^{1/2}(\hat{\psi} - \psi_0) = A^{-1} n^{-1/2} \sum_{i=1}^{n} U_i(\psi_0) + o_p(1),$$

and the asymptotic linear representation of the second-stage estimator is

$$n^{1/2}\left(\widehat{\mathcal{C}}_y^L - \mathcal{C}_y^L\right) = n^{-1/2} \sum_{i=1}^{n} \varphi_i^C + BA^{-1} n^{-1/2} \sum_{i=1}^{n} U_i(\psi_0) + o_p(1),$$

where φ_i^C is the influence function of the concentration index treating literacy ranks as known. Define

$$V_C := \mathrm{Var}(\varphi_i^C), \qquad \Omega := \mathrm{Var}(U_i), \qquad \Gamma_{U\varphi} := \mathrm{Cov}(U_i, \varphi_i^C).$$

Equivalently, the asymptotic covariance matrix of the first-stage estimator is

$$V_\psi = A^{-1} \Omega A^{-1}.$$

The Murphy–Topel-type asymptotic variance of $n^{1/2}\,\widehat{\mathcal{C}}_y^L$ is therefore

$$V_{MT} = V_C + BA^{-1}\Omega A^{-1}B' + 2BA^{-1}\Gamma_{U\varphi} = V_C + BV_\psi B' + 2BA^{-1}\Gamma_{U\varphi}. \tag{D.2}$$

Influence function of the concentration index. Write the population concentration index as a smooth function of two moments:

$$\mathcal{C}_y^L = g(\mu_{yr}, \mu_y) := \frac{2\mu_{yr}}{\mu_y} - 1, \qquad \mu_{yr} = \mathrm{E}[y_i r_i^L], \qquad \mu_y = \mathrm{E}[y_i].$$

A first-order Taylor expansion of g around (μ_{yr}, μ_y) yields the influence function

$$\varphi_i^C = \frac{\partial g}{\partial \mu_{yr}}\left(y_i r_i^L - \mu_{yr}\right) + \frac{\partial g}{\partial \mu_y}\left(y_i - \mu_y\right),$$

up to a higher-order remainder term. Since

$$\frac{\partial g}{\partial \mu_{yr}} = \frac{2}{\mu_y}, \qquad \frac{\partial g}{\partial \mu_y} = -\frac{2\mu_{yr}}{\mu_y^2},$$

it follows that

$$\varphi_i^C = \frac{2}{\mu_y}\Big(y_i r_i^L - \mu_{yr}\Big) - \frac{2\mu_{yr}}{\mu_y^2}(y_i - \mu_y).$$

Using $\mathcal{C}_y^L = \frac{2\mu_{yr}}{\mu_y} - 1$, we get $\frac{\mu_{yr}}{\mu_y} = \frac{1+\mathcal{C}_y^L}{2}$, hence

$$\varphi_i^C = \frac{y_i}{\mu_y}\left(2r_i^L - 1 - \mathcal{C}_y^L\right). \tag{D.3}$$

One can verify directly that $\mathrm{E}[\varphi_i^C] = 0$. The sample analogue, evaluated at estimated quantities, is

$$\hat{\varphi}_i^C = \frac{w_i\, y_i}{W\, \bar{y}}\left(2\hat{r}_i^L - 1 - \widehat{\mathcal{C}}_y^L\right).$$

The variance of $n^{1/2}\,\widehat{\mathcal{C}}_y^L$ treating literacy ranks as known is estimated by

$$\widehat{V}_C = n\sum_{i=1}^n (\hat{\varphi}_i^C)^2.$$

First-stage covariance and cross term. The estimated score matrix $\hat{U} = (\hat{U}_1', \ldots, \hat{U}_n')'$ is obtained from the fitted IRT model using `estfun.AllModelClass()`. Let $\widehat{\Omega} = \frac{1}{n}\sum_{i=1}^n \hat{U}_i\hat{U}_i'$ denote the empirical covariance matrix of the first-stage score contributions, and let $\widehat{A}^{-1}$ denote the estimated inverse information matrix. Then the implied first-stage covariance matrix is

$$\widehat{V}_\psi = \widehat{A}^{-1}\widehat{\Omega}\widehat{A}^{-1}.$$

In the implementation, we also extract `vcov()` from the fitted IRT object as a numerical check on the first-stage covariance calculation. The cross-covariance term in (D.2) is estimated by

$$\widehat{\Gamma}_{U\varphi} = \frac{1}{n}\sum_{i=1}^n \hat{U}_i\left(\hat{\varphi}_i^C - \bar{\varphi}^C\right), \qquad \bar{\varphi}^C = \frac{1}{n}\sum_{i=1}^n \hat{\varphi}_i^C. \tag{D.4}$$

Kernel-smoothed Jacobian. The weighted midpoint rank $\hat{r}_i^L$ is a non-smooth step function of the estimated literacy score, so $\partial\hat{r}_i^L/\partial\psi$ does not exist in the classical sense. To compute $\hat{B}$, we replace the exact rank by the smooth approximation

$$\tilde{r}_i^L(h) = \sum_{j=1}^n \frac{w_j}{W}\Phi\left(\frac{\hat{\theta}_i^{(G)} - \hat{\theta}_j^{(G)}}{h}\right), \tag{D.5}$$

where $\Phi(\cdot)$ is the standard normal CDF and h is a bandwidth chosen by Silverman's rule applied to $\{\hat{\theta}_i^{(G)}\}_{i=1}^n$. The smoothed rank converges to the exact midpoint rank as $h \to 0$ and is used only for differentiation; the point estimate continues to use the exact rank. Its derivative with respect to ψ is

$$\frac{\partial\tilde{r}_i^L(h)}{\partial\psi'} = \sum_{j=1}^n \frac{w_j}{Wh}\,\phi\left(\frac{\hat{\theta}_i^{(G)} - \hat{\theta}_j^{(G)}}{h}\right)\left(\frac{\partial\hat{\theta}_i^{(G)}}{\partial\psi'} - \frac{\partial\hat{\theta}_j^{(G)}}{\partial\psi'}\right), \tag{D.6}$$

where $\phi(\cdot)$ is the standard normal density. The Jacobian of the EAP score satisfies

$$\frac{\partial \hat{\theta}_i^{(G)}}{\partial \psi} = \mathrm{Cov}\left(\eta^{(G)},\ \frac{\partial \log p(\boldsymbol{y}_i \mid \eta, \psi)}{\partial \psi} \;\middle|\; \boldsymbol{y}_i\right), \tag{D.7}$$

which is evaluated numerically on a Monte Carlo quadrature grid. The estimated gradient of the concentration index is then

$$\hat{B} = \frac{2}{\bar{y}W} \sum_{i=1}^{n} w_i (y_i - \bar{y}) \frac{\partial \tilde{r}_i^L(h)}{\partial \psi'}. \tag{D.8}$$

Final variance estimator. Substituting the sample analogues into (D.2), the implemented variance estimator is

$$\widehat{\mathrm{Var}}\left(\widehat{\mathcal{C}}_y^L\right) = \frac{1}{n}\left(\widehat{V}_C + \hat{B}\,\widehat{A}^{-1}\widehat{\Omega}\widehat{A}^{-1}\hat{B}' + 2\hat{B}\,\widehat{A}^{-1}\widehat{\Gamma}_{U\varphi}\right), \tag{D.9}$$

and the corresponding standard error is

$$\mathrm{SE} = \sqrt{\widehat{\mathrm{Var}}\left(\widehat{\mathcal{C}}_y^L\right)}.$$