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Is Digital Inclination Associated with Lifelong Learning in Aging South Korea?

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ABSTRACT

This study examines the relationship between digital learning inclination and lifelong learning participation among Korean adults through generational and educational level analysis. Using data from the Korean Educational Development Institute's 2024 Individual Survey on Lifelong Learning (N = 30,829, ages 25-79), this research analyzed relationships between age, educational attainment, digital learning preferences, and participation rates through an ecological analysis approach using aggregated cross-sectional survey data. Digital learning inclination was operationalized using proxy indicators including learning media preferences, informal digital learning participation patterns, and information access pathways. Korea's overall lifelong learning participation rate was 33.1% in 2024, declining from 44.6% (ages 25-29) to 24.1% (ages 70-79). Educational attainment emerged as a critical moderating variable, with university graduates showing participation rates (40.4%) that were 17.8 percentage points higher than those with middle school education or less (22.6%). The Digital Learning Inclination Index revealed a five-fold difference between the youngest (81.2) and oldest (16.1) age groups, with age 50 emerging as a critical threshold. Statistical analysis revealed significant associations between age and educational level (χ^2 = 1,847.3, $p < .001$) and moderate correlations between digital learning inclination and participation rates ($r = .52$, $p < .001$). The findings highlight the necessity for digital literacy support policies tailored to specific generational and educational characteristics. This study provides a replicable methodological framework for contexts where comprehensive digital competency assessments are unavailable, offering valuable insights for policymakers and educators in nations facing similar demographic transitions and digital transformation challenges in adult education systems.

Keywords: digital learning inclination, lifelong learning participation, generational differences, educational attainment, Korea, adult education policy

INTRODUCTION

The rapid advancement of digital technology in the 21st century has fundamentally transformed educational and learning environments. Digital learning inclination, defined as learners' familiarity with and preference for digital learning environments and technologies, has emerged as a key factor determining learning accessibility and participation in modern society (Hänninen, 2025). As traditional educational boundaries dissolve and learning becomes increasingly digitized, population groups with varying levels of digital learning inclination may exhibit different patterns of participation in lifelong learning opportunities.

The COVID-19 pandemic has further accelerated the digital transformation of education, intensifying existing digital divide issues (Lai & Widmar, 2021). Educational institutions, policymakers, and researchers are increasingly recognizing that effective lifelong learning strategies must consider the different levels of digital learning inclination across various population groups. Particularly in societies like Korea that have experienced rapid digitization, intergenerational and inter-educational level differences in digital learning engagement may translate into inequalities in lifelong learning participation (Kang et al., 2023). Recent analysis of Korea's lifelong learning system evolution from 2007 to 2024 demonstrates how major crises—including the 2008 global financial crisis, the 2015 MERS outbreak, and the COVID-19 pandemic—have consistently accelerated digital transformation while simultaneously exposing and exacerbating existing digital divides in adult education access (Yoo, 2025).

Understanding the relationship between digital learning inclination and lifelong learning participation is crucial for developing inclusive educational policies. While previous research has focused on digital competency as technical skill proficiency, this study explores how preferences for and engagement with digital learning environments influence participation in lifelong learning. Specifically, existing studies have primarily examined (1) digital literacy as a set of discrete technical skills (Ferrari, 2013; Vuorikari et al., 2022), (2) generational differences in technology adoption without connecting these to learning participation patterns (Hargittai, 2002; Van Dijk, 2020), and (3) lifelong learning participation rates without adequately considering the role of digital learning preferences as a mediating factor (OECD, 2019; UNESCO Institute for Lifelong Learning, 2022).

This study addresses these gaps by examining how digital learning inclination—operationalized through behavioral proxies including learning media preferences, informal digital learning participation, and information access pathways—correlates with lifelong learning participation across different age and educational groups in Korea's rapidly aging society. This approach recognizes that successful integration into digital learning ecosystems depends not only on technical abilities but also on learners' comfort, preference, and familiarity with digital learning modalities. This distinction between digital competency and digital learning inclination is particularly important in aging societies where technical skill gaps may be compounded by psychological barriers and preference-based resistance to digital learning formats (Van Dijk, 2020; Hargittai, 2002).

Cultural Context of Technology Adoption and Digital Learning Participation in Korea

Understanding technology adoption and digital learning participation in Korea requires consideration of unique cultural factors that influence how individuals and organizations approach digital technologies. Korea's rapid technological advancement, combined with distinctive cultural values, creates a complex environment for digital learning implementation and adoption.

Korea's organizational culture, characterized by collectivism, a collectivist orientation, and hierarchical structures influence digital learning adoption patterns (Yoo & Huang, 2016). These cultural dimensions have particular relevance for understanding age-based differences in digital learning adoption, as older generations may show greater deference to traditional educational hierarchies and methods, while younger generations demonstrate more willingness to adopt peer-driven digital learning platforms.

Korea's cultural emphasis on collective learning and social influence provides important implications for understanding lifelong learning participation patterns. Research has shown that Korean adults' acceptance of digital learning is significantly influenced by peer adoption, community support, and social norms regarding technology use (Yoo & Kim, 2017).

THEORETICAL FRAMEWORK AND BACKGROUND

Theoretical Framework

This study is grounded in two complementary theoretical frameworks: (1) Bourdieu's (1986) theory of cultural capital, which explains how educational attainment and social class shape access to and engagement with learning opportunities, and (2) Van Dijk's (2020) digital divide framework, which identifies multiple levels of digital inequality—from physical access to usage skills and actual usage patterns. These frameworks together explain how both traditional educational capital and digital learning inclination interact to influence lifelong learning participation, particularly in societies undergoing rapid digital transformation.

Bourdieu's concept of cultural capital suggests that educational attainment represents accumulated knowledge, skills, and credentials that facilitate further learning engagement. This accumulated capital provides not only cognitive scaffolding for new learning but also confidence and familiarity with formal educational structures. Van Dijk's digital divide framework extends this understanding to the digital realm, arguing that digital inequality manifests in multiple dimensions: motivational access (psychological engagement with technology), material access (physical device availability), skills access (operational and information skills), and usage access (meaningful application of digital tools). The integration of these theoretical perspectives enables us to examine how traditional educational capital and digital learning inclination jointly shape lifelong learning participation patterns across different demographic groups.

Concept and Development of Lifelong Education

Lifelong education, defined by UNESCO as an educational system that provides opportunities and environments for individuals to learn throughout their entire lives, has gained global attention since the 1970s. The OECD (2019) defines lifelong learning as all learning activities undertaken throughout life for personal, civic, social, and employment-related purposes.

The importance of lifelong education in modern society has grown due to rapid technological change, labor market flexibilization, and population aging. According to the OECD Education at a Glance 2023 (OECD, 2023), the average adult lifelong learning participation rate in OECD countries was 40.7%, with Finland showing the highest rate at 54.2%, followed by Sweden at 50.8% and Switzerland at 49.6%. Korea's participation rate (33.1%) was 7.6 percentage points below the OECD average, suggesting room for improvement and highlighting the relevance of this research for other nations striving to enhance adult learning participation. Longitudinal analysis of Korea's participation rates from 2007 to 2024 reveals cyclical patterns strongly correlated with economic crises and public health emergencies, with rates declining during crisis periods before recovering during stability phases, underscoring the vulnerability of lifelong learning systems to external shocks (Yoo, 2025) and the critical importance of maintaining accessible learning infrastructure across multiple delivery modalities (OECD, 2021; World Economic Forum, 2020). Recent UNESCO reports emphasize the growing importance of digital inclusion in adult learning and education systems globally (UNESCO Institute for Lifelong Learning, 2022).

Digital Learning Inclination and Modern Lifelong Education

The advent of the Fourth Industrial Revolution era has fundamentally changed lifelong education paradigms. Research shows close relationships between lifelong education and university education paradigms in the Fourth Industrial Revolution era across educational systems, educational subjects, and curricula (Singaram et al., 2023). The integration of digital technologies into lifelong learning systems has occurred unevenly across demographic groups, creating new forms of educational inequality based on digital access and engagement patterns (Livingstone & Guile, 2012; Selwyn, 2016).

Recent updates to the European Digital Competence Framework emphasize the multidimensional nature of digital skills, encompassing operational, information, communication, content creation, and problem-solving competencies (Vuorikari et al., 2022). Ferrari (2013) proposed a comprehensive framework for digital competence (DIGCOMP) that has been widely adopted in European education policy contexts. This framework identifies five key competency areas: information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving.

Digital learning inclination represents a distinct but related construct to digital competency. While digital competency focuses on actual skills and abilities, digital learning inclination captures individuals' psychological orientation, comfort level, and preference for engaging with digital learning environments. This distinction is crucial because technical capability alone does not guarantee engagement with digital learning opportunities; individuals must also possess the willingness and confidence to utilize digital platforms for learning purposes.

Research on technology acceptance models demonstrates that behavioral intention to use technology is influenced not only by perceived usefulness and ease of use but also by social norms, facilitating conditions, and personal innovativeness (Dede & Richards, 2021). In the context of lifelong learning, these factors translate into varying levels of digital learning inclination that may differ substantially across age groups and educational backgrounds.

Research Questions

Based on the theoretical background and literature review, this study addresses the following research questions:

> Research Question 1: How does digital learning inclination vary across age groups and educational levels in South Korea's aging society?
>
> Research Question 2: What is the relationship between digital learning inclination and lifelong learning participation across different demographic segments?
>
> Research Question 3: How do patterns of digital learning inclination and lifelong learning participation vary across different age groups and educational levels?
>
> Research Question 4: What policy implications emerge from the patterns of digital learning inclination and participation across age and educational groups?

METHOD

This study employed an ecological analysis approach using aggregated cross-sectional survey data. Ecological analysis examines relationships between variables at the group level rather than the individual level (Morgenstern, 1995). This design was selected because it enables examination of population-level patterns and trends across demographic groups while acknowledging the ecological fallacy inherent in drawing individual-level inferences from group-level data (Hart, 2011). The cross-sectional nature of the data limits causal inference (Mann, 2012), focusing instead on describing associations between digital learning inclination and lifelong learning participation patterns across age and educational groups.

Sample and Sampling Procedure

Data were drawn from the Korean Educational Development Institute's (KEDI) 2024 Individual Survey on Lifelong Learning, which employs a stratified multi-stage probability sampling design to ensure national representativeness. The sample consisted of 30,829 Korean adults aged 25-79 years, representing approximately 0.08% of Korea's adult population in this age range. The response rate was 42.3%, which is considered acceptable for large-scale national surveys in Korea (Korean Educational Development Institute, 2024).

Instrumentation

Digital learning inclination was operationalized using a composite index derived from three proxy indicators available in the KEDI survey: (1) learning media preferences (preference for digital versus traditional learning formats), (2) informal digital learning participation patterns (engagement with online learning platforms, educational videos, and digital resources), and (3) information access pathways (primary methods for seeking educational information). These indicators reflect behavioral manifestations of digital learning inclination rather than self-reported attitudes or technical competencies.

Lifelong learning participation was measured as a binary variable indicating whether respondents engaged in any formal or non-formal learning activities during the 12 months preceding the survey. Educational attainment was categorized into four levels: middle school or less, high school, some university or associate degree, and university degree or higher. Age was analyzed both as a continuous variable and in five-year cohorts from 25-29 to 70-79 years.

Data Collection and Ethical Considerations

This study utilized secondary data from the Korean Educational Development Institute's 2024 Individual Survey on Lifelong Learning, a publicly available national dataset. The original data collection by KEDI adhered to ethical research standards, including informed consent procedures and confidentiality protections for all participants. As this research involved analysis of de-identified, publicly available data, additional institutional review board approval was not required. All data handling and analysis procedures maintained participant confidentiality and followed data protection protocols established by KEDI.

Data Analysis

Data analysis proceeded in three stages. First, descriptive statistics characterized lifelong learning participation rates and digital learning inclination scores across age and educational groups. Second, chi-square tests examined associations between categorical variables (age groups and educational levels). Third, Pearson correlation coefficients assessed the strength and direction of linear relationships between continuous variables (digital learning inclination index scores and participation rates at the group level). Assumptions for Pearson correlation, including linearity, normal distribution of variables, and homoscedasticity, were evaluated through visual inspection of scatterplots and residual plots. All statistical analyses were conducted using SPSS version 28.0, with statistical significance set at $\alpha = .05$.

Variables and Measures

Dependent Variable: Lifelong Learning Participation

The dependent variable was operationalized as participation in either formal or non-formal lifelong learning activities within the past year. Formal lifelong education includes structured educational programs leading to officially recognized credentials, such as degree programs, credit-bearing courses, and qualification training. Non-formal lifelong education encompasses structured learning activities without credential pathways, including workplace training, community education, online courses, and skill development programs. This dual-category approach aligns with UNESCO and OECD standards for measuring adult learning participation.

It is important to distinguish between "informal digital learning participation" as measured in this study and the broader concept of "informal lifelong education" used in international frameworks. Following Schugurensky (2000), informal learning in this context refers to unstructured, self-directed learning activities that occur outside formal educational institutions. The measures employed in this study specifically capture digital manifestations of such informal learning behaviors—learning through YouTube, online media, and social platforms—rather than all forms of informal adult education, including community-based learning, workplace training, and other non-digital informal learning pathways. This focused operationalization enables a detailed examination of the relationship between digital learning inclination and participation in structured lifelong learning programs.

Independent Variables

Age groups were categorized into six levels: 25-29, 30-39, 40-49, 50-59, 60-69, and 70-79 years. These age boundaries align with conventional generational cohort definitions used in the Korean labor market and education policy analysis, facilitating comparability with existing literature and policy frameworks. Educational attainment was classified into three categories: middle school or less, high school, and university or higher. This three-category classification balances analytical granularity with statistical power considerations, as finer classifications would create some age-education cells with insufficient sample sizes for reliable group-level estimates, particularly among younger cohorts with very low representation in the lowest education category.

Digital Learning Inclination (Proxy Measures)

Due to the absence of direct digital competency measurements in the original dataset, this study operationalized digital learning inclination through a composite of proxy indicators derived from the KEDI survey. This approach represents a methodological adaptation that may be useful for other researchers and policymakers working with national surveys lacking comprehensive digital competency assessments. The validity of this proxy measurement approach depends on the assumption that observable behaviors (Diamantopoulos & Winklhofer, 2001) — learning media preferences, informal digital learning participation, and information access pathways—serve as meaningful indicators of underlying digital learning inclination.

Learning Media Preferences. Traditional preference was measured as preference for books and blackboard-centered learning, while digital preference was measured as preference for internet lectures or computer-based learning, including e-books, tablet PCs, and smartphones. These preferences were measured on a 5-point Likert scale and dichotomized as preference or non-preference.

Informal Digital Learning Participation Patterns. This dimension captured three types of informal digital learning: YouTube-based learning, measured as acquisition of new information or skills through YouTube, online media utilization measured as acquisition of new information through internet news, e-books, and other online media, and social media learning, measured as acquisition of new information through Twitter, Facebook, blogs, and communities. All measures were captured as binary participation indicators.

Information Access Pathways. Digital channels included the internet, institutional websites, and mobile phones, while traditional channels included family, neighbors, friends, local government newsletters, and mass media. These were measured as primary information source preferences.

Digital Learning Inclination Index Construction

A composite Digital Learning Inclination Index was created using the following weighting: digital learning media preference (40%), YouTube-based informal learning participation (30%), and digital information access pathway utilization (30%). This study uses the term digital learning inclination rather than digital competency to accurately reflect that these measures capture learners' familiarity with and preference for digital learning environments rather than actual digital skill proficiency.

Research Methodology

This study adopted an ecological analysis approach, examining relationships at the population group level. Ecological analysis is a research method that uses groups rather than individuals as units of analysis to explore relationships between group-level characteristics and outcome variables (Robinson, 1950; Morgenstern, 1995). This approach is useful for understanding group-level phenomena and deriving policy implications for demographic segments, though findings should not be interpreted as individual-level relationships due to the ecological fallacy.

The analysis proceeded through several stages. First, descriptive statistics were calculated for participation rates and digital learning inclination indicators across age and educational groups. Second, correlation analyses examined relationships between digital learning inclination components and participation rates at the group level. Third, chi-square tests assessed associations between categorical demographic variables. All statistical analyses were conducted using appropriate significance levels ($\alpha = .05$) with attention to effect sizes and confidence intervals.

RESULTS

Descriptive Statistics

Korea's overall lifelong learning participation rate in 2024 was 33.1%. Analysis by age groups revealed a consistent decline in participation from 44.6% among adults aged 25-29 years to 24.1% among those aged 70-79 years. Educational attainment demonstrated substantial influence on participation patterns, with university graduates achieving a 40.4% participation rate compared to 22.6% for those with middle school education or less—a difference of 17.8 percentage points.

Participation Patterns by Age and Educational Level

Korea's 33.1% overall participation rate represents approximately one-third of the adult population aged 25-79 engaging in formal or non-formal learning activities during the survey year. This aggregate figure masks substantial variation across demographic segments, with participation declining systematically with age while increasing with educational attainment.

Table 1 presents detailed participation rates across the intersection of age and educational categories, revealing clear gradients along both demographic dimensions. Statistical analysis confirmed significant associations between these variables ($\chi^2 = 1{,}847.3$, $df = 10$, $p < .001$), indicating that age and educational attainment jointly shape lifelong learning participation in non-random patterns. Among the youngest cohort (25-29 years), participation rates ranged from 28.5% for those with middle school education or less to 48.3% for university graduates, yielding a 19.8 percentage point educational gap.

Table 1. Lifelong Learning Participation Rates by Age and Educational Level (N = 30,829)

Age Group	Middle School or Less	High School	University or Higher	Total
25-29	28.5% (n=342)	38.7% (n=1,245)	48.3% (n=2,156)	44.6% (n=3,743)
30-39	26.8% (n=458)	36.4% (n=2,134)	45.1% (n=3,987)	41.2% (n=6,579)
40-49	25.2% (n=612)	33.8% (n=2,456)	42.6% (n=3,745)	37.8% (n=6,813)
50-59	23.1% (n=845)	30.5% (n=2,678)	38.9% (n=2,934)	33.5% (n=6,457)
60-69	21.4% (n=1,234)	27.8% (n=2,145)	34.2% (n=1,856)	28.7% (n=5,235)
70-79	18.9% (n=867)	24.3% (n=845)	29.6% (n=290)	24.1% (n=2,002)
Total	22.6% (n=4,358)	32.1% (n=11,503)	40.4% (n=14,968)	33.1% (n=30,829)

Note: Percentages represent the proportion of individuals within each demographic group who participated in formal or non-formal lifelong learning activities in 2024. Sample sizes (n) are provided in parentheses. χ^2 = 1,847.3, *df* = 10, $p < .001$.

The overall age group rate of 44.6% exceeded the national average by 11.5 points, establishing this cohort as the most actively engaged in lifelong learning.

The 30-39 age group showed slightly lower but still substantial participation: 26.8% among the least educated, rising to 45.1% among university graduates, with an 18.3 point gap and 41.2% overall rate. This age group, typically engaged in career establishment and family formation, maintains relatively high learning engagement despite competing life demands. Participation declined further in the 40-49 age group: 25.2% for middle school or less, 33.8% for high school, and 42.6% for university graduates (17.4 point gap). The overall rate of 37.8% remained moderately above the national average but represented a 3.4 percentage point decline from the previous cohort. The 50-59 age group exhibited a notable acceleration in decline, with rates of 23.1%, 30.5%, and 38.9% across educational levels (15.8-point gap). The overall rate of 33.5% marked the first age group falling below the national average. Among 60–69-year-olds, participation rates decreased further to 21.4%, 27.8%, and 34.2% across educational levels, with the gap narrowing to 12.8 percentage points. The overall rate of 28.7% falls notably below the national average. The oldest cohort (70-79 years) showed the lowest participation rates across all groups: 18.9% for middle school or less, 24.3% for high school, and 29.6% for university graduates, with an educational gap of 10.7 percentage points and an overall rate of 24.1%.

Association Between Age and Educational Level

Chi-square analysis revealed a statistically significant association between age group and educational attainment (χ^2 = 1,847.3, *df* = 10, $p < .001$) (see **Table 2**). Younger cohorts demonstrated substantially higher educational attainment, with 67.3% of adults aged 25-29 holding university degrees compared to only 12.8% of those aged 70-79.

Table 2. Association Between Age Group and Educational Level (Chi-Square Test)

Variable	Category	n	χ^2	df	p	Interpretation
Age Group × Educational Level	Middle School or Less / High School / University or Higher	30,829	1,847.3	10	< .001	Significant association indicating a non-random relationship between age and educational attainment.

Note: Results indicate that younger cohorts exhibit substantially higher educational attainment than older cohorts, suggesting potential cohort effects that influence lifelong learning participation. Statistical significance was determined at $\alpha = .05$.

Table 3. Digital Learning Inclination Indicators by Age Group

Age Group	Digital Preference (%)	Traditional Preference (%)	YouTube Learning (%)	Online Media Access (%)	Digital Learning Inclination Index
25-29	76.8	18.2	82.4	85.6	81.2
30-39	68.5	24.7	74.3	78.9	73.6
40-49	57.8	35.4	62.1	68.4	62.4
50-59	34.1	58.7	42.6	48.2	41.2
60-69	21.3	72.4	28.5	32.1	27.1
70-79	12.5	79.4	16.2	19.7	16.1
Total	45.2	48.1	50.4	55.2	50.2

Note: The Digital Learning Inclination Index is calculated as a weighted composite: Digital preference (40%) + YouTube learning (30%) + Online media access (30%). All values represent percentages except the Index, which is a composite score (0-100 scale). Correlation between Digital Learning Inclination Index and participation rates: $r = .52$, $p < .001$ ($n = 18$ age-education group cells).

This generational shift in educational composition has important implications for understanding lifelong learning participation patterns, as it suggests that observed age differences may partly reflect cohort effects in educational attainment rather than purely age-related factors.

Digital Learning Inclination Patterns

Clear generational divides in digital learning inclination emerge across multiple indicators, as detailed in **Table 3**. The Digital Learning Inclination Index, calculated as a weighted composite of digital media preferences (40%), YouTube learning participation (30%), and online media access (30%), reveals a pronounced age gradient with younger adults (25-29) achieving an index score of 81.2, while the oldest group (70-79) scores only 16.1, a five-fold difference that underscores the magnitude of digital divides in learning preferences.

Figure 1 presents three complementary perspectives on the relationship between age, education, digital learning inclination, and participation. Panel A shows participation rates by educational level, revealing consistent educational gradients across all age groups, with university graduates maintaining higher participation than high school graduates and those with middle school education or less. Panel B illustrates the decline in digital learning inclination components with age, highlighting digital preference, YouTube learning, and online media access, with a marked acceleration of decline occurring around age 50. Panel C demonstrates the positive correlation ($r = .52$, $p < .001$) between the Digital Learning Inclination Index and participation rates across 18 age-education group cells, with different colored dots representing different education levels.

Component Analysis of Digital Learning Inclination

Correlation analysis at the aggregate group level revealed a statistically significant moderate positive correlation ($r = .52$, $p < .001$) between digital learning inclination and participation rates across 18 age-education group cells. This relationship suggests that approximately 27% of the variance in group-level participation rates is explained by digital learning inclination differences, with the remaining 73% attributable to other factors, including economic barriers, time constraints, and intrinsic motivation differences. Component-wise correlations revealed that digital preference showed the strongest association with participation rates ($r = .58$, $p < .001$), followed by YouTube learning participation ($r = .47$, $p < .01$) and online media access ($r = .44$, $p < .01$).

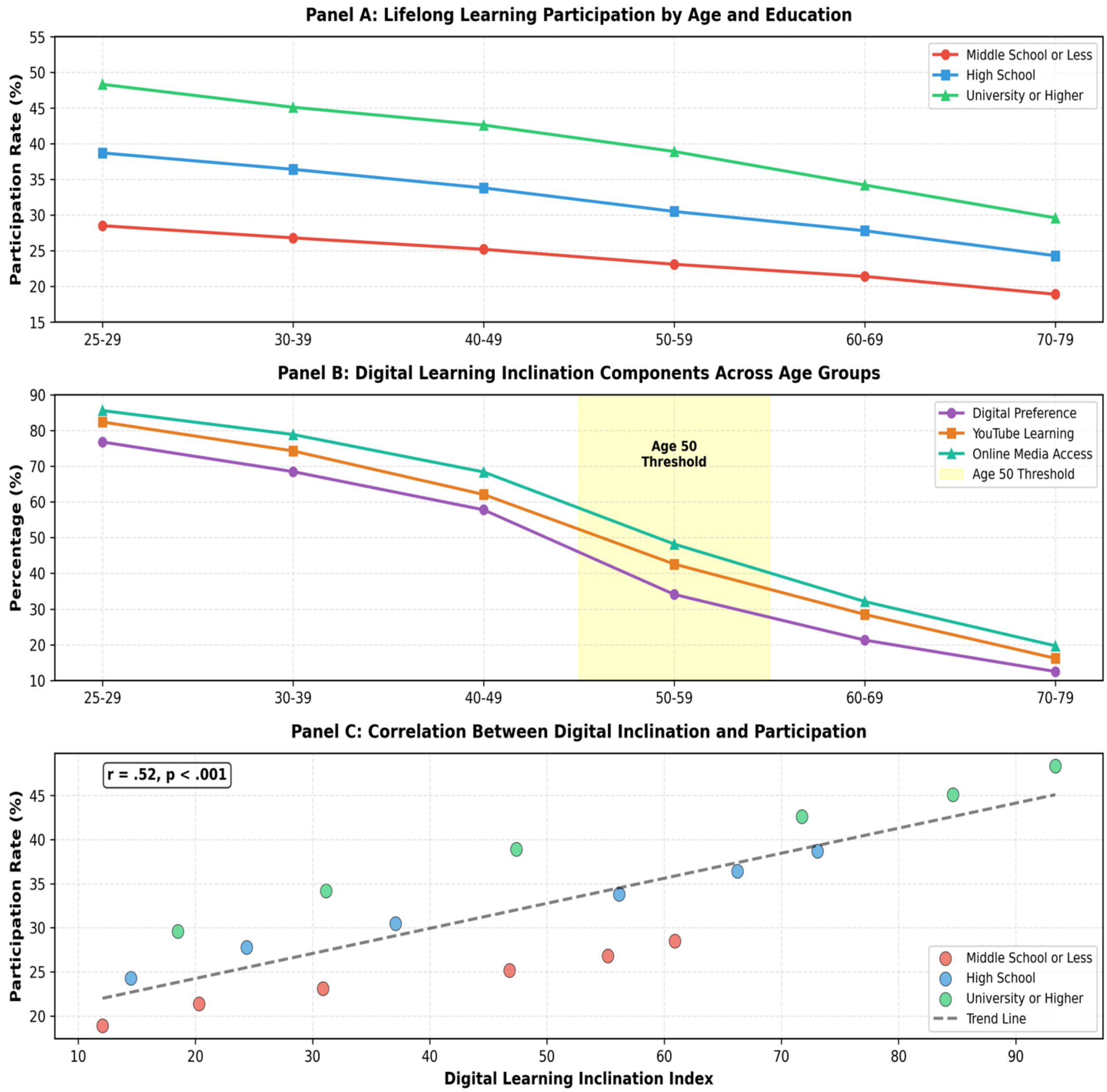

Figure 1. Key Findings of Lifelong Learning Participation and Digital Learning Inclination across Age Groups

Figure 2 illustrates the differential decline rates across three digital learning inclination dimensions: online media access (green), YouTube learning (yellow), digital preference (light blue), and traditional preference (gray dashed line). The red vertical dashed line marks the crossover point between digital and traditional learning preferences occurring between ages 40-49 and 50-59, representing a critical transition in learning modality preferences across the adult lifespan.

These differential correlations suggest that learning format preferences may be more strongly linked to actual learning participation than specific platform usage patterns, though all three dimensions show meaningful relationships. The component analysis reveals distinct decline patterns across the three digital learning inclination dimensions (see **Figure 2**). YouTube learning participation shows the steepest gradient, declining from 82.4% among 25–29-year-olds to 16.2% among 70–79-year-olds—a 66.2 percentage point drop.

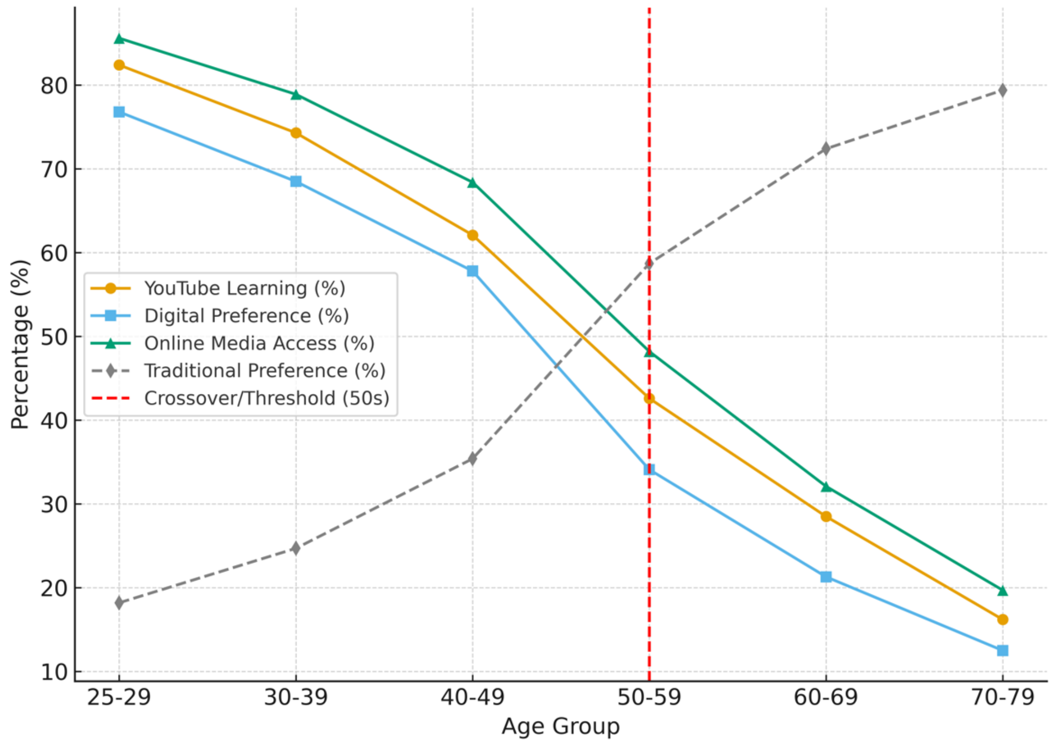

Figure 2. Decline Patterns in Digital Learning Inclination Components by Age

Digital preference declines from 76.8% to 12.5% (64.3-point drop), while online media access shows the highest baseline levels across all ages but follows a similar pattern, declining from 85.6% to 19.7% (65.9-point drop). A marked acceleration in decline occurs between the 40-49 and 50-59 age groups across all three components. Digital preference drops by 23.7 percentage points during this decade—the largest single-decade decline. **Figure 3** dramatically illustrates this age-50 threshold phenomenon through dual-axis visualization, showing the synchronized decline of both participation rates and the Digital Learning Inclination Index. The participation rate drops from 37.8% to 33.5% (4.3 points), while the Digital Learning Inclination Index plummets from 62.4 to 41.2 (21.2 points)—nearly double the rate of change compared to earlier age transitions.

Educational Gradient in Digital Learning Inclination

Educational level analysis within age groups revealed that the educational gradient in digital learning inclination, while present, is smaller than the age gradient. Among 50–59-year-olds, university graduates show 47% digital preference compared to 23% for those with middle school education or less, a 24-percentage-point gap. While substantial, this education gap is smaller than the 45-percentage point age gap between 30-39- and 60–69-year-olds with similar educational levels.

Figure 3 shows the parallel decline of both overall participation rates (dark blue line with circles, left y-axis) and the Digital Learning Inclination Index (orange line with squares, right y-axis) across age groups. The yellow shaded region marks the critical Age 50 threshold area where both measures experience their steepest declines. Participation rates drop from 37.8% (ages 40-49) to 33.5% (ages 50-59), a decline of 4.3 percentage points (marked in blue), while the Digital Learning Inclination Index plummets from 62.4 to 41.2, a drop of 21.2 points (marked in orange)—nearly double the rate of change compared to earlier age transitions. The red dashed vertical line at age 50-59 emphasizes this critical transition point, suggesting it as a key intervention target for digital learning support programs.

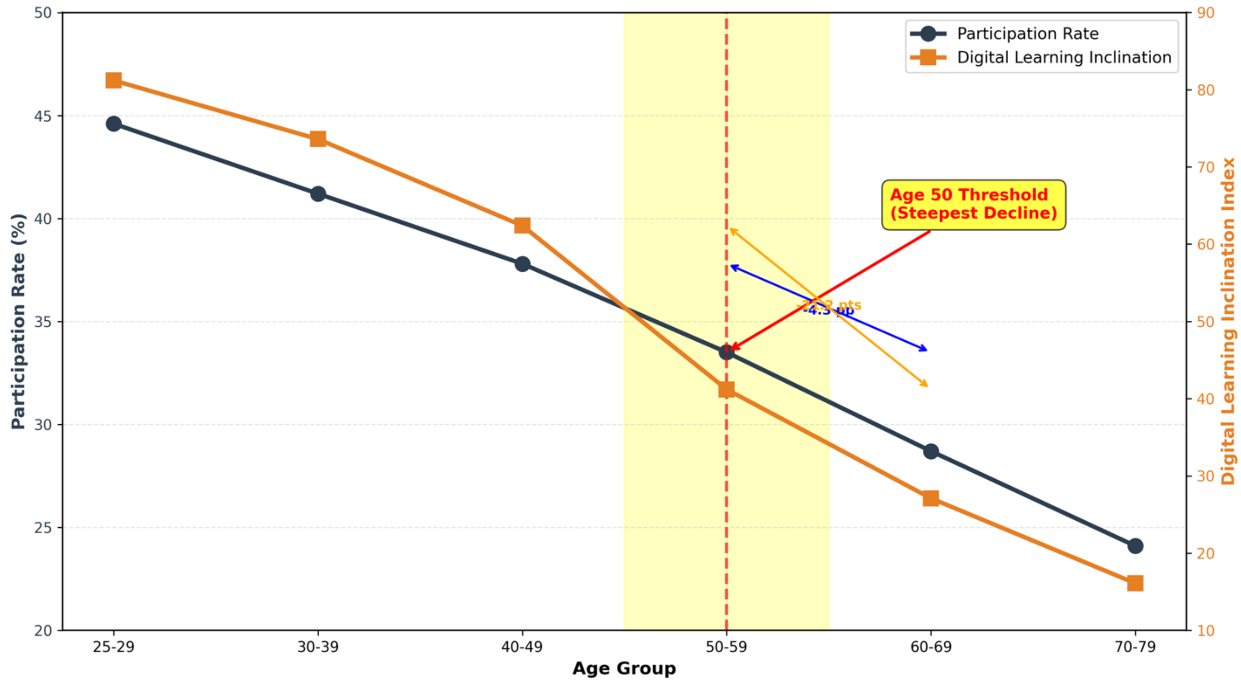

Figure 3. Age 50 Threshold Phenomenon: Parallel Decline in Participation and Digital Inclination

Participation Purposes and Motivation

Participation purpose analysis revealed distinct motivational profiles across age groups. Among 25–39-year-olds, 68% reported job-related or career development purposes as their primary learning motivation, compared to only 31% among 60–79-year-olds.

Conversely, personal interest and hobby-related learning motivations increased from 18% among young adults to 52% among older adults. This motivational shift has important implications for understanding participation patterns: older adults' lower overall participation may partially reflect reduced extrinsic labor market pressures combined with lower intrinsic motivation for structured learning activities.

Figure 4 presents the educational gradient within each age group through a grouped bar chart, clearly showing how the participation gap between educational levels varies across the lifespan. The figure demonstrates that while educational advantages persist across all ages, the magnitude of the gap is largest in younger cohorts (19.8 points at ages 25-29) and narrows somewhat in older cohorts (10.7 points at ages 70-79).

Figure 5 displays these motivational profiles through a stacked bar chart, showing the dramatic shift from career-focused learning (68% in young adults) to interest-focused learning (52% in older adults). This visualization highlights the need for program designers to emphasize intrinsic motivations and personal interest dimensions when developing offerings for older adult learners, rather than instrumental career outcomes that dominate programs designed for younger adults.

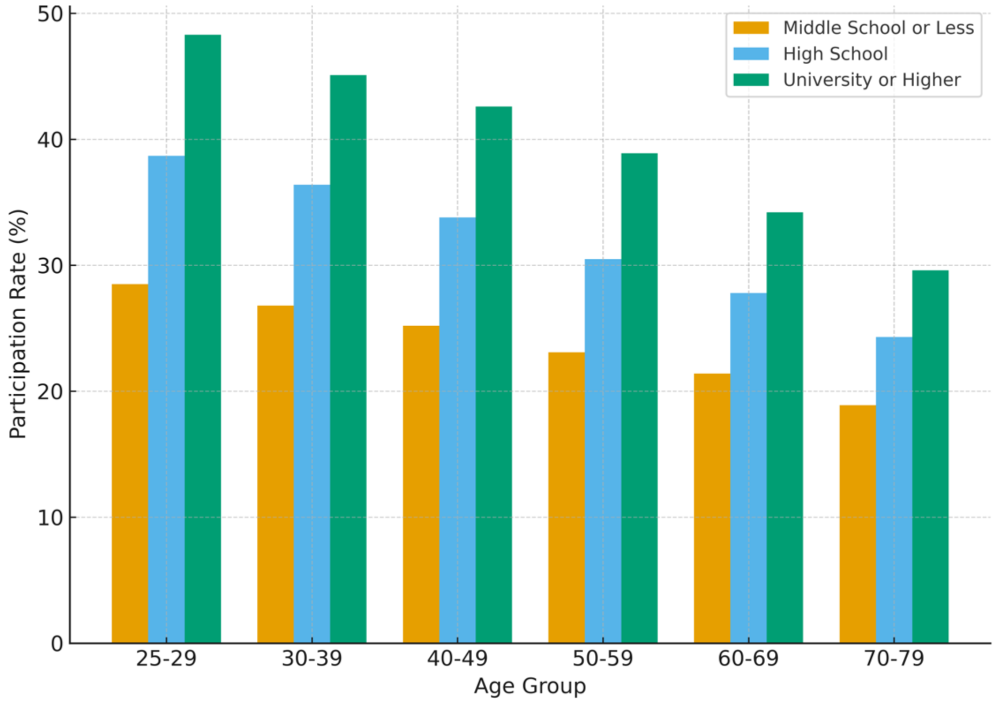

Figure 4. Educational Gradient in Lifelong Learning Participation by Age Group

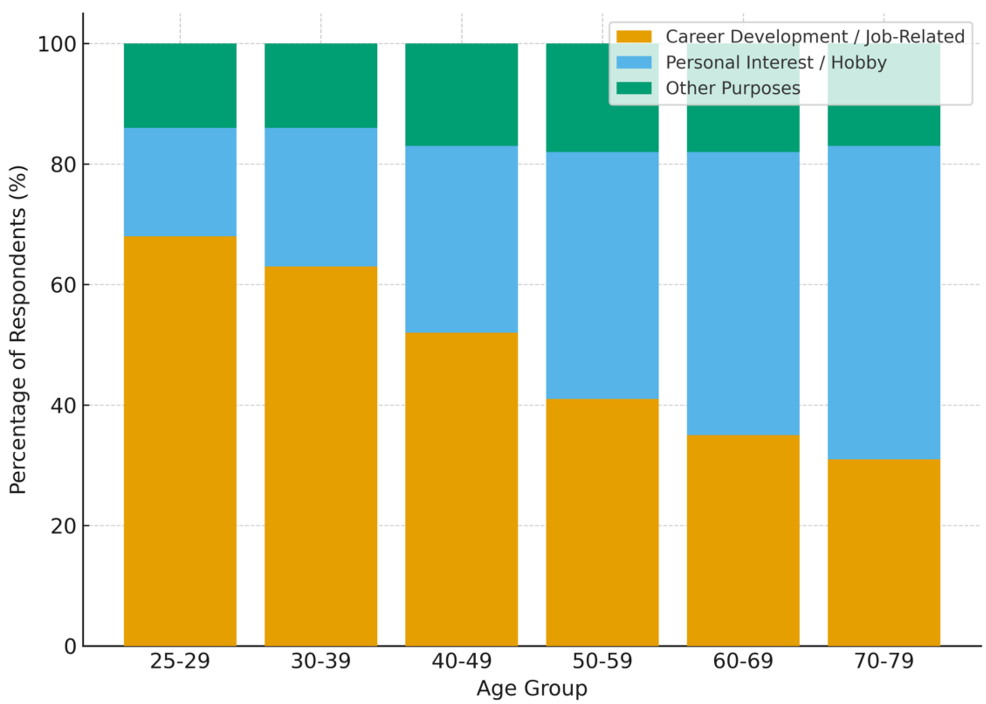

Figure 5. Participation Purposes and Motivations Across Age Groups

Educational Gap Across Age Groups

Figure 6 provides a detailed visualization of the educational gradient in lifelong learning participation. Panel A reveals that the participation gap between university graduates and those with the lowest educational attainment is most pronounced in early adulthood, reaching 19.8 percentage points in the youngest cohort. This gap gradually narrows with age, as seen in the 10.7 percentage point difference among those in their 70s. As illustrated in Panel B, the aggregate educational gradient of 17.8 percentage points highlights a persistent stratification that poses a significant challenge for equitable lifelong learning access.

Panel A in **Figure 6** displays the participation rate gap (in percentage points) between university graduates and those with middle school education or less across age groups; the red dashed line indicates the overall average gap (17.8 pp). Panel B presents the overall participation rates by education level—university or higher (40.4%), high school (32.1%), and middle school or less (22.6%)—relative to the national average (33.1%).

Correlation Between Digital Learning Inclination and Participation

Pearson correlation analysis examining the relationship between the Digital Learning Inclination Index and lifelong learning participation rates across age-education groups revealed a statistically significant moderate positive correlation ($r = .52$, $p < .001$) (see **Table 4**). The five-fold difference in the Digital Learning Inclination Index between the youngest and oldest cohorts underscores the magnitude of digital divides in learning preferences, with implications for both policy development and program design.

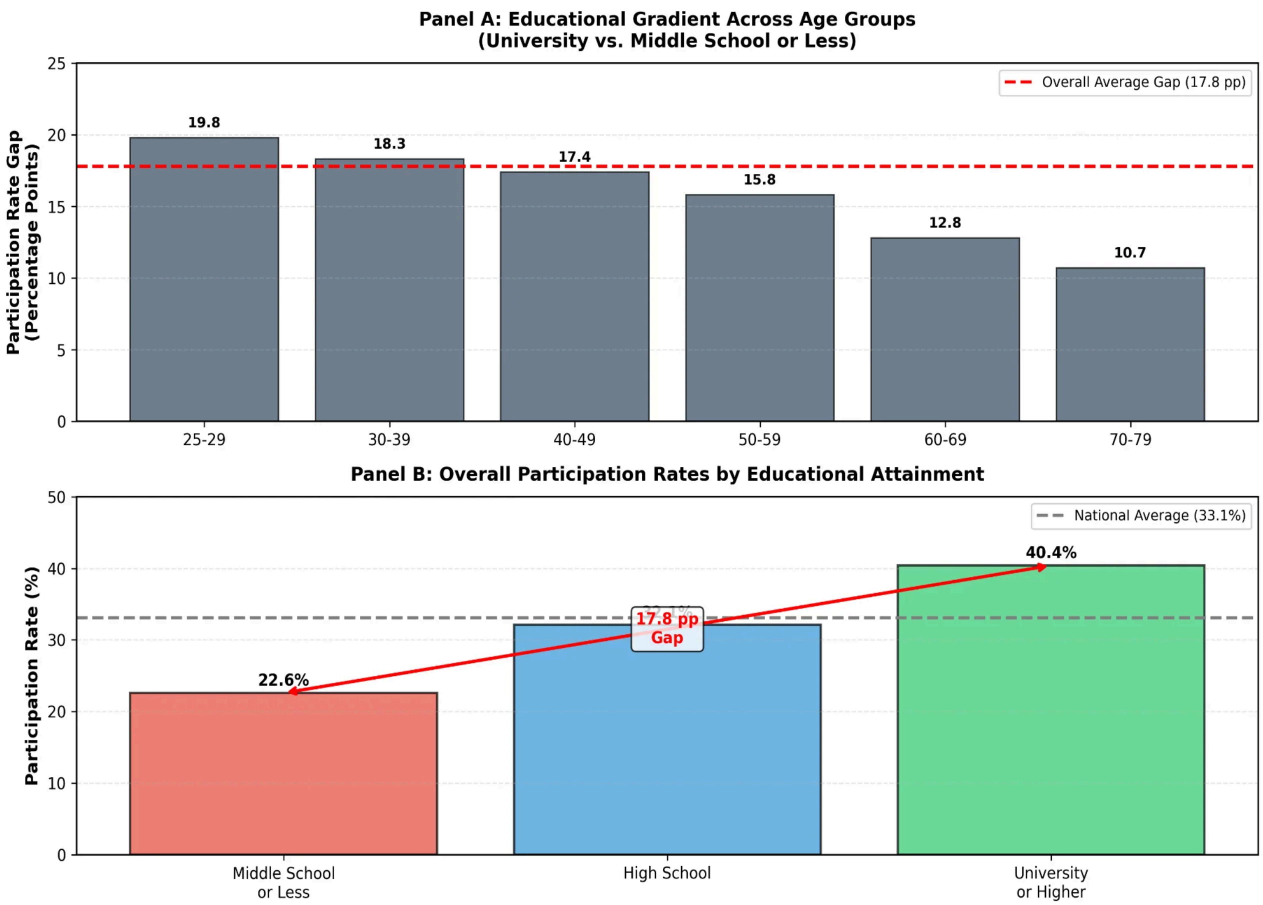

Figure 6. Educational Gradient in Lifelong Learning Participation

Table 4. Pearson Correlation Between Digital Learning Inclination and Lifelong Learning Participation

Variables	r	p	Interpretation
Digital Learning Inclination × Participation Rate	.52	< .001	Moderate positive correlation (explains approximately 27% of variance in participation rates).

Note. Pearson correlation computed across 18 aggregated age–education group cells. Significance determined at α = .05. Effect size interpretation follows Pallant (2020): r = .30–.70 represents a moderate correlation.

According to established guidelines for correlation interpretation (Pallant, 2020), correlation coefficients between 0.30 and 0.70 represent moderate relationships, while values above 0.70 indicate strong relationships. The observed correlation of .52 suggests that approximately 27% of the variance in participation rates can be explained by digital learning inclination scores at the group level.

DISCUSSION

This study examined the relationship between digital learning inclination and lifelong learning participation across age and educational backgrounds in Korea. It addressed four interrelated research questions regarding generational patterns, the effects of educational attainment, the correlation between digital inclination and participation, and the resulting policy implications.

Research Question 1: Generational Patterns in Digital Learning Inclination

Findings reveal systematic declines in both digital learning inclination and participation rates across age cohorts, with a particularly marked transition around age 50. This pattern aligns with Van Dijk's (2020) digital divide framework, suggesting that multiple levels of digital inequality—from motivational access to skills and usage patterns—compound across the lifespan to create widening gaps in learning participation. The five-fold difference in digital learning inclination between the youngest and oldest cohorts indicates that digital transformation in education may inadvertently create or exacerbate generational inequalities in learning access. The acceleration of decline at age 50 likely reflects cohort effects, as individuals currently in this age group would have been in their mid-20s during the early internet era of the late 1990s, missing key formative exposure to digital technologies during young adulthood.

This finding has practical implications: interventions targeting 40–49-year-olds could emphasize digital transition support to prevent decline, while interventions for those 50+ might need more intensive foundational digital familiarization.

Research Question 2: Relationship Between Digital Inclination and Participation

The moderate positive correlation (r = .52) between digital learning inclination and participation rates confirms that digital comfort and familiarity play important roles in learning engagement. However, the fact that digital inclination explains only 27% of participation variance suggests that other factors—including economic barriers, time constraints, family responsibilities, and intrinsic motivation—also substantially influence learning participation decisions.

Research Question 3: Educational Patterns Across Demographic Groups

Educational attainment creates lasting advantages in both digital learning inclination and participation rates, with university graduates achieving 40.4% participation compared to 22.6% for those with middle school education or less. The consistency of educational gradients across all age groups suggests that education instills durable capabilities, dispositions, and identities as learners that continue influencing behavior decades after formal schooling concludes, supporting Bourdieu's (1986) cultural capital theory.

Research Question 4: Policy Implications

The findings point to several policy priorities, detailed in the following subsections. The previous sections have established that digital learning inclination is not merely an individual trait but a socially stratified outcome influenced by age and educational background. The observed educational gradient—particularly the stark contrast in digital preferences between the highest and lowest education groups —necessitates a strategic shift from universal digital literacy initiatives toward targeted, demographically-sensitive policy interventions. By addressing the specific barriers and learning orientations identified in the present analysis, the following recommendations aim to mitigate the digital divide and foster a more inclusive lifelong learning ecosystem.

STRATEGIC FRAMEWORK FOR POLICY INTERVENTION

The findings of this study have significant implications for lifelong education policy development in Korea and other nations facing similar demographic and technological transitions. The policy recommendations are informed by the empirical patterns identified in this study, yet they should be regarded as hypotheses regarding intervention effectiveness—ones that require rigorous testing through controlled implementation studies rather than being treated as established best practices. Policy experimentation with careful outcome evaluation will be essential for validating and refining these recommended approaches.

Customized Digital Learning Inclination Development Programs

The six-fold educational level-based gap in digital learning preference—with university graduates showing 63.0% preference compared to 10.6% among middle school graduates—demonstrates that educational background profoundly shapes digital learning orientations beyond mere technical access or basic literacy. This pattern suggests that interventions must be carefully tailored to different educational demographics rather than applying uniform approaches.

For the lower-secondary educated group (those with a middle school education or less), interventions must prioritize psychological accessibility over technical proficiency. Programs should begin with foundational digital familiarization that builds confidence and reduces anxiety. Designed as low-stakes, high-success experiences, these programs should utilize familiar daily-life tasks to build fundamental digital self-efficacy. Implementing socially-embedded peer learning networks is particularly effective here, as peer modeling helps normalize technology use and reinforces the 'psychological bridge-head' concept.

For the upper-secondary educated group (high school graduates), bridge programs should focus on expanding from basic digital usage toward more sophisticated digital learning behaviors. Instead of mere access, these interventions should leverage existing partial familiarity to foster higher-order skills, such as critical information evaluation and self-directed online learning strategies. This transition is crucial for narrowing the gap toward deeper digital engagement.

University-educated groups, despite showing relatively high current digital learning inclination, may benefit from advanced metacognitive strategies. Policy support for this group should emphasize the strategic integration of diverse digital modalities, focusing on leveraging multiple platforms effectively and integrating digital and traditional learning modes strategically based on learning objectives. This approach fosters the ability to self-regulate learning in complex digital environments and maintain information quality amidst the rapid digital transition.

Age-Specific Intervention Strategies

The dramatic decline in digital learning inclination around age 50, with the steepest drops occurring in the 40-49 to 50-59 transition, suggests targeted interventions for different age cohorts. For the 40-49 age group, preventive interventions emphasizing digital transition support can help individuals maintain engagement as they approach the critical threshold. These programs might focus on building sustainable digital learning habits before significant decline occurs, leveraging this group's still-moderate digital inclination levels.

For the 50-59 age group and older, more intensive foundational digital familiarization programs are needed given substantially lower baseline inclinations. These interventions should acknowledge and address age-specific barriers including reduced working memory capacity, lower familiarity with digital interfaces, and potential technology anxiety or resistance. The successful implementation of such programs requires patience, encouragement, and recognition that learning trajectories for older adults may differ from those of younger participants (Kang et al., 2023).

Cultural factors identified earlier in this study suggest that older Korean adults' technology adoption may be particularly influenced by social norms and peer modeling. Programs that create supportive peer learning communities and emphasize social dimensions of learning may be especially effective for older cohorts (Hänninen, 2025). The steep YouTube gradient may partly reflect not only generational differences in platform familiarity but also the platform's design and cultural norms, which emphasize brief, informal, peer-created content that aligns well with younger adults' learning preferences but may seem alien or lacking credibility to older adults accustomed to more structured, authoritative educational formats.

Infrastructure and Access Equity

Given the strong correlation between digital information access and learning participation ($r = .44$, $p < .001$), policymakers should prioritize ensuring equitable digital infrastructure access, particularly in areas serving older adults and those with lower educational attainment. Addressing digital disparities requires not only ensuring physical access to devices and internet connectivity but also expanding accessible public digital learning spaces—such as libraries and community centers—equipped with appropriate technology and support staff. Crucially, for those aged 50 and older, infrastructure policy must move beyond 'physical provision' to address 'psychological proximity.' As identified in the 50-year-old threshold analysis, the decline in participation is driven not only by a lack of devices but also by a diminished digital learning inclination rooted in cohort-specific formative experiences. Therefore, public digital spaces should function as 'psychological bridge-heads' where social support reduces technology anxiety. Community-based shared infrastructure offers a cost-effective and equitable strategy for reaching disadvantaged groups, as these public access points provide not only connectivity and devices but also social learning environments and technical assistance that private home-based access cannot replicate. Investment in such infrastructure should prioritize communities with the lowest digital inclination indices, thereby directing resources toward areas of greatest need and avoiding the reinforcement of existing advantages. Evidence from both developed and developing countries supports the effectiveness and transferability of this community-based infrastructure model across diverse national contexts (Van Dijk, 2020; Hargittai, 2002).

Institutional Format Diversification Strategies

The polarized preferences between digital formats (76.8% among 25–29-year-olds) and traditional formats (79.4% among 70–79-year-olds) suggest that lifelong learning institutions should maintain diverse delivery methods rather than pursuing singular digital transformation approaches. Educational institutions and policymakers should resist the temptation to universally digitize all learning offerings, recognizing that such approaches would effectively exclude significant portions of the adult learning population. Instead, a portfolio approach that offers parallel pathways in both digital and traditional formats, with optional bridge programs for those wishing to transition between modalities, would better serve the diverse needs of the adult learning population.

International Policy Implications and Cross-National Learning

The findings from Korea's experience offer valuable insights for policymakers in other nations, particularly those facing similar challenges of rapid digital transformation combined with aging populations and educational disparities. Countries in East Asia with comparable cultural contexts and technological adoption histories, cultural attitudes toward aging and technology, and educational system characteristics may find the Korean patterns particularly relevant (UNESCO, 2025). However, the broader lessons about digital divides, the compound effects of age and education, and the need for differentiated policy responses transcend specific national contexts. International organizations such as UNESCO and OECD can draw on these findings to develop more nuanced frameworks for lifelong learning that account for digital learning inclination as a key dimension of educational access and equity (OECD, 2025).

Theoretical Contributions

This study contributes to theoretical understanding of adult learning participation in several ways. First, it introduces and operationalizes the construct of digital learning inclination as distinct from but related to digital competency. This distinction helps explain why technological access alone does not guarantee learning participation; psychological orientation and comfort with digital learning environments also play crucial roles.

Second, the findings support and extend cultural capital theory (Bourdieu, 1986) by demonstrating how educational background creates lasting advantages in digital learning inclination that persist across the life course. The consistency of educational gradients across age groups suggests that education instills durable capabilities, dispositions, and identities as learners that continue influencing behavior decades after formal schooling concludes.

Third, the identification of age 50 as a critical threshold contributes to theories of technology adoption and life-course development. This finding suggests potential cohort effects, as individuals currently aged 50 would have been in their mid-20s during the early internet era of the late 1990s, missing key formative exposure to digital technologies during young adulthood. Alternatively, this threshold might reflect life-stage factors: the 50-59 age group may face competing demands from career peaks, family caregiving responsibilities, and early retirement planning that reduce both time and motivation for adopting new learning modalities, regardless of cohort membership.

Implications for Individual Learners

Beyond policy and institutional implications, this study's findings offer insights for individual learners seeking to enhance their lifelong learning engagement. The strong relationship between digital learning inclination and participation suggests that developing comfort and familiarity with digital learning platforms can enhance overall learning participation and outcomes. This growth mindset toward digital learning capability is particularly important for older learners who may perceive themselves as inherently less suited to digital learning environments.

The data showing substantial variation in digital learning inclination even within age cohorts demonstrates that chronological age does not determine digital learning capability. Learners of all ages can benefit from recognizing that digital learning inclination represents a developable set of competencies and attitudes rather than an innate characteristic, opening possibilities for continued growth and adaptation throughout the lifespan.

Growth mindset interventions that explicitly address age-related technology stereotypes may be particularly valuable for older adult learners. Research on stereotype threat suggests that negative age-based assumptions about technology capability can become self-fulfilling prophecies when internalized (Steele & Aronson, 1995; Dweck, 2006), undermining learning effort and performance.

For the older demographic segments, the concept of lifelong education itself may be less familiar compared to younger cohorts, as lifelong learning opportunities and infrastructure were not widely available during their formative years. Considering the economic situation in Korea from the 1960s through the 1980s, the lower-secondary-educated older generation primarily prioritized economic survival over self-development. This historical trajectory has resulted in a 'double exclusion' in the digital era: a lack of familiarization with lifelong education concepts combined with a low digital learning inclination due to missing formative digital exposure. Longitudinal analysis demonstrates that these historical patterns continue to shape contemporary participation trends, with crisis periods consistently reducing participation rates, particularly among economically vulnerable groups, while also revealing the system's capacity for recovery during periods of stability (Yoo, 2025). This dual unfamiliarity with both digital technologies and lifelong learning concepts may have created compounding barriers to participation for these demographic segments.

CONCLUSION

This study comprehensively analyzed the relationship between Korean adults' digital learning inclination and lifelong learning participation from age-based, educational level-based, and demographic perspectives. The operationalization of digital learning inclination through proxy measures, including learning media preferences, informal digital learning participation, and information access pathways, revealed meaningful patterns that inform both research methodology and policy development.

The findings demonstrate three key conclusions that directly address the research questions posed at the outset. First, digital learning inclination, as measured through learning media preferences, informal digital learning participation, and information access pathways, serves as a crucial predictor of lifelong learning participation, with moderate positive correlations ($r = .52$, $p < .001$) confirming this relationship across demographic groups. This finding establishes digital learning inclination as an essential dimension of educational access in the digital era, one that operates independently of technical skill proficiency and reflects deeper patterns of comfort, familiarity, and preference for digital learning modalities.

Second, educational attainment creates lasting advantages in both digital learning inclination and participation rates, with university graduates achieving 40.4% participation compared to 22.6% for those with middle school education or less, while simultaneously showing six-fold higher digital format preferences (63.0% versus 10.6%). This educational gradient persists across all age groups, suggesting that early educational experiences create durable advantages that compound over the lifespan.

Third, the combined influences of educational background and age continuously influence digital learning preferences, with particularly vulnerable populations such as older adults with lower education facing compound disadvantages in accessing modern learning opportunities. The 70-79 age group with middle school education or less shows only 18.9% participation rates and minimal digital learning inclination, highlighting how multiple forms of disadvantage accumulate to create severe barriers to lifelong learning engagement.

An emergent finding is the identification of a critical transition period around age 50 where both digital learning inclination and participation rates show accelerated decline, suggesting this as a key target for preventive interventions.

These results reveal that lifelong education in the digital era requires a fundamental shift from one-size-fits-all approaches to demographic-specific strategies that acknowledge both the benefits and barriers of digital transformation. The evidence suggests that lifelong education policies must secure equity in learning opportunities through integrated approaches simultaneously considering age-based, educational level-based, and digital learning inclination characteristics.

For the broader field of lifelong education, this study demonstrates that digital learning inclination represents a new form of cultural capital that influences learning access and participation. As educational systems continue to digitize, understanding and addressing digital learning divides becomes essential for maintaining the democratic ideals of lifelong learning, ensuring that learning opportunities remain accessible to all adults regardless of age, educational background, or technological familiarity. The Korean experience offers valuable lessons for other nations navigating similar transitions, particularly those in Asia facing comparable demographic shifts and digital transformation challenges.

Limitations and Future Research Directions

This study has several important limitations that should be considered when interpreting findings. First, the ecological analysis design examines relationships at the group level, which limits the ability to draw individual-level inferences due to the ecological fallacy (Robinson, 1950). While this approach effectively identifies population-level patterns and trends, it cannot determine whether observed group-level associations reflect individual-level relationships.

Second, the cross-sectional nature of the data precludes causal inference. Although findings reveal associations between digital learning inclination and participation rates, the temporal sequence and direction of causation cannot be established. It remains unclear whether higher digital learning inclination leads to increased participation, whether participation experiences enhance digital learning inclination, or whether bidirectional relationships exist. Longitudinal research would be necessary to disentangle these temporal relationships and establish causal mechanisms.

Third, the operationalization of digital learning inclination through proxy behavioral measures (learning media preferences, informal digital learning participation, and information access pathways) rather than direct competency assessments represents both a methodological limitation and a pragmatic response to data availability constraints. While this approach provides a replicable framework for contexts lacking comprehensive digital competency data, empirical validation through correlation with standardized assessments would strengthen construct validity.

Fourth, the integration of data from different surveys with potentially different sampling methodologies may affect demographic group comparability, though both employ nationally representative sampling procedures. Additionally, the age range differences between surveys required analytical adjustments that may not fully capture lifelong learning patterns across the complete adult lifespan.

Future research should address these limitations through several complementary approaches. Individual-level microdata analyses using integrated datasets that include both digital competency assessments and learning participation measures would enable more sophisticated statistical modeling. Longitudinal cohort studies tracking relationships between digital skill development and learning engagement over multiple years would establish temporal precedence and illuminate causal mechanisms. Qualitative research exploring subjective experiences and decision-making processes across different demographic segments would provide a deeper understanding of the mechanisms underlying the patterns observed in this ecological analysis. Intervention studies testing the effectiveness of targeted digital literacy programs designed for specific age-education groups would provide practical evidence for policy implementation.

Beyond these methodological advances, future research should extend the cultural dimensions framework introduced in this study through direct empirical investigation. While this study provided rich cultural context about Korean adult education and discussed the potential influence of collectivism and social norms on technology adoption, the current data did not permit direct measurement of cultural variables. Future research should directly measure cultural dimensions (e.g., collectivism, uncertainty avoidance, power distance) and examine their moderating effects on the relationship between digital learning inclination and participation across different cultural contexts. Cross-national comparative studies would be particularly valuable for testing whether the patterns observed in Korea—including the age-50 threshold phenomenon, 20/22 educational gradient effects, and the five-fold difference in digital learning inclination between youngest and oldest cohorts—generalize to other rapidly aging and digitizing societies, or whether these patterns reflect culturally-specific dynamics of technology adoption and lifelong learning engagement.

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Ethical statement: This study utilized secondary data from the Korean Educational Development Institute's 2024 Individual Survey on Lifelong Learning, a publicly available national dataset. The original data collection by KEDI adhered to ethical research standards, including informed consent procedures and confidentiality protections for all participants. As this research involved the analysis of de-identified, publicly available data, additional institutional review board approval was not required.

AI statement: This research utilized generative artificial intelligence tools (Claude 4.5, Anthropic) to assist in manuscript preparation. Specifically, AI assistance was employed for (1) formatting the manuscript according to academic journal standards, (2) refining academic writing style and language clarity, (3) creating data visualizations (Figures 1-3) based on analytical results, and (4) formatting references according to APA 7th edition guidelines. The authors take full responsibility for all intellectual content, including research design, data analysis, interpretation of results, and conclusions. All AI-assisted content was carefully reviewed and verified by the authors to ensure accuracy and scholarly rigor.

Data sharing statement: The data that support the findings of this study are available from the Korean Educational Development Institute (KEDI). Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors upon reasonable request and with permission of KEDI.

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