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Multidimensional Digital Conditions among Undergraduates in Shandong, China

Xinyue Kang

Department of Educational Studies, Faculty of Human Development, Universiti Pendidikan Sultan Idris (UPSI), Perak, Malaysia

Norazlin Mohd Rusdin

Department of Educational Studies, Faculty of Human Development, Universiti Pendidikan Sultan Idris (UPSI) Tanjong Malim, Perak, Malaysia

Email: norazlin@fpm.upsi.edu.my

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Abstract

University enrolment does not establish equally favourable conditions for digital participation. This cross-sectional study examined physical, motivational, skills, and usage access among 616 undergraduates recruited through eighteen universities in Shandong, China. A student-adapted access measure retained 53 items following measurement assessment. Item-level data were used to recompute scores and internal consistency, compare domains using repeated-measures analysis, and examine overall-score differences by gender, academic year, and field. Overall digital conditions averaged 3.673 on a five-point scale (SD = 0.565). Physical access averaged 3.794, motivational access 3.756, skills access 3.595, and usage access 3.547. The Greenhouse–Geisser-corrected domain effect was significant, $F(2.80, 1721.06) = 35.97$, $p < .001$, partial $\eta^2 = .055$. Holm-adjusted comparisons showed higher physical and motivational ratings than skills and usage ratings, but no significant physical–motivational or skills–usage contrast. An academic-year difference remained significant after adjustment across the three demographic tests; Games–Howell comparisons showed higher first-year scores than those of each later year. Gender and field differences were not significant. The findings support examining resources, capabilities, and participation separately and considering year-specific support needs. Voluntary online recruitment, self-report measurement, possible institutional clustering, and cross-sectional comparisons limit population and developmental interpretations.

Keywords: Digital Conditions, Digital Divide, Digital Access, Undergraduate Students, Higher Education, China

Introduction

Digital participation in higher education depends on more than an Internet connection. Students need suitable resources, reasons to engage, capabilities for completing academic tasks, and opportunities to use technologies meaningfully. Digital divide scholarship has consequently expanded from binary distinctions between users and non-users towards

differences in skills, practices, and the benefits obtained from participation (Scheerder et al., 2017; van Dijk, 2020). This broader perspective makes it necessary to ask what conditions students actually report, even when they are already enrolled in universities and routinely encounter digital learning requirements.

The expansion of the concept does not render material resources unimportant. Van Deursen and van Dijk (2019) showed why first-level access must encompass the quality and range of material provision rather than connectivity alone. Lythreatis et al. (2022) likewise documented the varied forms and determinants of digital inequality. Together, these contributions support examining several access domains without assuming that progress in one domain resolves difficulties in others. For universities, an adequate account should distinguish the availability of technology from students' willingness, capabilities, and participation.

Higher education research also challenges assumptions of uniform competence among young adults. Hargittai (2010) identified variation in Internet skills and uses within the so-called net generation. More recent undergraduate research has examined ICT learning challenges in Bangladesh and demographic differences in digital literacy and support in the United Kingdom (Aziz & Hossain, 2024; Zhou et al., 2025). These contributions establish that student populations are heterogeneous, but they address different aspects of participation. They leave a specific question for the present analysis: how do physical, motivational, skills, and usage ratings compare within the same undergraduate sample, and how does the overall profile vary across student groups? Section 2.3 develops this gap through a comparison of the purposes, measures, and populations of previous studies.

The present article uses digital conditions to denote students' reported physical, motivational, skills, and usage access. This terminology makes the scoring direction explicit: higher scores indicate more favourable conditions, not a larger digital divide. Digital divide theory provides the interpretive framework, while the empirical focus is a multidimensional description of access. The study does not classify students as digitally excluded or assume that a mean above the response midpoint establishes adequate participation.

Three questions guide this exploratory analysis. First, what overall and domain-level digital conditions do the participating undergraduates report? Second, do their mean ratings differ across physical, motivational, skills, and usage access? Third, does the overall digital-condition score differ by gender, academic year, or academic field? These questions connect multidimensional description with focused comparisons. They concern general digital conditions rather than relationships with generative AI literacy or technology anxiety. Because the comparisons were developed after the wider survey, they are treated as exploratory rather than preregistered hypothesis tests.

Conceptual Background

Access as a multidimensional educational condition

Van Dijk's (2005, 2020) framework distinguishes motivational, material or physical, skills, and usage access. These domains direct attention to different requirements of technological participation. Physical access concerns resources and infrastructure; motivational access concerns willingness and perceived value; skills access concerns what people can do with

technologies; and usage access concerns participation in digital activities. Their theoretical relationship supports examining them together, but a cross-sectional description cannot establish that individuals pass through a fixed developmental sequence.

For educational interpretation, it is useful to retain the distinction between conditions, participation, and benefits. Scheerder et al. (2017) reviewed research on skills, uses, and outcomes, whereas van Deursen and van Dijk (2014) examined differences in Internet use. Neither participation frequency nor possession of a device should therefore be treated as a direct measure of educational benefit. In this article, digital conditions describe an access-related foundation. Academic performance, learning gains, and wider benefits are outside the measured outcomes.

The measurement approach draws on the Faculty's Information and Communication Technology Access instrument, or FICTA. Soomro et al. (2018) developed a 57-item instrument with eight subcomponents across four broad access domains among higher education faculty. Soomro et al. (2020) subsequently applied it to examine faculty digital inequalities. Its domain coverage is relevant to a broad account of university technology participation. However, adapting faculty-oriented items for undergraduates and using a common agreement scale creates a distinct operationalisation requiring evaluation in the new population.

Digital participation within university populations

Student status does not eliminate differences in access environments or learning demands. Aziz and Hossain (2024) investigated undergraduate digital access, resources, and ICT learning challenges in Bangladesh. Ajani (2025) examined learning management system experiences in a rural South African university. Although these contexts differ from Shandong, both studies show the usefulness of connecting access questions with students' educational activities. Their contribution here is contextual rather than a basis for transferring specific prevalence estimates.

Zhou et al. (2025), surveying 595 students in two UK business schools, considered demographic differences in digital literacy and support. Their study illustrates why institutional membership and year of study may warrant attention alongside resources and skills. The present analysis examines gender, academic year, and field as separate grouping characteristics, without assuming that these categories cause digital differences. Within-person domain contrasts and between-group comparisons answer different questions: the former describe the shape of an access profile, whereas the latter examine whether overall scores vary among student categories.

A multidimensional description can still inform institutional enquiry. A comparatively favourable resource mean alongside lower skills or usage ratings may justify examining whether available technologies are easy to apply to academic tasks. Conversely, lower usage ratings could reflect curriculum requirements, personal preferences, or restricted opportunities rather than inability. Domain scores are therefore starting points for investigation, not diagnoses of individual deficits. The substantive interpretation must remain tied to the content and limitations of the questionnaire.

Research gap and contribution

The studies reviewed above establish the importance of digital inequality, but their different analytical purposes leave a specific evidential gap. Van Deursen and van Dijk (2019) show that material access extends beyond an Internet connection, while van Deursen and van Dijk (2014) examine inequalities in Internet use. These contributions explain why resources and participation require separate attention. However, evidence about material provision or patterns of use does not, by itself, establish whether physical, motivational, skills, and usage access receive similar ratings within the same undergraduate population. The unresolved issue is therefore the relative configuration of these theoretically distinct conditions, rather than whether digital inequality exists.

Undergraduate studies provide complementary but differently bounded evidence. Aziz and Hossain (2024) use semi-structured interviews to explain ICT learning experiences and challenges in Bangladesh. This approach illuminates how students encounter barriers, but it does not estimate the magnitude of paired differences between four access-domain scores. Ajani (2025) focuses on learning management system experiences in a rural South African university; this platform-specific setting offers insight into educational participation, but does not supply a general four-domain comparison for students across different fields in Shandong. Zhou et al. (2025) extend the evidence through a survey of 595 students in two UK business schools, examining demographic differences in digital literacy and support. Their findings justify attention to student heterogeneity, but their disciplinary setting and measures do not establish the access profile of undergraduates spanning humanities, natural sciences, and engineering in the present context.

A related distinction concerns the level of comparison. Differences between demographic groups and differences between domains within students answer separate questions. A group comparison can identify variation in an overall score without showing whether resources, motivation, skills, and usage are similarly rated. Conversely, a domain profile cannot establish whether overall conditions differ by gender, academic year, or field. The reviewed studies motivate both questions, but their findings cannot be combined into a single within-sample estimate because their populations and operationalisations differ. Although the FICTA instrument offers four-domain coverage, its development and subsequent application concerned faculty (Soomro et al., 2018, 2020); undergraduate adaptation therefore requires explicit measurement qualification rather than an assumption that faculty-based evidence transfers unchanged.

The present study addresses this gap by examining four access domains together among 616 undergraduates recruited through eighteen universities in Shandong. It combines domain-level description, paired comparisons within respondents, and exploratory demographic comparisons of an equally weighted overall score. Its contribution is to distinguish the shape of reported digital conditions from variation between student categories within one dataset. This provides context-specific evidence relevant to the allocation of university support, without claiming a new digital divide theory, population-representative estimates, objective competence measurement, or causal explanations of group differences.

Methods

Design and relationship to the wider survey

This article reports an exploratory cross-sectional analysis of digital conditions from a wider doctoral survey of undergraduates in Shandong Province, China. Data collection took place from 14 April to 12 June 2026. The present article addresses general digital access and its domain and demographic differences. Digital-condition scores, reliability coefficients, and comparative analyses were computed from the retained respondents' item-level data.

Recruitment and participants

The target population comprised full-time undergraduates aged eighteen years or above. The institutional sampling frame contained 72 undergraduate institutions. Institutions were stratified by location into Eastern, Central, and Western Shandong, containing 24, 36, and 12 institutions, respectively. Proportionate institutional selection yielded eighteen universities: six, nine, and three from the respective regions. Within participating universities, contacts distributed the online questionnaire through institutional and class-based communication channels. Student participation was voluntary. Regional allocation of institutions did not establish proportional or random sampling of individual students.

The final sample comprised 616 undergraduates. Table 1 presents its composition. The sample covered all four undergraduate years and humanities, natural sciences, and engineering. These characteristics describe the respondents rather than demonstrate representativeness of the provincial undergraduate population. Institutional and regional comparisons were not undertaken.

Table 1
Participant characteristics

Characteristic	Category	n	%
Gender	Male	315	51.1
Gender	Female	301	48.9
Academic year	First	219	35.6
Academic year	Second	159	25.8
Academic year	Third	144	23.4
Academic year	Fourth	94	15.3
Academic field	Humanities	228	37.0
Academic field	Natural sciences	202	32.8
Academic field	Engineering	186	30.2

Note. N = 616. Percentages may not sum to 100 because of rounding.

Instrument adaptation and scoring

Digital conditions were measured using a student-adapted FICTA instrument based on Soomro et al. (2018, 2020). The administered measure contained 57 items addressing physical access (13 items), motivational access (8), skills access (19), and usage access (17). Wording

was contextualised to undergraduate learning and academic activities. The original physical-access checklist and the response formats used for other domains were harmonised into five-point agreement responses, from 1 (strongly disagree) to 5 (strongly agree). This adaptation was not treated as an unchanged reproduction of the original instrument.

Two bilingual researchers independently translated the English access items into Chinese. Discrepancies were discussed, and a separate bilingual expert back-translated the reconciled version to examine semantic equivalence. A pilot involving 64 respondents preceded the main survey. Measurement assessment in the main sample resulted in removal of four items, leaving 53 indicators: 12 physical, 6 motivational, 19 skills, and 16 usage items. The two negatively worded access items, Q18 and Q27 in the full questionnaire, were reverse-scored before score calculation.

Domain scores were calculated as means of their retained items. The overall score was the mean of the four domain scores, thereby giving each domain equal weight despite unequal item counts. Higher scores represented more favourable reported digital conditions. The overall score was a descriptive composite; it was not a latent factor score. No externally validated cutoffs were available to classify students as digitally advantaged, disadvantaged, or excluded. The scale midpoint was used only as a descriptive reference.

Ethics and response screening

The wider survey received approval from the Human Research Ethics Committee of Universiti Pendidikan Sultan Idris. Prospective participants received information about eligibility, study purpose, voluntary participation, and confidentiality before consenting to complete the questionnaire. Findings are reported in aggregate form.

Of 852 submissions, ten were excluded because their IP locations fell outside Shandong. A further 148 were excluded for forty or more consecutive identical responses across the eighty substantive survey items. Review of five negatively worded items across the wider questionnaire identified 55 submissions with three or more content-based inconsistencies. Another 23 submissions with one or two inconsistencies were excluded when completion time was below 120 seconds or more than thirty consecutive identical responses were present. Each exclusion was counted once. The remaining 616 cases represented 72.3% of submissions; this is a retention proportion, not a response rate. Screening concerned the wider survey and therefore included items not analysed in this article. These operational rules may influence the retained sample and were not treated as definitive tests of respondent attentiveness (Meade & Craig, 2012).

Analysis

The original survey was managed in IBM SPSS Statistics 30, and its measurement models were assessed in AMOS 31. For this focused analysis, the SPSS data file was imported with pyreadstat 1.3.7, and score calculations and statistical comparisons were conducted in Python using SciPy 1.17.0 and Pingouin 0.7.0 (Vallat, 2018). All five reverse-coded variables in the wider file were checked against 6 minus their original responses. The 53 retained access items and three demographic variables contained no missing values. Means, SDs, observed ranges, pointwise 95% confidence intervals, and Cronbach's alpha described the scores. Confidence

intervals and tests were calculated under an individual-observation model and were not adjusted for institutional clustering.

A one-factor repeated-measures ANOVA compared the four domain means within students. Because Mauchly's test indicated a sphericity violation, Greenhouse–Geisser correction was applied (Greenhouse & Geisser, 1959). Six paired t tests were followed by Holm adjustment within the domain-comparison family (Holm, 1979). Paired contrasts report mean differences, pointwise 95% confidence intervals, and Cohen's dz, calculated using the SD of the within-person difference. These contrasts describe ratings of different content domains on a common response scale; they do not compare equivalent objective abilities. A Friedman test was used as a sensitivity analysis for the overall domain pattern.

Overall-score differences were examined using a Welch t test for gender and Welch ANOVAs for academic year and field, accommodating unequal group variances. Holm correction was applied across these three demographic tests. A significant adjusted omnibus result was followed by Games–Howell comparisons, which accommodate unequal sample sizes and variances (Games & Howell, 1976). Their p-values and confidence intervals were adjusted within the relevant pairwise family. Independent-group contrasts use Hedges' g, signed as the first group minus the second. Pairwise tests were two-sided, and the significance level was .05. Group tests were unadjusted for other demographic characteristics; they do not estimate independent demographic effects.

The previously fitted four-factor access model supplied measurement context (CFI = .958; TLI = .956; RMSEA = .033). Its item refinement removed Q10, Q22, Q23, and Q46 from the 57 administered items. The current report does not re-estimate or independently validate that factor model. Cronbach's alpha was recalculated from the current retained-item data. The earlier physical-access AVE of .498 indicates that convergent evidence for that domain remains qualified. Model fit and reliability address different aspects of measurement and do not establish cross-group equivalence (Fornell & Larcker, 1981; Marsh et al., 2004).

Results

Overall and domain-level digital conditions

The overall digital-condition mean was 3.673 (SD = 0.565; 95% CI [3.628, 3.718]), with observed values from 1.86 to 5.00. All domain means exceeded the response midpoint (Table 2). Physical access had the highest numerical mean, followed by motivation, skills, and usage. Cronbach's alpha was .968 across the 53 retained items and ranged from .880 to .961 across domains. These coefficients describe item consistency, not the magnitude of a digital divide or evidence that all domains measure an identical attribute.

Table 2
Digital-condition scores and recomputed internal consistency

Score	Mean	SD	95% CI	Range	Alpha
Overall	3.673	0.565	[3.628, 3.718]	1.86–5.00	.968
Physical access	3.794	0.644	[3.743, 3.845]	1.33–5.00	.922
Motivational access	3.756	0.729	[3.699, 3.814]	1.00–5.00	.880
Skills access	3.595	0.677	[3.541, 3.649]	1.32–5.00	.954
Usage access	3.547	0.785	[3.485, 3.609]	1.44–5.00	.961

Note. N = 616. Overall = mean of the four retained-item domain means; domain item counts are 12, 6, 19, and 16. Confidence intervals are pointwise and do not account for institutional clustering. Alpha was recomputed from the item-level responses.

Usage access had the greatest dispersion (SD = 0.785), while physical access had the smallest domain-level dispersion (SD = 0.644). Low observed scores were present even though overall means were comparatively favourable. Summary statistics do not identify which individuals experienced multiple difficulties, nor do they estimate the prevalence of exclusion. The recomputed scores reproduced the corresponding descriptive statistics in the wider study.

Skewness was negative for the overall score and each domain, consistent with a tendency towards more favourable ratings. Physical access showed the most negative skewness (−0.961) and the largest kurtosis (1.460). These composite-score summaries do not establish item-level multivariate normality or exclude response-style effects. They also cannot determine how closely reported conditions correspond to observed performance or independently verified resources.

Differences across access domains

Mauchly's test indicated a sphericity violation, $W = .905$, $p < .001$. With Greenhouse–Geisser $\varepsilon = .933$, the repeated-measures domain effect was significant, $F(2.80, 1721.06) = 35.97$, $p < .001$, partial $\eta^2 = .055$. A Friedman sensitivity test also detected domain differences, $\chi^2(3) = 72.56$, $p < .001$, Kendall's $W = .039$. The rank-based result supports the presence of a domain pattern without equating the two tests' effect-size measures.

Holm-adjusted paired comparisons showed that physical access exceeded skills and usage access and that motivational access likewise exceeded both (all adjusted $p < .001$; Table 3). Physical and motivational access did not differ significantly (adjusted $p = .228$), and neither did skills and usage access (adjusted $p = .228$). The significant paired differences ranged from 0.162 to 0.247 points on the five-point scale, with dz from 0.250 to 0.336. The largest contrast was physical versus usage access. These magnitudes warrant attention without establishing a threshold of educational inadequacy.

Table 3
Paired comparisons of digital-access domain scores

Contrast	Mean diff.	95% CI	t	p Holm	dz
Physical − Motivation	0.037	[-0.014, 0.089]	1.42	.228	0.057
Physical − Skills	0.199	[0.149, 0.248]	7.89	< .001	0.318
Physical − Usage	0.247	[0.189, 0.305]	8.35	< .001	0.336
Motivation − Skills	0.162	[0.110, 0.213]	6.21	< .001	0.250
Motivation − Usage	0.209	[0.146, 0.273]	6.46	< .001	0.260
Skills − Usage	0.048	[-0.012, 0.107]	1.58	.228	0.064

Note. Every paired t test has df = 615. Holm correction covers the six domain contrasts. Confidence intervals are unadjusted pointwise 95% intervals; decisions use the adjusted p-values. Positive differences indicate higher scores for the first domain. dz uses the SD of paired differences.

Demographic differences in overall digital conditions

Table 4 presents overall digital conditions by demographic category. After Holm correction across the three demographic tests, academic year differed significantly, Welch F(3, 299.32) = 8.51, adjusted p < .001. First-year students had the highest mean (3.820), followed by fourth-year (3.632), third-year (3.619), and second-year students (3.543). This is a cross-sectional comparison of different students, not an estimate of within-student change.

Table 4
Overall digital conditions by demographic category

Factor	Group	n	Mean	SD	95% CI
Gender	Male	315	3.655	0.601	[3.588, 3.722]
Gender	Female	301	3.692	0.525	[3.632, 3.752]
Academic year	First year	219	3.820	0.523	[3.751, 3.890]
Academic year	Second year	159	3.543	0.653	[3.441, 3.645]
Academic year	Third year	144	3.619	0.555	[3.528, 3.711]
Academic year	Fourth year	94	3.632	0.433	[3.543, 3.721]
Field	Humanities	228	3.697	0.482	[3.634, 3.760]
Field	Natural sciences	202	3.623	0.574	[3.544, 3.703]
Field	Engineering	186	3.698	0.643	[3.605, 3.791]

Note. Gender: Welch t(609.27) = −0.81, raw p = .417, Holm-adjusted p = .619. Academic year: Welch F(3, 299.32) = 8.51, raw and adjusted p < .001. Field: Welch F(2, 385.54) = 1.18, raw p = .310, adjusted p = .619. Intervals are pointwise and not cluster-adjusted.

Games–Howell follow-up comparisons showed that first-year students scored higher than second-year students (difference = 0.277, adjusted p < .001, g = 0.477), third-year students

(difference = 0.201, adjusted p = .004, g = 0.374), and fourth-year students (difference = 0.188, adjusted p = .006, g = 0.377). Comparisons among second-, third-, and fourth-year students were not significant (all adjusted p ≥ .561; Table 5).

Table 5
Games–Howell comparisons between academic years

Contrast	Mean diff.	Adjusted 95% CI	p GH	Hedges g
Year 1 − Year 2	0.277	[0.116, 0.439]	< .001	0.477
Year 1 − Year 3	0.201	[0.051, 0.351]	.004	0.374
Year 1 − Year 4	0.188	[0.041, 0.336]	.006	0.377
Year 2 − Year 3	-0.077	[-0.256, 0.103]	.688	-0.125
Year 2 − Year 4	-0.089	[-0.266, 0.088]	.561	-0.153
Year 3 − Year 4	-0.013	[-0.179, 0.154]	.997	-0.025

Note. Games–Howell adjusts the six pairwise year comparisons for unequal variances and sample sizes. Confidence intervals and p-values use the studentized-range distribution. Positive effects indicate higher scores in the first-listed year.

Gender differences were not significant, Welch t(609.27) = −0.81, raw p = .417, Holm-adjusted p = .619. The male–female mean difference was −0.037 (pointwise 95% CI [−0.126, 0.052]; Hedges' g = −0.065). Field differences were also not significant, Welch F(2, 385.54) = 1.18, raw p = .310, Holm-adjusted p = .619. Natural sciences had a numerically lower mean than humanities and engineering, but this pattern was not supported by the omnibus test. Nonsignificant results do not establish equivalence or rule out differences within particular domains.

Discussion

Interpreting a favourable but differentiated profile

The participating students reported digital conditions above the response midpoint, with significant differences between particular access domains. The paired comparisons refine the descriptive ranking: physical and motivational ratings were higher than skills and usage ratings, while contrasts within each of those pairs were not significant. The result is therefore more specific than a four-step hierarchy. The effect sizes and mean differences indicate a discernible but limited separation, not evidence that students lack skills or that their educational participation is inadequate.

This interpretation is compatible with the broader move from connectivity towards differentiated participation in digital divide research (Lythreatis et al., 2022). Physical provision remains a necessary object of enquiry, but resource availability and academic capability require separate evidence. The present findings identify an access profile in one voluntarily recruited sample. They cannot establish the prevalence of disadvantage across Shandong or rank the participating universities. The term digital conditions is consequently more precise for these results than a claim to have measured the size of a provincial digital divide.

Resources and willingness require opportunities for application

The significant contrasts suggest that resource and motivational ratings should not be treated as interchangeable with skills and participation ratings. A plausible educational explanation is that students encounter technologies without equally extensive opportunities to practise academic uses. However, the study does not test that explanation. Lower usage ratings could reflect course requirements, preferences, or the activities sampled by the instrument. The contrasts concern different content domains measured through agreement responses; they do not locate a causal barrier or compare equivalent objective abilities.

Van Deursen and van Dijk (2019) caution against reducing material access to simple connectivity, while Soomro et al. (2020) demonstrate the value of retaining several access domains. For university practice, this means that capability support should accompany continued attention to workable devices, software, connectivity, and study environments. The comparatively favourable physical mean cannot justify withdrawing material assistance. Nor does the profile establish that skills training would have a larger effect than improved provision; no intervention or comparative effectiveness analysis was conducted.

Variation in use and implications for student support

Usage access had the lowest numerical mean and the greatest dispersion, but it was not significantly lower than skills access after multiplicity correction. It would therefore overstate the evidence to identify usage alone as the weakest domain. Considered together, the skills and usage results support examining how academic tasks connect capability development with opportunities for application. Individual-level follow-up is still required to establish whether lower ratings concern access to relevant tasks, uncertainty about procedures, or limited interest in particular activities.

Evidence from Bangladesh, South Africa, and the United Kingdom places resources and support within particular educational environments (Aziz & Hossain, 2024; Ajani, 2025; Zhou et al., 2025). The current study adds a different contextual profile but does not directly compare countries. Institutional follow-up could combine short student consultations with task observation to distinguish difficulties in obtaining access, knowing how to proceed, and finding relevant opportunities to participate. These activities would test the support needs suggested by the profile instead of assuming that questionnaire scores identify their causes.

Academic-year differences and the limits of demographic categories

First-year students reported higher overall digital conditions than students in each later year. The evidence does not follow a monotonic sequence: second-, third-, and fourth-year students did not differ significantly from one another. One possible explanation is that academic tasks become more demanding and students evaluate their conditions against different expectations. Cohort composition, prior experience, recruitment patterns, and institutional contexts are also possible explanations. The cross-sectional design cannot distinguish them or establish deterioration during undergraduate study.

The year finding complements the context-sensitive approach taken by Zhou et al. (2025), but their UK study used different digital indicators and found a different year profile. The present result should not be presented as a universal stage of digital development. Follow-up assessment can examine whether expectations, support access, or disciplinary demands

differ across academic years. Because the current comparisons did not adjust for other characteristics, the year association may also reflect differences in the composition of the recruited groups.

Gender and field differences were not significant after correction. These findings do not support using either category alone to allocate support in this sample. They also do not establish that gender or disciplinary inequalities are absent: domain-specific differences, intersecting characteristics, and institutional context were not tested. Needs assessment should therefore remain accessible across groups, alongside examination of the academic-year pattern.

Educational implications

Universities can use the four domains as a framework for needs assessment, while using the academic-year result to identify questions for follow-up rather than to label later-year students as deficient. A resource review could examine whether required applications work on available devices and connections. Brief academic tasks could assess locating credible information, organising sources, or preparing collaborative documents. Students' explanations of difficulty would help distinguish unavailable resources from uncertainty about procedures. The study did not test whether any particular support strategy improves these conditions.

Support could then be embedded in ordinary coursework. Explicit demonstrations, guided practice, and feedback may provide opportunities to apply digital skills in relevant contexts. Participation should not depend on privately purchased tools where equivalent institutional access is unavailable. At the same time, students should have ways to request help without being classified solely by demographic category or a total questionnaire score. Evaluation should examine whether support improves completion of relevant tasks and access to learning activities, rather than relying only on increased confidence ratings.

Measurement implications and limitations

Internal consistency recomputed from the 53 retained access items was high overall and within domains. The earlier factor model provides context for those scores but was refined and assessed in the same sample. Changes in response format, student-oriented wording, item removals, and the physical-access AVE shortfall constrain generalisation. Measurement invariance across gender, year, and field was not examined in this focused analysis. Observed-score group differences may therefore include differences in interpretation or response styles, and cannot automatically be treated as differences in an equivalent latent trait.

Several further limitations define the findings. First, voluntary recruitment within selected institutions and online administration limit population inference and may underrepresent students with the greatest access difficulties. Second, agreement ratings do not independently verify resources or demonstrated digital skills. Third, screening decisions may alter the retained distribution; sensitivity to alternative exclusion rules was not evaluated. Fourth, the comparative analyses were exploratory and demographic tests examined one grouping factor at a time, without estimating independent associations or adjusting for socioeconomic circumstances. Fifth, the available analytical file did not provide a usable university or class identifier. Standard errors, confidence intervals, and p-values consequently

assume independent students and do not account for possible clustering within the eighteen universities or classes. Positive intracluster dependence could make the reported inference too optimistic. Sixth, cross-sectional year comparisons cannot identify individual developmental trajectories. These limitations favour cautious, sample-specific interpretations over population or causal claims.

Future research should evaluate the adapted measure in an independent sample, examine cross-group equivalence, and retain institutional or class identifiers for appropriate clustered analyses. Longitudinal assessment could distinguish cohort differences from within-student change, while performance tasks could test whether access ratings correspond to observed academic capabilities. Item-level follow-up would help locate needs concealed by composite scores. Such work would strengthen the practical meaning of the observed domain and academic-year differences.

Conclusion

Among 616 participating undergraduates in Shandong, digital conditions were above the response midpoint, with physical and motivational ratings significantly higher than skills and usage ratings after correction. Physical versus motivational access and skills versus usage access did not differ significantly. First-year students reported higher overall conditions than students in later years, while gender and field differences were not significant. The findings support multidimensional, task-relevant needs assessment and investigation of academic-year support needs. They remain exploratory, self-reported, and dependent on individual-level assumptions that do not account for possible institutional clustering.

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