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Visibility without benefit: the AI divide and life satisfaction among people with and without disabilities in South Korea

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Research Article

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Abstract

Purpose

Artificial intelligence (AI) is widely expected to enhance the quality of life of people with disabilities (PWD), yet evidence on whether AI engagement is accompanied by greater subjective well-being remains scarce. This study examines the emerging AI divide by comparing three dimensions of AI engagement—awareness, use, and perceived impact between PWD and people without disabilities (PWOD), and by testing how each dimension relates to life satisfaction in the two groups.

Methods

Data came from the 2023 Digital Divide Survey, a nationally representative South Korean survey (N = 7,809; 5,640 PWOD and 2,169 PWD, aged 18–69). Survey-weighted hierarchical regression models, including disability × AI engagement interactions and group-specific models, were estimated controlling for sociodemographic characteristics, social capital, and digital self-efficacy.

Results

PWD reported markedly lower AI awareness (generative AI: 20.5% vs. 46.9%), lower use (40% vs. 55%), and less favorable perceptions than PWOD. In population-weighted models, AI use was not positively associated with life satisfaction in either group; awareness was negatively associated in both groups (PWD: $\beta = -.13$); and favorable perceived impact was associated with life satisfaction only among PWOD ($\beta = .11$). Interaction terms were nonsignificant ($\Delta R^2 = .001$). Digital self-efficacy was the strongest correlate of life satisfaction among PWD ($\beta = .37$).

Conclusion

The well-being benefits promised for PWD were not evident; where AI related to well-being at all, it did so through nondisabled optimism rather than use. Universal access to AI requires accessible-by-design systems and self-efficacy education rather than awareness-raising alone.

Introduction

Artificial intelligence (AI) has been heralded as a transformative force with the potential to significantly enhance the quality of life of people with disabilities (PWD) by bridging accessibility gaps in healthcare, education, employment, and daily living [1, 2]. AI-powered tools, such as advanced speech-to-text systems, predictive navigation, and personalized assistive technologies, are widely expected to offer PWD unprecedented opportunities for autonomy and social participation [2]. A systematic review by Chemnad and Othman [3], analyzing 43 studies published between 2018 and 2023, documented the

breadth of these expectations, showing that AI applications have been proposed to support people with visual, auditory, motor, and cognitive access needs.

Yet this optimistic narrative rests largely on projections, prototypes, and technical demonstrations rather than on evidence about the lived outcomes of disabled people themselves. Whether AI has actually improved the everyday lives of PWD, and whether it has done so to the same extent as for people without disabilities (PWOD), remains an open empirical question. The same systematic review revealed that existing research is heavily skewed toward AI-driven accessibility for the visually impaired, leaving other groups underexamined, and that many systems fail to adhere to established accessibility standards [3]. While the digital divide has long been a subject of scholarly inquiry, the emergence of an AI divide demands renewed investigation into whether the benefits of AI are being equitably distributed or whether they are reinforcing existing social inequalities [4].

The perspective of crip technoscience sharpens this question. Crip technoscience challenges the dominant framing of PWD as passive beneficiaries of technological innovation, insisting instead that they be recognized as "knowers and makers" who actively design, adapt, and contest technology [5]. From this standpoint, the taken-for-granted assumption that AI will inevitably "fix" or empower disability reflects what disability scholars have termed "technoableism," a rhetoric that celebrates technology as a cure while devaluing disabled ways of living and sidelining disabled people's own judgments about what benefits them [6]. Crip technoscience thus cautions against the curative imaginary that pervades AI discourse: AI systems are frequently designed for rather than with disabled people, trained on data in which disabled bodies and modes of interaction are underrepresented, and evaluated against nondisabled norms of use [7, 8]. Consequently, the benefits of AI for PWD cannot be presumed; they must be empirically examined with disabled people's own assessments of their lives placed at the center of the analysis. The present study takes up this call by treating PWD not as objects of technological intervention but as evaluators of it, comparing how AI engagement relates to self-reported life satisfaction among PWD and PWOD.

The relationship between AI engagement and life satisfaction can be understood through the lens of digital well-being theory [9]. Büchi's [9] theoretical model comprises three core structures: individuals' digital practices, harms/benefits, and well-being, with connectedness, convenience, and information positioned as positive mediators. Digital practices encompass behaviors related to the purposes of digital media use, such as social interaction, information seeking, transactions, and entertainment, and are conceptualized as multiplex network ties that connect individuals to others [9]. From this perspective, the capacity to meaningfully engage with digital technology, including AI, shapes individuals' access to resources, social interactions, and sense of efficacy in navigating an increasingly digital environment, which in turn can strengthen social capital and contribute to greater life satisfaction. Because AI services, such as chatbots and recommendation systems, offer more personalized convenience and interaction than traditional Internet services, this framework predicts that the influence of AI on life satisfaction will be pronounced.

Complementing digital well-being theory, the Technology Acceptance Model (TAM) provides the primary theoretical framework linking AI engagement to life satisfaction [10, 11]. TAM posits that an individual's behavioral intention to use technology is driven primarily by awareness of the technology and perceptions of its usefulness and ease of use. In the context of AI, we hypothesize that how individuals are informed about AI services and how they perceive the technology's impact on their daily lives are critical antecedents to its adoption. Prior studies have shown that positive perceptions of technology not only facilitate greater usage but are also significantly associated with enhanced subjective well-being and quality of life [12–14]. Although limited, prior research has also linked digital inclusion to social capital among PWD. For instance, Newman et al. [15] found that the online social capital of young PWD was closely related to their offline social capital, with Internet use serving as a window to society, and social media activities can strengthen the social support of PWD, positively affecting their psychological well-being [16]. Drawing on TAM, this study empirically investigates how distinct dimensions of AI engagement (awareness, usage, and perceived impact) relate to life satisfaction, and whether these relationships differ between PWD and PWOD.

Methods

Data and Sampling Procedure

This study used a cross-sectional dataset from the 2023 Digital Divide Survey (DDS) conducted between September 2023 and December 2023 in South Korea. Although it is not longitudinal, the DDS has been administered by the Korean Ministry of Science, Information and Communication Technology (ICT) & Future Planning since 2002. The purpose of the annual survey is to measure the use of digital technology and digital divide across diverse populations, including general citizens, PWD, low-income people, farmers/fishers, North Korean defectors, and marriage-based immigrant families. This survey employs a multistage, stratified random sampling technique by sociodemographic characteristics (e.g., age, gender, and residence) to create a nationally representative sample of each subgroup. Trained interviewers conducted face-to-face structured interviews with selected participants. This direct interaction allows for the collection of detailed and reliable data on individuals' digital access, capabilities, and usage patterns. The sampling and data collection procedures have been reported in detail elsewhere [21].

This study selected two sample groups: 7000 PWOD and 2200 PWD, to compare life satisfaction in relation to AI usage between the two groups. PWD were identified based on their disability registry of South Korea. In the system, disability status is determined through a formal medical assessment and government review process and individuals must meet standardized clinical and administrative criteria to be officially registered. This registry includes a wide range of disability types, including physical and sensory disabilities, such as visual and hearing impairments, as well as intellectual and developmental disabilities, mental health disorders, and internal organ disabilities. These are further classified by severity under the national disability rating scheme, which distinguishes between severe and mild categories. Accordingly, PWD in this survey present individuals formally recognized by the government

and eligible for national disability benefits. This measure of disability status in this study is intended to capture administratively registered disabilities.

To ensure consistency in the age range between the two groups, 572 individuals under 18 and 812 individuals over 70 years of age were excluded, resulting in 5642 PWOD and 2174 PWD. Additionally, seven individuals were excluded because they had no access to the Internet (e.g., via a computer or smartphone) in the past month. The final sample included 7809 participants, comprising 5640 PWOD and 2169 PWD between the ages of 18 and 69.

Measures

The dependent variable in this study is life satisfaction. Respondents rated five items on a 4-point Likert scale, with scores ranging from 1 for strongly dissatisfied to 4 for strongly satisfied. To measure a subjective evaluation of one's life satisfaction, the five items included "In most ways, my life is close to my ideal", "The conditions of my life are excellent", "I am satisfied with my life", "So far, I have gotten the important things I want in life", and "If I could live my life over, I would change almost nothing." These items align with the standard Satisfaction with Life Scale developed by Diener et al. [22]. Item scores were averaged, yielding a possible range of 1 to 4. Higher scores indicate greater life satisfaction. The reliability of this measure was supported by a Cronbach's alpha of 0.85.

Disability status was measured as a binary variable: 0 for PWOD and 1 for PWD. Demographic information known to be associated with life satisfaction were included : *age* as a continuous variable; *sex* as a binary variable (0 for male and 1 for female); *education level* as an ordinal variable with four categories, ranging from 1 = less than elementary school to 4 = bachelor's degree or higher; and *household income* as an ordinal variable with eleven categories, ranging from 1 = less than 1 million KRW to 11 = 10 million KRW or more.

Social capital was measured using ten items on a 4-point Likert scale (1 = strongly disagree; 4 = strongly agree) to assess a person's access to and perception of supportive social networks, including the emotional, informational, and instrumental resources embedded in their social relationships. Example items included "There is someone I can turn to for advice when making very important decisions", "People would help me if I had to stand up against injustice", "Interacting with others makes me feel connected to a larger world", and "I am willing to spend time participating in community activities." Scores on the social capital measure varied between 10 and 40, with higher scores reflecting greater social capital in the context of digital device usage. The measure demonstrated strong internal consistency indicated by a Cronbach's alpha of 0.86.

Digital self-efficacy was measured using four items to assess a person's belief in their ability to learn, use, adapt, and engage with digital devices. The four items included "I am confident in learning how to use digital devices", "I am confident in using digital devices", "I can quickly figure out how to use new digital devices," and "I would like to use digital devices more frequently." Higher scores reflected higher self-

efficacy in using digital devices. Strong internal consistency was observed for this measure, with a Cronbach's alpha of 0.90.

This study included three variables to measure AI engagement. The survey defined an AI service as one that utilizes AI technology to provide convenience across various industries and areas of daily life, such as automatic translation, voice recognition, AI-generated images, videos, or literature, personalized asset management, recommendation services, chatbots, robot vacuum cleaners, and autonomous driving services. First, *awareness of AI services* was assessed across ten domains: document creation, information retrieval, generative AI, financial services, communication and social connection, healthcare, smart home and convenience, media-related services, transportation, and education. The original response format was binary (0 = no, 1 = yes), and responses were summed across the ten domains to create an overall awareness score ranging from 0 to 10, with higher scores indicating awareness of a greater number of AI services. Second, *experience with AI service use* was measured as a binary variable (0 = no experience, 1 = yes). Respondents were asked, "Have you ever used an AI service?" Third, *perceived impact of AI* was measured using eight items on a 4-point Likert scale (1 = strongly disagree; 4 = strongly agree). The eight items included statements such as AI will make my life more convenient, create many economic opportunities, provide better information services, help me access better information, reduce the number of available jobs, increase concerns about personal data and privacy breaches, worsen the spread of misinformation and fake content, and improve people's relationships. Three items related to job reduction, privacy concerns, and misinformation were reverse-coded such that higher scores reflected a more positive perception of AI.

Statistical Strategies

Descriptive statistics were computed to examine sample characteristics for the full sample and for the PWOD and PWD groups separately, and bivariate analyses (t-tests, Wilcoxon rank sum tests, and Pearson's chi-squared tests) were conducted to examine unweighted group differences across the study variables. Because the DDS employs a multistage, stratified sampling design that deliberately oversamples PWD, all regression models were estimated with the cross-sectional survey weights provided with the DDS, so that estimates generalize to the corresponding national populations. The survey weight variable was "WT_T." Survey-weight analyses conducted in R using the "survey" package, with survey design objects specified and standard errors and statistical tests were estimated using the design-based procedures implemented in the "survey" package. The analyses incorporate the survey weights but do not explicitly incorporate strata. The R script contains the data preparation, survey-design specification, and model-estimation procedures reproduce the reported models.

Hierarchical survey-weighted linear regression models were estimated for the full sample: Model 1 included disability status, demographic covariates, social capital, digital self-efficacy, and the three AI engagement variables; Model 2 added interaction terms between disability status and each AI engagement variable. To characterize group-specific associations with adequate precision, the same model was then estimated separately for PWOD and PWD. Following recommendations to evaluate

substantive rather than only statistical significance [23], we report unstandardized coefficients with 95% confidence intervals and standardized coefficients (β), and we interpret magnitudes against benchmarks typical of subjective well-being research. Unweighted models, which yielded partly different estimates, are reported in the online supplementary material (Tables S1–S3) as a sensitivity analysis. All analyses were conducted using R version 4.4.0 [24].

Results

Descriptive Statistics

Table 1 presents survey-weighted descriptive statistics for the entire sample (N = 7,809) and separately for PWOD (n = 5,640) and PWD (n = 2,169). Significant group differences were observed across all variables examined. On average, PWD were older (M = 56.31, SD = 11.63) than PWOD (M = 44.37, SD = 14.64; t = 33.65, p < .001), and a greater proportion of PWD were male (68.6% vs. 51.1%; F = 100.66, p < .001). PWD reported lower educational attainment and lower household income than PWOD (both p < .001). PWD also reported lower social capital (t = − 22.26, p < .001), lower digital self-efficacy (t = − 31.23, p < .001), and lower life satisfaction (t = − 29.86, p < .001) than PWOD; the life satisfaction gap (2.20 vs. 2.71 on the 1–4 metric) corresponds to approximately one pooled standard deviation, a large descriptive difference (see Table 1).

Table 1

Survey Weighted Descriptive Statistics for the Full Sample and by Disability Status (N = 7,809)

	Entire Sample	**Non-Disability**	**Disability**	**Difference[3]**
	n = 7,809	**n = 5,640**	**n = 2,169**	
	N (%) or M (SD)	N (%) or M (SD)	N (%) or M (SD)	
Age[1]	47.73 (14.86)	44.37 (14.64)	56.31 (11.63)	t = 33.65***
Sex[2]				F = 100.66***
Male	4,474 (56.0%)	2,895 (51.1%)	1,579 (68.6%)	
Female	3,335 (44.0%)	2,745 (48.9%)	590 (31.4%)	
Education[2]				F = 242.82***
Less than elementary school	244 (3.3%)	57 (0.9%)	187 (9.4%)	
Middle school degree	893 (12.0%)	466 (8.1%)	427 (22.1%)	
High school diploma	3,577 (46.1%)	2,439 (43.7%)	1,138 (52.1%)	
Bachelor's degree or higher	3,095 (38.6%)	2,678 (47.3%)	417 (16.4%)	
Household Income (million KRW) [3]				z = -37.25***
Less than 1M	457 (5.9%)	90 (1.6%)	367 (17%)	
1-1.99M	636 (8.1%)	208 (3.7%)	428 (20%)	
2-2.99M	1,050 (12.9%)	614 (10.1%)	436 (20.3%)	
3-3.99M	1,337 (16.6%)	990 (16.7%)	347 (16.3%)	
4-4.99M	1,393 (18.4%)	1,094 (20.4%)	299 (13.4%)	
5-5.99M	1,375 (17.8%)	1,184 (21.3%)	191 (8.7%)	
6-6.99M	822 (10.7%)	763 (13.9%)	59 (2.5%)	
7-7.99M	381 (5.0%)	360 (6.7%)	21 (0.8%)	
8-8.99M	229 (3.1%)	215 (4.0%)	14 (0.8%)	
9-9.99M	56 (0.7%)	54 (1.0%)	2 (0.1%)	
Above 10M	73 (1.0%)	68 (1.3%)	5 (0.3%)	
Social Capital[1]	2.85 (0.48)	2.96 (0.40)	2.56 (0.55)	t = -22.26***

	Entire Sample	Non-Disability	Disability	Difference[3]
	n = 7,809	n = 5,640	n = 2,169	
Digital Self-Efficacy[1]	2.72 (0.74)	2.91 (0.66)	2.24 (0.70)	t = -31.23***
AI Engagement				
Awareness of AI Services[1]	5.21 (3.52)	5.92 (3.41)	3.42 (3.13)	t = -25.57***
AI Service Use: Yes[2]	4,101 (50.9%)	3,209 (55.3%)	892 (39.6%)	F = 98.87***
Perceived Impact of AI[1]	2.99 (0.56)	3.03 (0.53)	2.90 (0.62)	t = -6.60***
Life Satisfaction[1]	2.57 (0.57)	2.71 (0.50)	2.20 (0.57)	t = -29.86 ***

1Survey-adjusted t test; 2Rao–Scott design-adjusted F test; 3Survey-weighted Wilcoxon rank-sum test.

Note

Based on the average exchange rate in 2023 (exchange-rates.org), where 1 USD was equivalent to approximately 1,305 KRW.

Differences in AI Engagement between PWOD and PWD

PWOD reported significantly greater awareness of AI services than PWD (M = 5.92 vs. 3.42 of ten services; t = − 25.57, p < .001), higher rates of AI service use (55.3% vs. 39.6%; F = 98.87, p < .001), and more favorable perceived impact of AI (t = − 6.60, p < .001) (Table 1). Table 2 shows that PWOD reported greater awareness than PWD in every one of the ten service domains. In both groups, awareness was highest for smart home and convenience services (77% for PWOD; 64.7% for PWD). The largest relative gaps appeared in creative services using generative AI (46.9% vs. 20.5%) and information retrieval services (56.5% vs. 27.2%). Notably, only 31.3% of PWD were aware of healthcare-related AI services.

Table 2

Awareness of AI Services

Items	Entire Sample	Non-Disability	Disability	
	N (%)	N (%)	N (%)	Difference
Document Creation Services	4578 (58.6%)	3735 (66.2%)	843 (38.9%)	χ^2 = 482.24***
Information Retrieval Services	3778 (48.4%)	3188 (56.5%)	590 (27.2%)	χ^2 = 538.2***
Creative Services Using Generative AI	3088 (39.5%)	2644 (46.9%)	444 (20.5%)	χ^2 = 455.91***
Financial Services	3278 (42.0%)	2777 (49.2%)	501 (23.1%)	χ^2 = 438.39***
Communication and Social Connection Services	5003 (64.1%)	3896 (69.1%)	1107 (51%)	χ^2 = 220.69***
Healthcare Services	3974 (50.9%)	3295 (58.4%)	679 (31.3%)	χ^2 = 459.84***
Smart Home and Convenience Services	5747 (73.6%)	4344 (77%)	1403 (64.7%)	χ^2 = 122.06***
Media-Related Services	3436 (44.0%)	2860 (50.7%)	576 (26.6%)	χ^2 = 369.92***
Transportation Services	5406 (69.2%)	4228 (75%)	1178 (54.3%)	χ^2 = 312.72***
Education Services	3405 (43.6%)	2870 (50.9%)	535 (24.7%)	χ^2 = 436.92***
*** $p < .001$				
Note. Unweighted sample distributions are presented				

Table 3 shows that PWOD reported more favorable perceptions of AI than PWD on all eight impact items (all $p < .001$), with both groups rating AI's potential to improve people's relationships least favorably.

Table 3
Perceived Impact of AI Services

Items (AI will…)	Entire Sample	Non-Disability	Disability	
	M (SD)	M (SD)	M (SD)	Difference
Make my life more convenient	3.07 (0.59)	3.13 (0.57)	2.91 (0.62)	t = 14.65***
Create many economic opportunities	3.05 (0.78)	3.15 (0.74)	2.79 (0.80)	t = 18.06***
Provide better information services	3.09 (0.68)	3.18 (0.63)	2.86 (0.76)	t = 17.48***
Help me access better information	3.09 (0.68)	3.18 (0.64)	2.85 (0.73)	t = 18.56***
Reduce the number of available jobs[1]	2.85 (0.75)	3.05 (0.71)	2.77 (0.80)	t = 13.89***
Increase concerns about personal data and privacy breaches[1]	2.90 (0.72)	3.11 (0.67)	2.82 (0.80)	t = 15.52***
Worsen the spread of misinformation and fake content[1]	2.98 (0.73)	3.19 (0.69)	2.90 (0.80)	t = 14.65***
Improve people's relationships	2.59 (0.72)	2.66 (0.69)	2.40 (0.76)	t = 13.81***

[1]Reverse coded variables with higher scores indicating positive impact of AI.

Note

Unweighted sample distributions are presented

Associations Between AI Engagement and Life Satisfaction

Hierarchical survey-weighted regression models for the full sample are presented in Table 4. Model 1, containing main effects only, explained 36.5% of the variance in life satisfaction (R^2 = .365, adjusted R^2 = .365, $F(10, 7798) = 242.29$, $p < .001$). Adding the three disability × AI engagement interaction terms in Model 2 left explanatory power essentially unchanged (R^2 = .366; ΔR^2 = .001, F change$(3, 7795) = 1.11$, p = .346).

In Model 1, disability status showed by far the largest association in the model: PWD reported lower life satisfaction than PWOD (B = − 0.254, 95% CI [− 0.281, − 0.226], β = −.435), holding all other variables constant. Social capital (β = .239) and digital self-efficacy (β = .294) were the strongest continuous correlates of life satisfaction. The AI engagement associations were small and not uniformly positive.

Perceived impact of AI was positively associated with life satisfaction, but modestly so (B = 0.131, 95% CI [0.094, 0.167], β = .069). AI service use was negatively associated with life satisfaction in Model 1 (B = − 0.035, 95% CI [− 0.059, − 0.010], β = −.059, *p* = .005) and was not associated with it once interaction terms were included (B = − 0.015, 95% CI [− 0.045, 0.015], *p* = .320); in neither specification was AI use positively associated with life satisfaction. Greater awareness of AI services was associated with slightly lower life satisfaction (B = − 0.010, 95% CI [− 0.014, − 0.007], β = −.062). Among the covariates, age, education, and household income were positively associated with life satisfaction, whereas sex was not (*p* = .385).

None of the three interaction terms was statistically significant: disability × awareness (B = − 0.006, 95% CI [− 0.017, 0.005], *p* = .270), disability × AI use (B = 0.019, 95% CI [− 0.048, 0.085], p = .581), and disability × perceived impact (B = − 0.066, 95% CI [− 0.157, 0.024], *p* = .151). Together with the negligible ΔR^2, these results provide no evidence that disability status moderates the associations between AI engagement and life satisfaction. Group-specific patterns reported below are therefore descriptive characterizations of each population rather than formally established differences.

Table 4
Survey Weighted Hierarchical Regression Models Predicting Life Satisfaction in the Full Sample (N = 7,809)

Predictor	**B**	**95% CI**	**β**	***p***
Model 1: Main effects				
Disability Status: Yes	-0.254	[-0.281, -0.226]	-0.435	**< .001**
Age	0.004	[0.003, 0.004]	0.089	**< .001**
Sex: Female	-0.01	[-0.031, 0.012]	-0.016	0.385
Education Level	0.031	[0.015, 0.047]	0.041	**< .001**
Household Income	0.027	[0.021, 0.033]	0.097	**< .001**
Social Capital	0.298	[0.271, 0.326]	0.239	**< .001**
Digital Self-Efficacy	0.233	[0.212, 0.253]	0.294	**< .001**
Awareness of AI Services	-0.01	[-0.014, -0.007]	-0.062	**< .001**
AI Service Use: Yes	-0.035	[-0.059, -0.010]	-0.059	**0.005**
Perceived Impact of AI	0.131	[0.094, 0.167]	0.069	**< .001**
Model 1 fit: R^2 = 0.365, Adjusted R^2 = 0.365, F(10, 7798) = 242.29, p < .001				
Model 2: Interactions added				
Predictor	**B**	**95% CI**	**β**	**p**
Disability Status: Yes	-0.249	[-0.300, -0.198]	-0.436	**< .001**
Age	0.003	[0.002, 0.004]	0.081	**< .001**
Sex: Female	-0.013	[-0.038, 0.012]	-0.023	0.299
Education Level	0.029	[0.010, 0.049]	0.04	**0.003**
Household Income	0.029	[0.022, 0.036]	0.106	**< .001**
Social Capital	0.283	[0.245, 0.321]	0.238	**< .001**
Digital Self-Efficacy	0.226	[0.200, 0.252]	0.291	**< .001**
Awareness of AI Services	-0.011	[-0.015, -0.006]	-0.067	**< .001**
AI Service Use: Yes	-0.015	[-0.045, 0.015]	-0.026	0.320
Perceived Impact of AI	0.154	[0.108, 0.200]	0.083	**< .001**
Model 2 fit: R^2 = .366, Adjusted R^2 = .365, F(13, 7795) = 196.06, p < .001; ΔR^2 (Model 2 − Model 1) = .001, $F_{change}(3, 7795) = 1.11$, p = .346				

Predictor	B	95% CI	β	*p*
Model 1: Main effects				
Disability × Awareness	-0.006	[-0.017, 0.005]	-0.037	0.270
Disability × AI Use	0.019	[-0.048, 0.085]	0.033	0.581
Disability × Perceived Impact	-0.066	[-0.157, 0.024]	-0.036	0.151
Model 2 fit: R^2 = .366, Adjusted R^2 = .365, $F(13, 7795) = 196.06$, $p < .001$; ΔR^2 (Model 2 − Model 1) = .001, $F_{change}(3, 7795) = 1.11$, $p = .346$				

Subgroup Analyses by Disability Status

Survey-weighted models estimated separately by disability status are presented in Tables 5 and 6. Among PWOD (Table 5; R^2 = .200, $F(9, 5630) = 156.00$, $p < .001$), the only AI engagement dimension positively associated with life satisfaction was perceived impact of AI (B = 0.183, 95% CI [0.136, 0.230], β = .107). AI service use was not associated with life satisfaction (B = − 0.009, 95% CI [− 0.038, 0.021], p = .564), and greater awareness of AI services was associated with slightly lower life satisfaction (B = − 0.008, 95% CI [− 0.013, − 0.004], β = −.058). Social capital (β = .224) and digital self-efficacy (β = .256) remained the strongest correlates.

Among PWD (Table 6; R^2 = .337, $F(9, 2159) = 121.73$, $p < .001$), no dimension of AI engagement was positively associated with life satisfaction. AI service use was not associated with life satisfaction, and the estimate was precise (B = − 0.016, 95% CI [− 0.077, 0.045]): the interval excludes all but small associations in either direction, and the point estimate is slightly negative. Perceived impact of AI was likewise not associated with life satisfaction (B = 0.041, 95% CI [− 0.039, 0.122], β = .023, p = .316). Awareness of AI services was negatively associated with life satisfaction, and more strongly so than among PWOD (B = − 0.023, 95% CI [− 0.033, − 0.013], β = −.128). Digital self-efficacy was the strongest correlate of life satisfaction among PWD (B = 0.298, 95% CI [0.244, 0.351], β = .367), a standardized association noticeably larger than that observed among PWOD, followed by social capital (β = .252) and household income (β = .173). Education was not associated with life satisfaction among PWD (p = .770), and the association of age was weaker than among PWOD (B = 0.002, p = .015).

In sum, once population weights were applied, AI service use was not positively associated with life satisfaction in either group, awareness of AI services was negatively associated with life satisfaction in both groups, and a positive association for perceived impact of AI appeared only among PWOD. Because the formal interaction tests were null, these group-specific patterns should be read as descriptive; what the weighted estimates establish with precision is the absence of any more than small positive associations between AI engagement and life satisfaction among PWD.

Table 5
Survey Weighted Hierarchical Regression Models Predicting Life Satisfaction among PWOD (n = 5,640)

Predictor	**B**	**95% CI**	**β**	***p***
Age	0.003	[0.002, 0.004]	0.091	**< .001**
Sex: Female	-0.011	[-0.037, 0.015]	-0.022	0.403
Education Level	0.033	[0.011, 0.055]	0.044	**0.003**
Household Income	0.021	[0.014, 0.029]	0.08	**< .001**
Social Capital	0.281	[0.240, 0.322]	0.224	**< .001**
Digital Self-Efficacy	0.195	[0.167, 0.222]	0.256	**< .001**
Awareness of AI Services	-0.008	[-0.013, -0.004]	-0.058	**< .001**
AI Service Use: Yes	-0.009	[-0.038, 0.021]	-0.017	0.564
Perceived Impact of AI	0.183	[0.136, 0.230]	0.107	**< .001**
Model fit: R^2 = 0.2, Adjusted R^2 = 0.198, F(9, 5630) = 156, p < .001				

Table 6
Survey Weighted Hierarchical Regression Models Predicting Life Satisfaction among PWD (n = 2,169)

Predictor	**B**	**95% CI**	**β**	***p***
Age	0.002	[0.000, 0.005]	0.051	**0.015**
Sex: Female	-0.021	[-0.078, 0.037]	-0.036	0.481
Education Level	0.006	[-0.033, 0.044]	0.008	0.770
Household Income	0.054	[0.038, 0.070]	0.173	**< .001**
Social Capital	0.262	[0.190, 0.334]	0.252	**< .001**
Digital Self-Efficacy	0.298	[0.244, 0.351]	0.367	**< .001**
Awareness of AI Services	-0.023	[-0.033, -0.013]	-0.128	**< .001**
AI Service Use: Yes	-0.016	[-0.077, 0.045]	-0.029	0.600
Perceived Impact of AI	0.041	[-0.039, 0.122]	0.023	0.316
Model fit: R^2 = 0.337, Adjusted R^2 = 0.334, F(9, 2159) = 121.73, p < .001				

Note

All models were estimated with the DDS cross-sectional survey weights. B = unstandardized coefficient; CI = confidence interval; β = standardized coefficient (continuous variables standardized; binary variables

retained in original units).

Discussion

This study examined differences between PWD and PWOD in AI engagement, including awareness, use, and perceived impact of AI technology, and compared how these dimensions of engagement relate to life satisfaction across the two groups. Rather than assuming that AI benefits disabled people, the study followed the call of crip technoscience to treat PWD as evaluators of technology, placing their own reported life satisfaction at the center of the analysis. Two contributions follow. First, using a nationally representative sample, the study documents a multi-layered AI divide in South Korea: PWD reported lower awareness of AI services across all ten domains examined, lower rates of AI use (40% vs. 55%), and less favorable perceptions of AI's impact. Second, in population-weighted models, the study finds no evidence that AI engagement is positively associated with life satisfaction among PWD on any dimension, and no evidence that AI use is positively associated with life satisfaction in either group. Because the data are cross-sectional, all findings are interpreted as associations rather than causal effects.

The descriptive findings reveal a stark disparity in AI awareness. PWD were less likely to be informed about AI services in every domain, with particularly low awareness of creative services using generative AI (20.5%) and information retrieval services (27.2%). Especially notable is the low awareness of healthcare-related AI services among PWD (31.3%). This highlights a tension: a population that stands to gain considerably from health-monitoring and rehabilitation technologies exhibits low awareness of them. One plausible explanation involves structural accessibility barriers; many AI healthcare interfaces are not yet optimized for screen readers or alternative input devices, which may render such services effectively invisible or unusable to the very demographic they are designed to serve [3]. To the extent that this is the case, limited awareness may restrict opportunities for PWD to benefit from early detection and personalized rehabilitation [1], although the present data cannot test this pathway directly.

This study also found significant group differences in the perceived impact of AI technology. This aligns with Cho and Kim [25], who found that PWD were less likely than PWOD to recognize the benefits of digital services. While PWOD tend to hold positive beliefs about the utility of new technologies, PWD often remain on the periphery of this technological optimism. This pattern suggests that the digital disability divide [26] is not merely about physical access to devices, but also about cognitive access, that is, opportunities to understand how these tools might be relevant to one's own life.

Beyond statistical significance, the magnitudes of the estimated associations warrant direct attention [23]. In the survey-weighted models, the standardized associations for social capital ($\beta = .239$) and digital self-efficacy ($\beta = .294$) fall in the moderate range typical of robust correlates in subjective well-being research, whereas every AI engagement coefficient was small ($|\beta| \leq .13$ in all models). The disability gap itself was the largest quantity in the analysis ($\beta = -.435$). Substantively, this ordering indicates that social connectedness and confidence in one's ability to command digital technology are

far more closely tied to well-being than AI engagement per se, and that whatever role AI currently plays in life satisfaction is marginal relative to the disadvantage associated with disability status itself.

The central finding concerns the direction and location of the AI engagement associations. Contrary to the expectation, derived from the Technology Acceptance Model and digital well-being theory, that adoption of AI would accompany higher well-being, AI service use was not positively associated with life satisfaction in either group, and in the full-sample main-effects model the association was slightly negative. The only positive association appeared for perceived impact of AI, and only among PWOD ($\beta = .107$); among PWD, perceptions of AI's impact bore no relation to life satisfaction ($p = .316$). In other words, where AI connects to well-being at all in these data, it does so through nondisabled people's optimism about the technology rather than through anyone's actual use of it. The negative association between AI awareness and life satisfaction in both groups, and most strongly among PWD ($\beta = -.128$), was not anticipated. One possibility is that awareness of AI services, in the absence of the resources or accessible interfaces needed to benefit from them, functions as awareness of one's own exclusion; another is reverse ordering, whereby less satisfied individuals attend more closely to technological change. These interpretations cannot be adjudicated with cross-sectional data, but the pattern resonates with emerging evidence that perceptions of AI relate to life satisfaction in ways that are not uniformly positive [27]. The formal moderation tests were null ($\Delta R^2 = .001$), so group differences in these patterns are descriptive; what is established with precision is that among PWD, no dimension of AI engagement showed more than a small positive association with life satisfaction.

It is also informative that the weighted and unweighted estimates diverged: unweighted models suggested positive associations for AI engagement that attenuated or reversed once the sample was weighted to population distributions (see supplementary Tables S1–S3). This divergence indicates that the positive associations observed in the raw sample were concentrated in demographic strata that the sampling design overrepresents, and it underscores the importance of design-consistent estimation when drawing population-level conclusions about who benefits from AI. Finally, social capital and digital self-efficacy were strongly and positively associated with life satisfaction in both groups, and among PWD digital self-efficacy was the strongest correlate in the model ($\beta = .367$). Prior literature suggests that digital practices can support social connection and cognitive social capital [28–31], and that online social resources matter for the well-being of PWD [15, 16]; because mediation was not formally tested here, such pathways remain hypotheses for future research.

Limitations

This study has several limitations that should be considered when interpreting its findings. First, and most importantly, the analysis is cross-sectional. The limitation this imposes goes beyond uncertainty about causal order. Respondents who engage with AI likely may differ from those who do not in stable, unmeasured ways (e.g., health status, personality, socioeconomic resources, and pre-existing attitudes toward technology). The estimated coefficients are also vulnerable to omitted-variable bias, and the unanticipated negative association between AI awareness and life satisfaction may partly reflect such

selection. Accordingly, no causal interpretation is warranted in either direction, and panel data with individual fixed effects are needed to determine whether AI engagement has any within-person association with life satisfaction.

Second, three interaction terms were tested and none was statistically significant ($\Delta R^2 = .001$); the study therefore provides no evidence of moderation by disability status, and the group-specific patterns should be treated as descriptive. Relatedly, estimates differed between weighted and unweighted specifications, indicating that the associations are heterogeneous across demographic strata; we privilege the design-consistent weighted estimates for population inference and report unweighted models in the online supplementary material (Tables S1–S3). Third, the measures of AI engagement were limited to basic awareness, a binary indicator of use, and general perceptions, failing to capture the depth or accessibility of AI utility. For instance, while AI solutions such as 'Be My Eyes' or 'Live Caption' exist to support PWD, this study could not verify whether participants used such accessibility-oriented features, how frequently they used any AI service, or whether appropriate accommodations were available. Fourth, the study did not empirically assess algorithmic bias. Although AI systems trained on non-diverse data may fail to recognize the needs of PWD, our data did not capture whether such technical barriers directly discouraged PWD from using AI services. Future research should measure these barriers directly to better characterize the AI divide.

Implications

Theoretically, this study extends scholarship on the digital divide as it evolves into an AI divide by showing that the divide is not confined to disparities in access, awareness, or skills; it extends to the returns associated with technology engagement, which in these population-weighted data were absent for PWD on every dimension examined. The findings qualify the Technology Acceptance Model [10] and digital well-being theory [9] more sharply than anticipated: the pathway from adoption to well-being implied by these frameworks was not observed for AI use in either group, and the only positive association ran through favorable perceptions among PWOD. This suggests that, at the current stage of diffusion, AI's relation to subjective well-being operates at the level of expectations rather than realized benefits, and that applications of these frameworks should model the conditions under which adoption could yield well-being gains rather than assuming that it does. The effect-size perspective adds a further calibration: all AI engagement associations were small ($|\beta| \leq .13$), whereas social capital and digital self-efficacy showed moderate associations, indicating where the substantively meaningful levers lie [23].

These findings lend empirical weight to the crip technoscience critique that framed this study. The optimistic narrative surrounding AI and disability rests on a curative imaginary in which technology is expected to "fix" or empower disabled lives [6]. When disabled people's own evaluations of their lives are placed at the center of the analysis, that promise finds no support in these cross-sectional data: neither using AI, nor being aware of it, nor holding favorable views of it was accompanied by greater life satisfaction among PWD, and greater awareness was associated with slightly lower satisfaction. One plausible interpretation, consistent with prior critiques, is that AI systems designed for rather than with disabled people, trained on data that underrepresent disabled bodies and modes of interaction, offer

PWD visibility of the technology without accessible benefit from it [7, 8]. Theoretically, this underscores the value of treating PWD not as passive beneficiaries of innovation but as “knowers and makers” [5] whose assessments should discipline claims about what AI accomplishes. Evaluations of AI’s societal benefits that omit disabled people’s reported experience risk mistaking technological availability for technological benefit.

Practically, the results redirect attention from AI exposure toward the factors that actually covaried with well-being. Digital self-efficacy was the strongest correlate of life satisfaction among PWD (β = .367, versus β = .256 among PWOD), several times the magnitude of any AI engagement variable. This pattern suggests that confidence in one’s ability to command digital technology, rather than exposure to AI as such, is where well-being differences concentrate. Interventions should accordingly prioritize tailored education that builds digital and AI self-efficacy, teaching PWD not only what AI services exist but how to control them to address concrete challenges in daily life, and should extend foundational AI literacy opportunities that PWD have historically been denied [4, 19]. Whether such interventions improve well-being is, on the present evidence, a hypothesis that merits testing in longitudinal and experimental designs.

For developers and designers, the finding that no dimension of AI engagement was positively associated with life satisfaction among PWD is a reason to reexamine how AI systems are built. Adherence to accessibility standards in AI interfaces should be treated as a fundamental requirement rather than an optional feature, and disabled users should be involved throughout design and evaluation rather than consulted after release. The awareness data sharpen this imperative in specific domains. Only 31.3% of PWD were aware of healthcare-related AI services, a striking mismatch given this population’s potential stake in health-monitoring and rehabilitation technologies; when interfaces are not optimized for assistive technologies, such services remain effectively invisible to the users they are meant to serve [3]. Likewise, awareness of creative services using generative AI was markedly lower among PWD than PWOD (20.5% vs. 46.9%). The negative association between awareness and life satisfaction, however, cautions that visibility without usability may be worse than neither: outreach should be paired with accessible pathways to actual benefit rather than pursued as an end in itself.

Finally, the results caution against promotion strategies that cultivate optimism about AI without securing its accessible benefits. In these data, favorable perceptions of AI accompanied higher life satisfaction only among PWOD; among PWD, neither favorable perceptions nor use showed any positive association, and awareness alone was associated with lower satisfaction. Campaigns aimed solely at raising awareness or improving attitudes are therefore unlikely to close the well-being gap and may instead widen the distance between expectation and lived reality. In line with Article 9 of the United Nations Convention on the Rights of Persons with Disabilities, governments should pair awareness-raising with enforceable accessibility requirements for AI services and with monitoring systems that track not only whether PWD use AI but whether that use is accompanied by improvements in their lives. Without inclusive design and sustained empowerment supports, the diffusion of AI risks deepening, rather than narrowing, the quality-of-life divide between PWD and PWOD.

Declarations

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Author Contribution

Minhae Cho wrote the method and result text and Kyung Mee Kim wrote the introduction, discussion and implication. All authors reviewed the manuscript.

Available data

suggest that, contrary to the optimistic narrative, disparities persist. The United Nations Convention on the Rights of Persons with Disabilities recommends, through Article 9 (Accessibility), that appropriate measures be taken to ensure the access of PWD to new information and communication technologies. Nevertheless, according to the 2023 Digital Information Gap Survey by the Ministry of Science and ICT of South Korea, although the digital competence of PWD has shown slight improvement, it remains substantially below that of the general population [17]. Similarly, the 2023 Seoul Digital Competency Survey reported that 60.9% of PWD had experienced difficulties using kiosks, and that the proportion of PWD with experience using generative AI was extremely low at 5.5% [18]. PWD also often lack access to fundamental AI literacy and coding education [4, 19], contributing to a concerning trend of diminishing motivation for technological learning [17].

This creates a paradox. While PWD are expected to benefit from AI-driven solutions that foster independence in line with the Fourth Industrial Revolution [20], AI technology exacerbates existing digital divide, and the field lacks empirical evidence on whether AI engagement translates into greater life satisfaction for PWD. AI thus presents a double-edged character for PWD: it can function as a vital tool for enhancing accessibility and creating new opportunities, yet, as crip technoscience warns, it can also erect new barriers through data biases, inaccessible interfaces, and design processes that exclude disabled users [7]. Addressing this gap will provide a greater understanding of the broader societal implications of AI and inform whether current AI development is serving, or bypassing, disabled people. Therefore, this study aims to compare how AI engagement, measured by awareness, usage, and perceived impact of AI, relates to life satisfaction between PWD and PWOD, thereby subjecting the promise of AI to the test of disabled people’s own reported experience.

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