

Article

Freemium Generative AI as a Socio-Technical System: Paid Commitment and the Premium Digital Divide in South Korea

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Highlights

- This study conceptualizes freemium GenAI adoption as a socio-technical system in which platform tiers, user capabilities, and institutional conditions jointly shape paid commitment.
- It introduces the premium digital divide as a tier-mediated extension of second-level digital inequality and models non-use, free use, and paid commitment as distinct observable system states.

What are the main findings and/or the implications of the main findings?

- Practical AI literacy is positively associated with both initial GenAI use and paid commitment, whereas critical AI awareness is associated with initial use but not payment.
- Negative emotions are negatively associated with initial use but positively associated with paid commitment among users, suggesting vigilant and intensive engagement.

Abstract

Free generative AI (GenAI) services appear to democratize access, but freemium platform models can create post-access stratification after basic connectivity and initial use have been achieved. This article conceptualizes paid commitment to GenAI as an emergent outcome of a socio-technical system composed of platform tiers, user capabilities, task environments, economic constraints, affective feedback, and institutional access. Using a cross-sectional 2025 survey of 2000 South Korean adults aged 18–69, the study models the observed states of non-use, free use, and paid commitment through sequential logit models. Descriptive results show that 70.6% of respondents used GenAI in the previous year, yet only 20.6% of users, or 14.6% of the total sample, paid for access. Practical AI literacy is positively associated with both initial use and paid commitment, whereas critical AI awareness is associated with initial use but not payment. Negative emotions are negatively associated with initial use but positively associated with paid commitment among users, a pattern consistent with vigilant and intensive engagement. The premium digital divide is defined not as a fourth level of the digital divide, but as a tier-mediated extension of second-level inequality that may condition access to later educational, occupational, or civic benefits. Because the data are cross-sectional and combine different GenAI platforms, the estimates are ecosystem-level associations and do not establish causal direction or platform-specific effects.

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Keywords: generative AI; socio-technical systems; freemium platforms; premium digital divide; AI literacy; paid commitment; South Korea; AI policy

1. Introduction

Generative artificial intelligence (GenAI) has evolved from a specialized technical field to widespread use in search, writing, translation, coding, learning, office work, and creative production. Many individuals are first exposed to GenAI through consumer platforms offering free, entry-level access rather than by employers, educational institutions, or public programs. This free-access model fosters the perception that GenAI is accessible to anyone with internet connectivity. However, these platforms are increasingly built on freemium models, with subscription tiers offering higher usage limits, advanced models, larger context windows, enhanced reliability, privacy controls, and integration with professional tools. Thus, the main inequality is not simply whether individuals have encountered GenAI, but whether they can move from occasional experimentation to sustained, high-quality, and valuable use.

This article frames the issue as a socio-technical systems problem. Freemium GenAI platforms create inequality beyond pricing alone, and users do not sort into tiers solely on the basis of individual skill. Premium stratification instead reflects the joint configuration of platform architecture, human capability, task relevance, economic access, affective feedback, and institutional context. Two individuals may both be classified as GenAI users, while one engages sporadically with a free chatbot and another relies on premium access for study, coding, writing, job search, or workplace decision support. Treating both as equivalent users hides a post-access divide generated partly by the platform's tiered architecture.

The concept of a premium digital divide is therefore positioned carefully within established digital-inequality theory. It is not proposed as a separate fourth level. It identifies a tier-mediated form of second-level inequality among people who have already crossed the basic access threshold. Commercial tiers can allocate differences in capacity, reliability, autonomy, privacy protection, and workflow integration, and those differences may affect whether users can convert GenAI engagement into later educational, occupational, economic, or civic benefits. Paid commitment is consequently treated as an intermediate post-access condition rather than as proof that third-level benefits have already been realized.

The empirical context is South Korea, a valuable environment for analysis because of its advanced digital infrastructure, high platform penetration, strong public interest in AI, and active debate on digital inclusion and AI governance. In such a connected society, premium stratification cannot be linked to connectivity alone; it reflects a post-access systems issue in which platform tiers, human capabilities, task opportunities, and institutional access conditions jointly structure unequal AI participation. The National Information Society Agency (NIA) plays a central role in this policy context; the World Bank describes NIA as Korea's leading government agency driving the development of an inclusive, innovative, and resilient digital society [1]. Recent empirical work on GenAI adoption in the United States, Denmark, and higher education likewise shows that adoption varies by work exposure, education, training, demographics, perceived utility, and perceived risks [2–4].

This analysis draws on a 2025 survey of 2000 Korean adults aged 18 to 69. The survey measures GenAI use, payment status, reasons for non-use and non-payment, practical AI literacy, critical AI awareness, emotions, benefit expectations, education, academic major, occupation, and demographic characteristics. These measures permit analysis of three ob-

servable system states: non-use, free use, and paid commitment. Because the survey is cross-sectional, the states are analytically ordered but are not observed longitudinal transitions, and the regression coefficients are interpreted as associations rather than causal effects.

This article makes five contributions. First, it conceptualizes paid commitment as a post-access system outcome rather than a simple consumer preference. Second, it distinguishes the premium digital divide from first-, second-, and third-level digital-divide frameworks and identifies it as a commercially structured extension of second-level inequality. Third, it integrates digital-divide theory with socio-technical systems theory by treating platform design, human capability, task demand, economic access, affective feedback, and institutional context as interdependent elements. Fourth, it distinguishes practical AI literacy from critical AI awareness. Fifth, it interprets concern among paid users as possible feedback from intensive system interaction rather than as simple resistance to AI. These contributions extend individual-level adoption models by focusing on paid commitment after initial access and use.

The results show a clear adoption gradient: 29.5% of respondents were non-users, 56.0% were free users, and 14.6% were paid users. Practical AI literacy is positively associated with both GenAI use and paid commitment. Critical AI awareness is associated with entry but not with payment among users. Negative emotions are negatively associated with initial use and positively associated with paid commitment among users. These patterns indicate that premium GenAI inequality cannot be reduced to affordability, literacy, or platform design alone; it is associated with the alignment and misalignment of technical, human, task, economic, affective, and institutional subsystems.

2. Theory: From Digital Access to Socio-Technical AI Stratification

2.1. Digital Divide Theory and Post-Access AI Inequality

Digital divide theory has evolved through several stages. First-level research examines material access to devices, networks, and connectivity. Second-level research investigates differences in skills, autonomy, frequency, types, and quality of use among people who already have access. Third-level research asks whether these differences produce unequal educational, occupational, civic, economic, or well-being outcomes [5–11]. GenAI aligns with this sequence but introduces a distinctive commercial mechanism: free entry can reduce the visibility of basic access inequality while paid tiers reallocate the quality, capacity, reliability, and autonomy of use within the existing user population.

The premium digital divide is not a fourth level of digital inequality. It is a tier-mediated subtype and extension of second-level inequality. Both free and paid users have crossed the basic access threshold, but their positions within the platform ecosystem can differ in usage limits, model quality, availability at peak times, context capacity, multi-modal functions, privacy arrangements, and integration with work or study routines. The contribution is therefore not a renaming of differentiated use. It identifies how a freemium business architecture converts differences in capability, task recurrence, resources, and institutional support into unequal access to advanced system capacities among people already counted as users.

Paid commitment is also distinct from a third-level outcome. The survey does not measure realized labor-market advancement, educational attainment, civic participation, productivity, or creative success. Premium access may nevertheless operate as an intermediate pathway: higher-capacity and more reliable access can support more intensive task integration, which may later contribute to third-level advantages. This pathway is contingent rather than automatic, because technical capacity must still be converted into meaningful results through user capability, task opportunities, and institutional condi-

tions. Table 1 summarizes how the premium digital divide is positioned within established digital-divide frameworks.

Table 1. Positioning the premium digital divide within established digital-divide frameworks.

Framework or Level	Core Inequality	Typical Empirical Focus	Relationship to the Premium Divide
First-level divide	Material access to devices, networks, and connectivity	Device ownership, connectivity, availability	A prerequisite; not the focal inequality among existing GenAI users
Second-level divide	Skills, autonomy, frequency, types, and quality of use	Digital literacy, use patterns, independence, intensity	The premium divide extends this level by adding commercially tiered access to advanced capacity
Third-level divide	Unequal offline or realized outcomes	Educational, occupational, economic, civic, or well-being benefits	Premium access may be a pathway to these outcomes, but the present study does not measure them
Premium digital divide	Free-only versus paid or institutionally supported access within the user population	Tier status, limits, quality, reliability, privacy, and workflow integration	A post-access, tier-mediated form of second-level stratification; not a separate fourth level

In this study, paid commitment is defined as an emergent system outcome in which users obtain sustained access to higher-quality, higher-capacity, or more autonomous GenAI services rather than relying exclusively on free access. It becomes observable when platform affordances, practical capability, recurring task demand, perceived marginal utility, and economic or institutional access align sufficiently to support payment. This definition does not assume that payment itself causes intensive or beneficial use; it treats payment as one visible indicator of alignment across platform, human, task, economic, and institutional subsystems.

2.2. Freemium GenAI Platforms as Socio-Technical Systems

Socio-technical systems theory conceptualizes technological outcomes as emergent properties of jointly configured technical, social, organizational, and environmental arrangements, rather than as direct effects of tools alone. Foundational studies emphasized that work systems integrate technical arrangements with human roles, task structures, and organizational environments [12,13]. Later information-systems and transition research showed that adoption depends on the interaction among artifacts, users, organizations, governance, infrastructure, regulation, and shared meanings [14–17].

Freemium GenAI platforms function as socio-technical systems because their outcomes result from the interplay of platform design, user capabilities, task environments, economic access, and institutional arrangements. The technical subsystem includes model quality, usage limits, reliability, context windows, privacy controls, and productivity-tool integration. The human subsystem includes practical AI literacy, critical awareness, confidence, trust, and emotional response. The task subsystem includes work, study, job search, creative production, and information-processing needs. The economic subsystem includes subscription prices, fee burden, employer support, and institutional access. Together, these subsystems shape whether users remain non-users, experiment with free tools, or transition to paid use.

No single subsystem is expected to be sufficient. Practical literacy may enable a user to recognize advanced affordances, but payment is less likely when recurring AI-relevant tasks are absent. Recurring tasks may create value, but subscription costs or lack of institutional support can prevent payment. Critical awareness can improve risk calibration while simultaneously discouraging deeper dependence on a provider. Affective feedback may reflect either deterrence before use or accumulated experience after intensive use. In

this article, interaction therefore refers primarily to socio-technical interdependence and joint configuration. The regression models estimate additive associations and do not claim to test every possible multiplicative statistical interaction.

This study examines the GenAI adoption system among South Korean adults, defined by consumer-facing freemium GenAI platforms, individual users aged 18 to 69, and the institutional context of South Korea's digital society. The system boundary excludes enterprise back-end AI infrastructure, providers' internal pricing strategies, and objective productivity outcomes, as these require different data. It incorporates policy and institutional access as external conditions because they can modify the costs, skills, protections, and access pathways through which users engage with GenAI.

Research on platforms and freemium models further supports this systems-based framing. Platform markets structure interactions through architectures, governance rules, and pricing mechanisms that allocate value and influence participation [18,19]. Freemium models enable free entry while reserving certain benefits for paying users; these models can shape perceived value, willingness to pay, and the distribution of benefits across user groups [20]. Within GenAI, the freemium model functions as more than a pricing strategy because it establishes a tiered access structure that interacts with user literacy, task demand, risk perception, institutional support, and public policy.

Table 2 summarizes the study's system boundary, components, and empirical operationalization.

Table 2. System boundary, components, and operationalization.

System Element	System Interpretation	Operationalization in the Manuscript
Platform tier structure	Technical access tiers that allocate model quality, reliability, limits, and autonomy	Free use vs. paid commitment
Human capability	User capacity to understand, evaluate, and integrate GenAI	Practical AI literacy; critical AI awareness
Task position	Location in work, study, or non-work routines that creates recurring AI-relevant demand	Occupation; student or knowledge-work role; home-maker/unemployed status
Socioeconomic position	Resource and credential conditions that shape access opportunities	Education; IT-related major; subjective fee-burden indicators
Affective feedback	Emotional signals generated by exposure to system benefits and limits	Negative emotion count
System outcome	Movement across observable system states	Non-use; free use; paid commitment
External environment	Policy, institutional, and national digital context shaping access and inclusion	South Korea's digital society and AI policy context

2.3. Human Capability Subsystem: Practical Literacy and Critical Awareness

AI literacy is frequently conceptualized as a single trait [21], yet GenAI adoption requires at least two analytically distinct capabilities. Practical AI literacy encompasses the knowledge, interest, understanding, information seeking, and confidence needed to use and integrate AI into routine tasks. Within a socio-technical system, practical literacy enables users to recognize platform affordances, develop workflows, identify valuable tasks, compare free and paid tiers, and assess whether premium access offers sufficient marginal value.

Critical AI awareness is a different capacity. It involves recognizing that AI outputs may be inaccurate, biased, privacy-invasive, or ethically complex [22–24]. Such awareness can sup-

port initial experimentation because users who understand risks may be better able to evaluate outputs. It does not necessarily increase willingness to pay, however. Awareness of hallucinations, copyright concerns, data tracking, privacy risks, or provider dependence can weaken the perceived desirability of deeper commercial commitment even when the service remains useful.

The expected relationship is therefore asymmetric: practical literacy should be positively associated with both initial use and paid commitment, whereas critical awareness should be more strongly associated with initial use than with payment. A non-significant payment association could reflect limited marginal value, but it could also reflect deliberate non-payment. Critically aware users may remain on free tiers to limit data exposure, avoid platform lock-in, preserve flexibility across providers, or maintain calibrated distance from commercial AI ecosystems. This interpretation is consistent with the AI trust paradox, in which use can coexist with limited or conditional trust [25]. Because the survey does not directly measure lock-in concerns or deliberate payment avoidance, this mechanism remains an interpretation for future testing rather than a finding established by the present data.

This distinction has policy implications. Productivity-focused AI literacy programs may increase premium adoption among groups already located in AI-relevant task environments. Critical-awareness initiatives may promote responsible experimentation without closing the free-versus-paid gap. A systems approach therefore requires public AI competence programs that integrate practical skills, critical evaluation, privacy knowledge, and institutional access pathways.

2.4. Task-Position and Economic-Access Subsystems

Affordability alone does not account for paid commitment. Users may be more willing to pay when GenAI is relevant to recurring tasks and premium features improve the speed, reliability, capacity, or autonomy of those tasks. Students completing assignments, software workers debugging code, office workers drafting documents, job seekers preparing applications, and professionals synthesizing information can face repeated AI-relevant demand. Users with fewer recurring tasks may remain on free tiers even when they could afford a subscription.

The task-position subsystem identifies respondents' roles within work, education, and daily routines. Occupation, student status, knowledge-work roles, IT-related majors, and non-work status are imperfect proxies for repeated exposure to AI-relevant tasks. The economic-access subsystem includes subscription cost, perceived fee burden, payment friction, and potential employer or institutional support. These mechanisms interact: fee burden can deter payment despite strong task demand, while weak task recurrence can make payment unnecessary despite adequate resources.

The available proxies do not cleanly disentangle task-driven demand from economic constraint. Education and occupation can reflect credentials, job content, income, and institutional opportunity at the same time. The analysis therefore does not infer that occupational differences are purely economic or purely task-based. Direct measures of income, disposable resources, price sensitivity, employer reimbursement, actual task frequency, and institutional licensing are needed to separate these mechanisms.

2.5. Affective Feedback and Vigilant Paid Use

A systems approach reframes emotion in relation to AI. Public responses are not limited to enthusiasm or fear; positive and negative attitudes can coexist [8,26,27]. The AI trust paradox indicates that individuals may use or support AI systems even when their expressed trust is limited [25]. Repeated GenAI use can reveal both capabilities and failures. Users may value the acceleration of routine tasks while also encountering hallucinations, bias, privacy concerns, and verification burdens.

It is therefore important to distinguish the meaning of negative emotions before and after entry into the user population. For non-users, anxiety, alienation, anger, or fatigue may accompany avoidance. Among users, the same emotions may reflect accumulated exposure to output instability, privacy trade-offs, or verification costs. Paid users can consequently constitute a high-intensity feedback group rather than a low-trust or anti-AI cohort. Concern among active users should not automatically be interpreted as rejection; it may indicate calibrated awareness developed through experience. Cross-sectional data cannot determine which direction of influence predominates, so this interpretation is evaluated cautiously.

2.6. Research Questions and Hypotheses

Research Question 1. *How are Korean adults distributed across the GenAI adoption ladder of non-use, free use, and paid commitment?*

Hypothesis 1. *Practical AI literacy is positively associated with both initial GenAI use and paid commitment.*

Hypothesis 2. *Critical AI awareness is positively associated with initial GenAI use but has a weaker or non-significant association with paid commitment.*

Hypothesis 3. *Negative emotions are negatively associated with initial GenAI use but positively associated with paid commitment among users.*

Research Question 2. *What barriers explain non-use and non-payment within the freemium GenAI system?*

Research Question 3. *Are the observed patterns robust to alternative model specifications?*

Figure 1 summarizes the proposed socio-technical system and locates the adoption ladder within its platform, capability, task-demand, economic-access, affective-feedback, and policy subsystems.

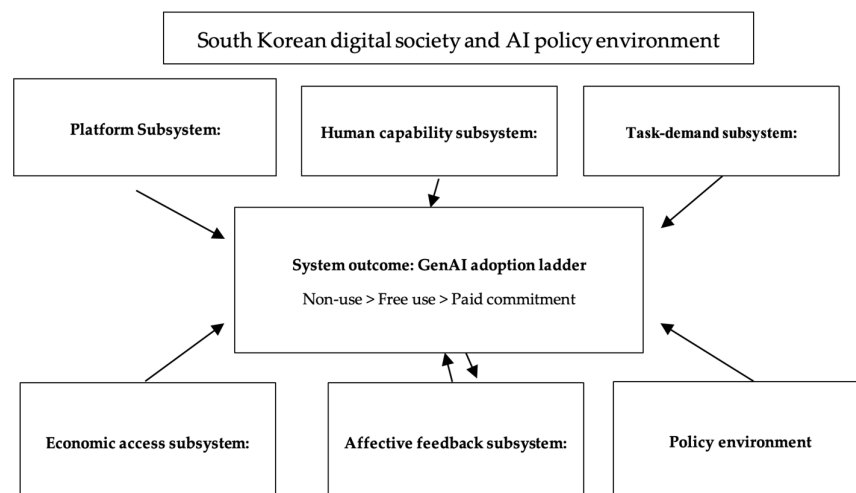


Figure 1. Socio-technical system of freemium GenAI adoption and premium stratification. *Note.* The adoption ladder is treated as a system outcome produced by interdependent platform, human-capability, task-demand, economic-access, affective-feedback, and policy subsystems within the South Korean digital-society context. The arrows depict conceptual interdependence, not estimated multiplicative interaction terms.

3. Data and Methods

3.1. Data Source, Sample, and System Environment

This analysis uses data from a 2025 South Korean public survey about AI, commissioned by the National Information Society Agency [28] to guide digital-society policy. The policy-oriented survey is appropriate for analyzing GenAI adoption as a socio-technical system rather than solely as an individual consumer choice. Balanced sampling across regions, gender categories, and ages yielded 2000 respondents and 75 questions. Respondents were aged 18–69: 17.9% were 18–29, 17.7% were in their 30s, 20.4% were in their 40s, 23.1% were in their 50s, and 20.9% were in their 60s. The sample was 50.9% men and 49.1% women.

The response matrix does not include a survey-weight variable, so the analysis uses unweighted estimates. Population-level inference should therefore be made cautiously even though demographic coverage is broad. The demographic control is treated as a binary gender variable because the available response matrix labels the item in those terms.

The system is bounded by consumer-facing freemium GenAI services and respondents' observed positions as non-users, free-only users, or paid users. The survey names examples of services but does not identify the platform or package for which a respondent paid, whether a person used several platforms, whether payment was individual or institutionally supported, or which premium capabilities were used. Commercial platforms differ in pricing, usage limits, multimodal functions, context capacity, search or coding specialization, ecosystem integration, privacy arrangements, and target users. The coefficients should therefore be interpreted as average associations across the South Korean consumer GenAI environment, not as platform-specific effects.

3.2. Measures

The primary outcome differentiates observable system states. Respondents who used a generative AI tool, such as ChatGPT, Gemini, Claude, or Perplexity, in the previous year are classified as GenAI users. Among users, those who reported currently paying for a GenAI service are paid users, while those using only free versions are free users. These indicators form a three-category adoption ladder: non-use, free use, and paid commitment. The term ladder describes analytic ordering and survey routing rather than longitudinal movement observed for the same individual over time.

Practical AI literacy is the mean of five five-point items measuring prior knowledge, interest, understanding, active information seeking, and confidence in applying AI to work or study (Cronbach's $\alpha = 0.84$). Critical AI awareness is the mean of two five-point items measuring awareness of possible inaccuracies or bias and attention to privacy, copyright, and ethical issues. For this narrow two-item scale, Cronbach's $\alpha = 0.62$, the inter-item correlation is $r = 0.45$, and the Spearman–Brown coefficient is 0.62 [29].

Expected AI benefits are the mean of ten items assessing perceived contributions to health, safety, welfare, social connection, education, culture, work–life balance, climate, civic participation, and trustworthy government ($\alpha = 0.89$). Hope regarding AI diffusion is a five-point item ranging from strong concern to strong expectation or hope that AI will become widespread. The negative-emotion count is the number of the respondent's top three AI emotions coded as anxiety, anger, alienation, or fatigue. Positive and negative emotions were not entered together because the survey required three ranked emotions, creating mechanically related counts. The negative-emotion count is therefore interpreted as an indicator of concern or vigilance rather than a comprehensive affect scale.

Education is categorized as high school or below, two-year college, university, or graduate school. An IT major is defined by an IT-related engineering degree. Knowledge-work or student roles include office, management, sales, professional or free-profession

occupations, and college or graduate students. Homemaker or unemployed status includes respondents outside paid employment or formal study. In the absence of direct income data, education, occupation, IT major, and the subjective fee-burden item are used as partial proxies. They cannot fully separate purchasing capacity from recurring task demand and are interpreted accordingly.

Table 3 summarizes the measures and their scale construction; Appendix A provides full coding notes.

Table 3. Measures and scale construction.

Construct	Survey Item(s)	Coding or Item Content	Reliability/Role
GenAI use	QC02	1 = used ChatGPT, Gemini, Claude, Perplexity, etc. in the past year; 0 = did not use	Binary entry outcome
Paid commitment	QC02-2	Among GenAI users, 1 = currently paid user; 0 = free-only user	Binary premium-tier outcome
Practical AI literacy	QC01-1 to QC01-5	Knowledge, interest, understanding, information seeking, work/study self-efficacy	Mean scale; alpha = 0.84
Critical AI awareness	QC01-6 to QC01-7	Awareness of inaccurate or bias-prone outputs and attention to privacy, copyright, and ethics	Two-item scale; alpha = 0.62; r = 0.45; Spearman-Brown = 0.62
Expected AI benefits	QB01-1 to QB01-10	Expected AI contribution to health, safety, welfare, education, work–life balance, climate, civic participation, trustworthy government, and related futures	Mean scale; alpha = 0.89
Negative emotion count	QA02	Count of top three emotions coded as anxiety, anger, alienation, or fatigue	0–3 count
SES and task proxies	DQ1, DQ1-1, DQ2	Education, IT-related major, occupation, knowledge-work/student role, homemaker/unemployed status	Controls and interpretation variables

3.3. Analytic Strategy: Conditional Models of Observed System States

The primary analysis uses a sequential binary hurdle specification. The first equation models whether a respondent reported GenAI use; the second models paid commitment among the 1411 respondents who had used GenAI. The sequence reflects the survey’s conditional structure: paid status is observed only for users. It should not be interpreted as evidence that the survey followed individuals through temporal transitions. Because both outcomes are binary, logistic regression is used. Continuous predictors are standardized so that coefficients represent a one-standard-deviation change. Controls include gender, age group, education, IT major, knowledge-work or student role, and homemaker or unemployed status. Results are reported as odds ratios with 95% confidence intervals, average marginal effects, and McFadden pseudo-R² [30].

The word predictor is used in the statistical sense. The cross-sectional design does not establish that literacy, awareness, perceived benefits, hope, or emotion precede use or payment. Reverse causality is plausible: practical literacy may support use, while repeated use may build literacy; intensive use may generate concern, while concern may also shape engagement. Omitted factors, including income, platform type, use frequency, employer reimbursement, task intensity, and personality, may affect both the explanatory variables and the observed states.

Potential selection also arises because the paid model includes only users. A Heckman-type selection correction is therefore reported as a robustness check [31,32]. A first-stage probit models GenAI use and generates an inverse Mills ratio for a second-stage probit of paid commitment. Expected societal diffusion of AI is used as an exclusion variable on the rationale

that diffusion expectations can stimulate awareness, curiosity, and trial, while payment should depend more directly on task demand, marginal premium value, economic burden, and use frequency. This restriction is plausible but not guaranteed, so the selection model is treated as a sensitivity analysis rather than a causal correction.

A multinomial logit model provides a second robustness check by treating non-use, free use, and paid use as one three-category outcome. Because the dependent variable is not continuous spending, the original continuous double-hurdle framework is not used [33]. Model stability is assessed by comparing the direction and substantive interpretation of the focal associations across the sequential logit, multinomial logit, and selection-corrected probit specifications. These alternative outcome and link specifications strengthen confidence when conclusions converge, but they do not eliminate omitted-variable bias or prove causal direction.

The archived model output available for this revision did not include the term-level design matrix needed to compute generalized variance inflation factors or leverage and influence diagnostics. We therefore do not report unverifiable values. Model stability is instead assessed through the two alternative specifications already estimated. Future replication materials should include the design matrix, generalized variance inflation factors, influence diagnostics, and alternative coding checks. This reporting limitation is considered when interpreting the robustness evidence.

4. Results

4.1. The Adoption Ladder: Broad Use, Limited Paid Commitment

GenAI use was widespread, but paid access remained a minority state. Among 2000 respondents, 1411 (70.6%) reported using a GenAI service in the previous year, and 291 (20.6% of users) reported current paid use. In the full sample, 589 respondents were non-users (29.5%), 1120 were free users (56.0%), and 291 were paid users (14.6%). Free availability therefore broadens entry without eliminating differentiation within the user population.

Table 4 shows descriptive gradients. Mean practical AI literacy rises from 2.86 among non-users to 3.45 among free users and 3.81 among paid users. Critical awareness also rises, although the free-to-paid difference is smaller. Paid users are descriptively younger, more highly educated, more frequently IT majors, more often in knowledge-work or student roles, and less often homemakers or unemployed. These patterns are consistent with task-position and opportunity differences, but the cross-sectional profile does not isolate the task and income mechanisms that generate them.

Negative emotions also vary across the ladder. Non-users report the highest mean count, while paid users report more negative emotions than free users. Because paid users simultaneously report the highest practical literacy and benefit expectations, their concern should not automatically be interpreted as rejection. The pattern is consistent with intensive users encountering both the advantages and limitations of GenAI, although the data do not establish whether use generates concern or concern affects use.

Table 4. Descriptive profile of the GenAI adoption ladder.

Variable	Non-User	Free User	Paid User
n (%)	589 (29.5%)	1120 (56.0%)	291 (14.6%)
Practical AI literacy	2.86	3.45	3.81
Critical AI awareness	3.44	3.84	3.98
Expected AI benefits	3.62	3.88	3.93
Hope about AI spread	3.25	3.56	3.75
Negative emotion count	0.77	0.46	0.60
Age 18–29 (%)	10.0	18.9	29.9

Age 60s (%)	32.1	18.1	8.9
College+ (%)	59.8	77.7	85.2
IT major (%)	7.3	11.2	19.2
Knowledge-work/student role (%)	39.4	61.2	74.9
Nonwork (%)	32.9	19.3	6.5

Note. Scale means use the original 1–5 response ranges except negative emotions, which ranges from 0 to 3. Knowledge-work/student role includes office, management, sales, professional/free profession, and college/graduate student. Nonwork includes homemaker and unemployed respondents.

4.2. Practical Literacy Predicts Both Stages, While Critical Awareness Predicts Only Initial Entry

Table 5 presents the sequential logit results. Practical AI literacy is the strongest focal statistical predictor in both equations. A one-standard-deviation increase is associated with more than twice the odds of initial use ($OR = 2.14, p < 0.001$) and nearly twice the odds of paid commitment among users ($OR = 1.97, p < 0.001$). The average marginal effects are 11.8 percentage points for initial use and 9.8 percentage points for paid use. Figure 2 illustrates the adjusted gradient: moving from one standard deviation below to one standard deviation above the mean is associated with predicted initial use rising from 58.7% to 84.5% and predicted paid commitment among users rising from 9.4% to 27.2%.

Critical AI awareness has a different pattern. It is positively associated with initial use ($OR = 1.31, p < 0.001$; $AME = 4.2$ percentage points) but is not associated with paid commitment among users ($OR = 0.95, p = 0.533$). Adjusted predictions place initial use at 66.8% one standard deviation below the mean and 75.5% one standard deviation above it, while paid commitment remains essentially unchanged. These results are consistent with H1 and H2: practical literacy differentiates both observed states, whereas critical awareness differentiates users from non-users but not paid from free users.

Expected AI benefits are positively associated with initial use but not payment. Hope about AI spread is not associated with initial use after adjustment and has a weak positive association with payment. Negative-emotion count is negatively associated with initial use ($OR = 0.78, p < 0.001$) and positively associated with paid commitment among users ($OR = 1.41, p < 0.001$). This sign reversal is consistent with H3 and the affective-feedback interpretation, but it is not evidence that negative emotion causes payment. Intensive use may expose users to both sufficient utility and more system failures, and the reciprocal pathway is also possible.

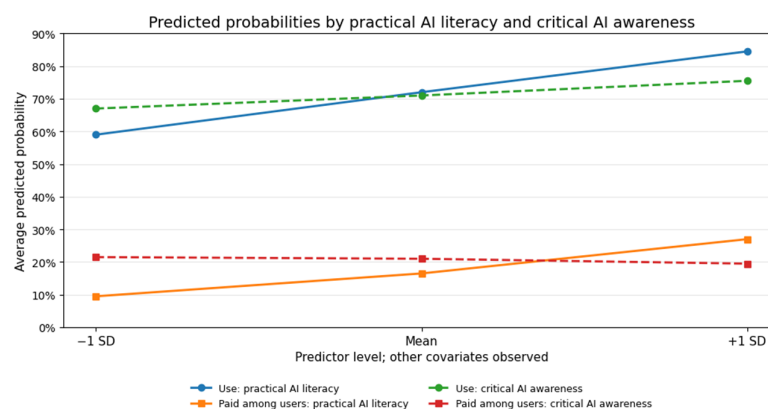


Figure 2. Predicted probabilities by practical AI literacy and critical AI awareness. Note. Predictions are from the sequential logit models. Continuous predictors are set to -1 SD, mean, and $+1$ SD while other covariates remain at their observed values. Paid commitment is predicted among GenAI users only.

Table 5. Sequential logit models of GenAI use and paid commitment.

Predictor	Use OR [95% CI]	Use AME	Paid OR [95% CI]	Paid AME
Practical AI literacy (z)	2.14 *** [1.84, 2.49]	0.118 ***	1.97 *** [1.59, 2.45]	0.098 ***
Critical AI awareness (z)	1.31 *** [1.16, 1.49]	0.042 ***	0.95 [0.79, 1.13]	−0.008
Expected AI benefits (z)	1.22 ** [1.06, 1.42]	0.031 **	0.89 [0.74, 1.08]	−0.016
Hope about AI spread (z)	0.90 [0.78, 1.04]	−0.016	1.20 * [1.01, 1.44]	0.027 *
Negative emotion count (z)	0.78 *** [0.69, 0.88]	−0.038 ***	1.41 *** [1.21, 1.64]	0.050 ***
Age 40s	0.59 ** [0.40, 0.87]	−0.082 **	0.53 ** [0.35, 0.80]	−0.093 **
Age 50s	0.43 *** [0.29, 0.63]	−0.130 ***	0.51 ** [0.33, 0.78]	−0.097 **
Age 60s	0.29 *** [0.19, 0.42]	−0.195 ***	0.37 *** [0.22, 0.62]	−0.144 ***
University	1.86 *** [1.36, 2.55]	0.097 ***	1.07 [0.63, 1.82]	0.010
Graduate school	2.66 *** [1.63, 4.34]	0.152 ***	1.50 [0.78, 2.90]	0.059
IT-related major	1.07 [0.71, 1.60]	0.010	1.46 + [1.00, 2.13]	0.054 +
Knowledge-work/student role	1.37 * [1.03, 1.82]	0.049 *	1.00 [0.69, 1.44]	0.000
Homemaker/unemployed	0.83 [0.60, 1.14]	−0.030	0.42 ** [0.23, 0.75]	−0.126 **
Controls included	Gender, age, education, IT major, occupation		Same controls	
N	2000		1411	
McFadden pseudo-R2	0.217		0.111	

Note. Continuous predictors are standardized. Reference groups: male; age 18–29; high school or below. AME = average marginal effect. McFadden pseudo-R2 is reported for the underlying logistic regression models and should not be interpreted as the proportion of variance explained as in ordinary least squares regression [25]. Significance: +: $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.3. Reported Barriers as System Frictions

Among non-users, the most frequently reported reason for not adopting GenAI is lack of perceived need (51.8%), followed by not knowing how to use it (31.9%), privacy concern (28.2%), cost burden (22.8%), lack of trust in outputs (15.3%), and the belief that AI is unethical (10.7%). These responses indicate that non-use is associated with a mixture of weak task demand, skill limitations, risk-governance concerns, and economic barriers. They are self-reports rather than causal decompositions of non-use.

Among free users, the most common reason for not paying is that the free version is sufficient (53.5%), followed by infrequent use that does not justify payment (41.6%), fee burden (35.3%), privacy concern (12.8%), and payment or cancellation inconvenience (6.8%). The first two responses are consistent with limited marginal utility and task recurrence, while the fee-burden response documents economic friction. These categories overlap, and the absence of direct income and task-frequency measures prevents a clean distinction between inability to pay and lack of task-driven demand.

Figure 3 presents the reported barriers, and Table 6 maps them onto system mechanisms. The results are interpreted as interacting frictions rather than isolated individual rationalizations: weak task demand, capability bottlenecks, risk-governance concerns, economic-access constraints, low marginal utility of premium tiers, insufficient task recurrence, and transaction friction can coexist for the same respondent.

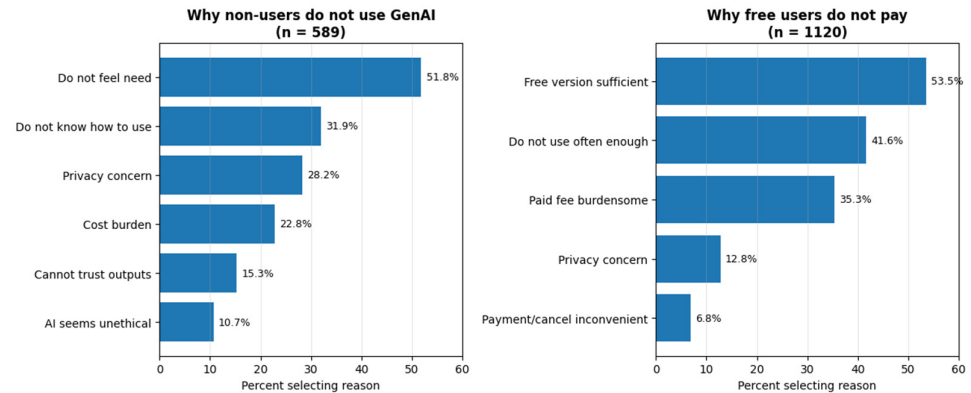


Figure 3. Reported barriers to GenAI non-use and non-payment. Note. Respondents could select multiple reasons. Non-use barriers are calculated among respondents who had not used GenAI in the prior year. Non-payment barriers are calculated among GenAI users who reported free-only use.

Table 6. Reported barriers interpreted as system frictions.

Barrier	Location in Adoption System	System Interpretation
Lack of need	Non-use	Weak task-demand subsystem
Do not know how to use	Non-use	Human capability bottleneck
Privacy concern	Non-use and non-payment	Risk-governance friction
Cost burden or paid fee burdensome	Non-use and non-payment	Economic access constraint
Cannot trust outputs	Non-use	Reliability and risk-calibration friction
AI seems unethical	Non-use	Governance legitimacy concern
Free version sufficient	Non-payment	Low perceived marginal utility of premium tier
Do not use often enough	Non-payment	Insufficient task recurrence
Payment/cancellation inconvenience	Non-payment	Platform transaction friction

4.4. Robustness Checks: Multinomial and Selection-Corrected Models

Table 7 reports two robustness checks and the first-stage selection equation. In the multinomial model, practical literacy is positively associated with both free and paid use relative to non-use, with a substantially larger relative risk ratio for paid use. Critical awareness is associated with both categories relative to non-use, but the sequential model shows that it does not differentiate paid users from free users after the user threshold has been crossed. The distinction illustrates why a binary use indicator and a paid-versus-free comparison answer different questions.

Expected societal diffusion is positively associated with initial use in the first-stage probit ($b = 0.193, p < 0.001$). The inverse Mills ratio is positive and significant in the paid-use equation, indicating non-random selection into the user subsample under the specified selection model. The key focal patterns remain substantively consistent: practical literacy is positively associated with paid commitment, critical awareness is non-significant in the paid-use equation, negative emotion is positively associated with paid commitment among users, and homemaker or unemployed status is negatively associated with paid commitment.

The convergence of these focal interpretations across a sequential logit, a multinomial outcome specification, and a selection-corrected probit provides evidence of model stability with respect to link function, outcome coding, and user-subsample selection. It does not demonstrate causal identification. Nor does it substitute for formal collinearity, leverage, or influence diagnostics, which should accompany the archived replication design

matrix. The robustness claim is therefore limited to specification sensitivity supported by the reported models.

Table 7. Robustness checks: multinomial logit and selection-corrected probit with first-stage selection equation.

Predictor	MNL: Free vs. Non-User RRR	MNL: Paid vs. Non-User RRR	First-Stage Probit: GenAI Use (b)	Selection-Corrected Probit: Paid Use (b)
Practical AI literacy (z)	1.95 ***	3.87 ***	0.473 ***	0.583 ***
Critical AI awareness (z)	1.32 ***	1.27 *	0.113 **	0.019
Expected AI benefits (z)	1.24 **	1.08	0.001	−0.042
Hope about AI spread (z)	0.88 +	1.05	−0.051	0.088 +
Negative emotion count (z)	0.74 ***	1.01	−0.148 ***	0.137 **
Female	1.23 +	1.18	0.099	0.048
Age 30s	0.95	0.96	−0.006	−0.023
Age 40s	0.66 *	0.37 ***	−0.284 *	−0.469 ***
Age 50s	0.48 ***	0.27 ***	−0.509 ***	−0.562 ***
Age 60s	0.33 ***	0.13 ***	−0.753 ***	−0.878 ***
Two-year college	1.57 *	1.21	0.260 *	−0.031
University	1.86 ***	1.95 *	0.358 ***	0.221
Graduate school	2.53 ***	3.56 ***	0.570 ***	0.478 *
IT-related major	1.00	1.39	0.018	0.192 +
Knowledge-work/student role	1.36 *	1.38	0.179 *	0.085
Homemaker/unemployed	0.89	0.38 **	−0.111	−0.543 ***
Expected societal diffusion (z)	—	—	0.193 ***	—
Inverse Mills ratio	—	—	—	1.065 **
N	2000	2000	2000	1411

Note. MNL = multinomial logit. RRR = relative risk ratio. Columns 4 and 5 report raw probit coefficients, not odds ratios or relative risk ratios, and should not be compared numerically with the MNL RRR estimates. The first-stage probit models initial GenAI use and includes expected societal diffusion of AI as the exclusion variable. The paid-use probit includes an inverse Mills ratio derived from that first-stage model. “—” indicates that the variable was not included in the corresponding model. Significance: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5. Discussion

5.1. Theoretical Contribution: A Tier-Mediated Premium Second-Level Divide

The findings advance digital-divide and socio-technical systems research by identifying paid commitment as a post-access stratification outcome. Free GenAI access reduces the visibility of a basic access divide but does not guarantee equivalent quality, reliability, capacity, autonomy, or workflow integration. The premium digital divide is conceptually novel because it specifies a commercial tiering mechanism that operates inside the population of existing users. It is not a fourth divide and is not synonymous with all differentiated use. Rather, it is a platform-mediated extension of second-level inequality through which differences in capability, recurring task demand, resources, and institutional support can be translated into unequal access to advanced system capacities.

This positioning also clarifies the relationship to third-level digital-divide outcomes. Payment is not itself a labor-market, educational, civic, or economic benefit. Premium or

institutionally supported access may, however, become an intermediate pathway to such outcomes when it enables more reliable task integration, higher usage intensity, or functions unavailable on free tiers. Whether those capacities generate realized benefits depends on the user's skills, tasks, institutional environment, and ability to evaluate outputs. Future research should therefore distinguish access, free experimentation, paid or institutional premium access, task integration, and realized outcomes rather than treating payment as evidence of advantage by itself.

The framework complements established technology-adoption models. The Technology Acceptance Model emphasizes perceived usefulness and perceived ease of use; UTAUT integrates performance expectancy, effort expectancy, social influence, and facilitating conditions; and UTAUT2 adds price value, hedonic motivation, and habit for consumer settings [34–36]. These models explain important antecedents of intention and use. The present study shifts attention to a post-access outcome within a commercially tiered platform architecture: paid commitment after initial GenAI use. Individual perceptions remain important, but they are embedded in platform feature allocation, recurring task environments, fee burdens, institutional access, and affective feedback. The contribution is thus a systems-level explanation of why usefulness, performance expectancy, or capability may be necessary yet insufficient for paid commitment.

5.2. Practical AI Literacy as a Capability Subsystem

Practical AI literacy is positively associated with both initial use and paid commitment. From a systems perspective, it functions as a capability subsystem that helps users identify platform affordances, formulate effective prompts, integrate outputs into workflows, compare free and premium tiers, and assess marginal value. Users with greater practical literacy may be better positioned to convert technical functions into task value. The cross-sectional design cannot determine how much of this association reflects literacy preceding use and how much reflects learning through use.

The policy implication is double-edged. Practical-literacy programs can enhance meaningful participation, yet they may also deepen stratification when they primarily benefit high-resource groups already located in AI-relevant task environments. Broad public training should therefore be paired with targeted access pathways for groups whose task needs are socially important but whose economic or institutional resources are constrained.

5.3. Critical Awareness, Calibrated Distrust, and Deliberate Non-Payment

Critical AI awareness is associated with initial use but not with payment among users. This does not imply that critical awareness is unimportant. It can function as risk-governance capacity by improving the intelligibility of AI systems and supporting evaluation of hallucinations, bias, privacy risks, copyright issues, and ethical boundaries. These capacities may make experimentation safer without creating the recurring task utility or economic rationale required for payment.

The non-significant payment association may also reflect deliberate non-payment among some critically aware users. People can perceive value in GenAI while limiting data exposure, resisting dependence on one provider, avoiding platform lock-in, or preserving flexibility across services. This possibility adds nuance to the AI trust paradox: active use can coexist with calibrated distrust and continued scrutiny [25]. The survey does not directly measure lock-in concerns, provider switching, or intentional refusal to subscribe, so this account remains a plausible interpretation rather than a tested mechanism.

AI literacy policy should therefore combine practical competence with critical judgment. Programs focused only on productivity or prompt engineering may increase paid

adoption among users already positioned to benefit. Programs focused only on critique may support caution without improving task capability or access. A socio-technical approach requires both elements and should provide institutional routes to secure use where individual commercial payment is not appropriate.

5.4. Vigilant Paid Use as Feedback from Intensive System Interaction

Negative emotions are negatively associated with initial use and positively associated with paid commitment among users. Paid users are not necessarily uncritical enthusiasts; they may encounter more hallucinations, privacy trade-offs, model inconsistency, output instability, and verification burdens because their use is more frequent or consequential. The pattern is consistent with vigilant intensity rather than simple resistance, but reverse causality remains possible and the data do not establish an emotional pathway to payment.

Platform designers and public agencies should not treat concern among active users as a failure of adoption. Concern can identify experienced users who understand both benefits and limitations. Source-verification tools, transparent data practices, deletion controls, model-limit explanations, privacy protections, and clearer tier information can make that concern actionable. The objective is calibrated rather than maximal trust [37–39].

5.5. Platform Heterogeneity and Scope of Generalization

The study aggregates consumer-facing services such as ChatGPT, Claude, Gemini, and Perplexity into one analytical environment. This is useful for identifying broad post-access stratification, but it limits platform-level generalization. Services and subscription packages can differ in price, usage limits, model quality, multimodal capacity, context windows, search or citation functions, coding performance, productivity-suite integration, privacy arrangements, and target users. A recurring coding task may be particularly relevant to payment for one service, while document processing, search, multimodal creation, or ecosystem integration may matter more for another.

The reported coefficients should therefore be read as average associations across the South Korean consumer GenAI environment, not as evidence that every platform has the same determinants or effect magnitudes. Future surveys should record the platform and package used, the payer, institutional licensing, multiple subscriptions, specific premium functions, task types, use frequency, and realized outcomes. Platform-level or multi-platform models could then test whether literacy, task demand, fee burden, trust, and critical awareness operate differently across service architectures.

5.6. System-Level Interventions

Because the premium divide is associated with multiple subsystems, policy should extend beyond individual literacy or affordability. Interventions should address human capability, institutional access, platform transparency, privacy protection, and the measurement of meaningful access. Market subscriptions may distribute productivity or learning opportunities unevenly when only some users can integrate GenAI into high-quality routines.

First, governments and public institutions should consider a universal basic AI competence program covering practical use, evaluation of hallucinations and bias, privacy and copyright, and domain-specific applications for job seeking, small business, lifelong learning, education, and public-service navigation. Delivery should extend beyond universities and firms to libraries, employment centers, local governments, senior-learning centers, and community organizations.

Second, institutional access can reduce economic barriers without requiring universal public funding of individual commercial subscriptions. Libraries, universities, em-

ployment centers, and public agencies could provide secure premium or high-capacity access for job seekers, small businesses, older workers changing careers, students from low-resource households, and local public servants. Institutional procurement can also impose stronger privacy, security, and accountability standards than fragmented individual subscriptions.

Third, platform transparency and risk-governance tools should be treated as inclusion infrastructure. Users need clear information about premium features, applicable privacy protections, data deletion, output-verification needs, known limitations, billing, and cancellation. Source-checking tools, citation support, and explanations of model limits can support responsible participation across both free and paid tiers.

Fourth, AI inclusion dashboards should measure more than experimentation. Indicators should include frequency of use, task integration, individual or institutional premium access, confidence in evaluating outputs, perceived financial burden, privacy concern, and access to secure tools in education, work, and public services. A dashboard limited to whether a person has ever tried GenAI can overstate inclusion in a freemium environment.

6. Limitations and Future Research

The analysis is cross-sectional and associational. The sequential equations characterize observed states and conditional survey routing, not temporal transitions. Reverse causality is plausible for literacy, perceived benefits, trust calibration, emotion, and payment, and omitted variables may affect both the predictors and outcomes. Randomized longitudinal panels or quasi-experimental access designs, natural experiments involving institutional licenses, platform logs, and linked administrative data are needed to assess direction, feedback loops, and causal effects.

Direct income data are absent. Education, occupation, IT major, nonwork status, and subjective fee burden provide partial information but cannot disentangle resource constraints from task-driven demand. The fact that 35.3% of free users report fee burden documents economic friction, while the greater frequency of ‘free version sufficient’ and ‘do not use often enough’ documents perceived marginal utility and task recurrence. These responses should not be treated as mutually exclusive or as a causal decomposition. Future surveys should measure household and disposable income, wealth, price sensitivity, employer reimbursement, institutional licensing, task frequency, and willingness to pay at different prices.

Paid commitment is an imperfect proxy for premium access. The study cannot differentiate individual payment, employer-supported payment, institutional access, shared accounts, subscription package, platform type, multiple subscriptions, or actual intensity of use. Some free users may obtain high-quality institutional access, while some paid users may use a service infrequently. Future work should measure who pays, what functions are available, how often they are used, which tasks are supported, and what outcomes are achieved.

Platform aggregation may conceal heterogeneous determinants. Pricing, capabilities, multimodality, privacy, integration, and target users vary across services and can change the relevance of literacy, task demand, trust, and fee burden. Platform-specific samples and multilevel or choice-based designs are required to separate ecosystem-wide patterns from service-specific effects.

The selection correction relies on an exclusion restriction that is theoretically plausible but not experimentally verified. Beliefs about societal diffusion may stimulate awareness and trial, yet they could also influence subscription. The significant inverse Mills ratio and stability of focal patterns across specifications are informative but do not establish causal identification. Formal term-level collinearity, leverage, and influence diagnostics

could not be reconstructed from the archived model output and should be reported when the replication design matrix is available. This remains a statistical-reporting limitation.

Finally, the system boundary is national. South Korea is analytically valuable because of its advanced infrastructure and active AI policy debate, but cross-national research is required to determine how platform tiers interact with welfare regimes, educational systems, labor markets, data-protection arrangements, and institutional access. Future work should also directly measure third-level educational, occupational, economic, civic, and well-being outcomes rather than assuming that paid access automatically produces them.

7. Conclusions

The diffusion of GenAI is often characterized as democratizing because free tools are widely available. The South Korean survey shows why that characterization is incomplete. Most respondents reported GenAI use, but a much smaller group reported paid access. Practical AI literacy, age, education, and nonwork status are associated with positions on the adoption ladder. Critical AI awareness differentiates use from non-use but not paid from free use among users. Paid users also report more negative emotion than free users, a pattern consistent with vigilant and intensive engagement rather than simple enthusiasm.

The premium digital divide is best understood as a tier-mediated extension of second-level digital inequality, not a fourth divide and not a realized third-level outcome. It arises within the user population when platform tiers interact with capability, task demand, economic access, affective feedback, and institutional context. Premium or institutionally supported access may become a pathway to later productivity, learning, or civic benefits, but the present cross-sectional analysis does not demonstrate that pathway causally.

Addressing unequal participation in a market-tiered AI ecosystem requires system-level interventions: broad practical and critical competence, secure institutional access, platform transparency, privacy safeguards, and indicators of meaningful use. Freemium GenAI services should consequently be examined not only as consumer technologies but also as socio-technical systems that structure participation in an emerging AI society.

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Informed Consent Statement: The authors did not obtain informed consent directly because they did not administer the original survey. Consent and respondent-protection procedures for the original survey were handled by the survey administrator. The authors analyzed only de-identified secondary data and had no access to identifiable respondent information.

Data Availability Statement: This study analyzes a 2025 South Korean survey response matrix and questionnaire on public perceptions of AI issues and policy, commissioned by the National Information Society Agency. The authors were granted access to the de-identified analytic file for secondary analysis. The dataset is not publicly redistributed because it is subject to source restrictions.

De-identified coding materials and replication syntax may be made available upon reasonable request, subject to permission from the data owner and applicable ethical or contractual restrictions.

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Appendix A

Table A1. Full coding notes for key variables.

Variable(s)	Role	Coding Note
QC02	Recent GenAI use	1 = used; 2 = not used. Converted to binary use = 1 when QC02 = 1.
QC02-2	Paid use	Asked only of GenAI users. 1 = paid use; 2 = not paid. Converted to paid commitment among users.
QC02-3	Reasons for non-use	Multiple response among non-users: know-how, trust, need, cost, privacy, ethics, other.
QC02-4	Reasons for non-payment	Multiple response among free users: fee burden, free version sufficient, payment/cancellation inconvenience, privacy, insufficient frequency, other.
QC01-1 to QC01-5	Practical literacy	Mean of five items, alpha = 0.84.
QC01-6 to QC01-7	Critical awareness	Mean of two items, alpha = 0.62; inter-item r = 0.45; Spearman-Brown = 0.62.
DQ1/DQ1-1/DQ2	SES and task-position proxies	Education, IT-related major, occupation, knowledge-work/student role, homemaker/unemployed status.

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