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Knowledge on Digital Health and its Associated Factors among Undergraduate Public Health Students of Nepal

Dipesh Shrestha[1], Jamuna Gautam[1], Pramana Adhikari[2], Mahesh Bhatta[3]

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[1]Department of Public Health, Purbanchal University School of Health Sciences, Gothgaun, Morang, Nepal
[2]Health Office, Silichong Rural Municipality, Sankhuwasabha, Koshi Province, Nepal
[3]Health Office Sankhuwasabha, Koshi Province, Nepal

Correspondence to:
Dipesh Shrestha
Department of Public Health, Purbanchal University School of Health Sciences, Gothgaun, Morang, Nepal
Email: dpesh.stha2016@gmail.com

ABSTRACT

Background: Digital health spans telehealth, mobile health, wearables, and electronic health records. Nepal has committed through the Digital Nepal Framework and e-Health Strategy, yet whether Bachelor of Public Health (BPH) programs equip students with the relevant skills remains an open question. The objective of this study was to assess the level of knowledge on digital health and its associated factors among undergraduate public health students in Nepal.

Methods: A web-based cross-sectional survey of 275 BPH students from three universities and two academies in Nepal, recruited by convenience sampling. A self-administered Google Forms questionnaire covered socio-demographics, prior digital health exposure, and 25 multiple-choice items across five domains (five items each). Associations were tested with Pearson's Chi-square and the Fisher–Freeman–Halton Exact test ($p < 0.05$), and by binary logistic regression with high knowledge (>80%) versus moderate or low as the outcome.

Results: Students scored a mean of 79.69% (SD = 17.43); 55.6% reached the high-knowledge category, 35.6% moderate, and 8.7% low, yet 91.3% reported low prior exposure. On bivariate testing, knowledge was associated with age group ($p = 0.004$), monthly family income ($p < 0.001$), and academic year ($p = 0.024$). In binary logistic regression only age retained significance: those aged 15–19 years had 87% lower odds of high knowledge than the 20–24 reference group (AOR = 0.13, 95% CI 0.02–0.72, $p = 0.019$), while the 25–29 (AOR = 1.12, 95% CI 0.58–2.18, $p = 0.740$) and 30–34 groups (AOR = 0.51, 95% CI 0.17–1.50, $p = 0.220$) did not differ. Income and academic year lost significance once age was accounted for.

Conclusions: BPH students scored well overall, but their knowledge is gained informally rather than through coursework. The curriculum is not preparing them for a digitally oriented workforce. A dedicated digital health module and a standardized competency framework should be priorities in the current curriculum reform.

Keywords: Digital health; Knowledge, Attitudes, Practice; Students, Health Occupations; Nepal

BACKGROUND

Digital health extends beyond eHealth to span telehealth, mobile health (mHealth), wearable devices, electronic health records (EHRs), big data, and artificial intelligence (1,2). Telehealth connects clinicians and patients across distance, mHealth delivers services on mobile devices (3,4), and EHRs consolidate a patient's clinical history (5,6).

Digital technologies touch roughly 70% of the Sustainable Development Goal targets (7), and WHO and CDC strategies urge countries to build a trained workforce (1,8). In Nepal, where terrain leaves about 83% of the population rural with limited healthcare access (9,10), the e-Health Strategy, Digital Nepal Framework, Health Sector Strategic Plan, and platforms such as DHIS2 and OpenIMIS all require trained personnel.

Bachelor of Public Health (BPH) programmes produce those graduates, yet evidence points to a mismatch between what national plans demand and what classrooms teach (11,12). The global market is projected to reach USD 1.39 trillion by 2034 (13). Studies from Nepal and comparable settings find that students and health workers learn most digital health on their own (14–16).

What this evidence does not provide is a measurement for the group Nepal depends on most directly. Work from Nepal has examined medical students' attitudes toward telemedicine (14), digital health literacy among health workers in Lalitpur (15), and eHealth skills among nursing students (16), but none reaches public health undergraduates, the cohort national strategy relies on to deploy these systems. BPH curriculum revision is therefore argued without a baseline: no published figure states what these students know, which domains are weakest, or whether it is attributable to teaching.

To our knowledge this is the first study to measure digital health knowledge among BPH students in Nepal, disaggregate it by domain, and test it against both socio-demographic characteristics and prior formal exposure, assessing knowledge and its associated factors among undergraduate public health students of Nepal.

METHODS

The study followed a descriptive cross-sectional design. We distributed a self-administered questionnaire through Google Forms to BPH students at universities across Nepal, choosing a web-based route mainly because it was the only realistic way to reach students scattered across different provinces, including those in remote areas, within the time and budget constraints of an undergraduate thesis.

We targeted every undergraduate currently enrolled in a BPH program in the country. Invitations went out to all universities and affiliated academies that offer the degree; in the end, students from three universities (Purbanchal University, Tribhuvan University, and Pokhara Universities) and two academies (Madan Bhandari Academy of Health Sciences and Karnali Academy of Health Sciences) actually participated. No single registry lists all BPH students in Nepal, so we estimated the total pool at about 2,000, a conservative figure drawn from the Medical Education Commission's 2025 seat allocation of roughly 670 students per intake year across the four-year program. To be included, a student had to (i) be enrolled in a BPH program at a Nepalese university, (ii) be in any year from first to final, (iii) have access to email or social media (a practical necessity for a web-based survey), and (iv) give electronic informed consent. Anyone who did not consent was excluded.

We sized the sample with the finite-population formula $n = (Z^2pqN)/(d^2(N-1) + Z^2pq)$, using $Z = 1.96$, $d = 0.05$, and $N = 2{,}000$. Because nobody has published a prevalence figure for digital health knowledge specifically among Nepalese BPH students, we borrowed the nearest local estimate we could find, 70.59%, reported for digital health literacy among health workers in Lalitpur (15); neither the construct nor the population matches ours closely, and we treat that as a limitation rather than an approximation. The formula returns 275.25, which by the usual convention of rounding a sample size upwards gives a minimum of 276; our original submission reported this as 275. We enrolled 275 respondents, one short of the rounded requirement and 99.6% of it, a difference too small to affect precision materially but one we state exactly rather than leave to the reader's arithmetic. Recruitment was by convenience sampling through academic networks at each institution.

That target, however, rests on the finite population correction, and on reflection this is the weakest step in the calculation. N = 2,000 was inferred from the Medical Education Commission's 2025 seat allocation of roughly 670 places per intake year across a four-year programme; it is an estimate, not a count drawn from a sampling frame, because no national register of BPH students exists. The correction further assumes probability sampling from that population, which convenience recruitment does not deliver. A third objection is more concrete still: the questionnaire link reached approximately 300 students, so the pool the study could actually draw on was never the 2,000 the correction assumes. Applying the formula without the correction, the same parameters require 319 respondents; substituting a conservative $p = 0.50$ raises the requirement to 323 with the correction and 385 without it. Against those benchmarks our 275 respondents fall short. The consequence is a loss of precision rather than a change of finding: at $n = 275$ the 95% confidence interval around the observed high-knowledge proportion of 55.6% runs from 49.8% to 61.5%, a half-width of ±5.9 percentage points against the ±5.0 the design assumed. We report the study on that basis, and return to what it means for interpretation in the Discussion.

We built the questionnaire after reviewing the relevant literature and then had the research supervisor and subject experts vet it. The 25-item knowledge scale showed good internal consistency in the analytic sample (Cronbach's alpha = 0.84). The instrument had three parts. Part one collected socio-demographics: age, sex, university, parental education, place of residence, monthly family income, educational background, and academic year. Part two asked about prior exposure to digital health: whether the BPH curriculum covered it, whether the student had attended any formal training, and whether they had taken online courses. Part three was the knowledge test itself: 25 multiple-choice questions spread equally across five domains (general digital health, telehealth, mHealth, wearable devices, and EHRs), five items per domain. A correct answer scored 1, an incorrect answer 0, giving a raw range of 0–25 that we converted to a percentage. Because the five domains carry equal numbers of items, the overall percentage is also the unweighted mean of the five domain scores, and no domain is over-represented in the total.

We grouped overall scores into low (<50%), moderate (50–80%), and high (>80%). These are the modified Bloom's cut-off points, a classification originally developed for Bloom's mastery-learning criteria (17) and adopted widely in knowledge-attitude-practice research in Nepal and South Asia; we used them so that our figures would be directly comparable with the local literature we cite rather than to any threshold of our own choosing. On a 25-item scale the boundaries fall at 12.5 and 20 items, so in practice a student needed at least 13 correct answers to be classed as moderate and at least 21 to be classed as high. We did not run a sensitivity analysis against alternative thresholds such as tertiles, and note this in the Limitations. For prior exposure, each of the three items was scored 0–2, giving a composite range of 0–6 that we similarly split into low (scores 0–2), moderate (scores 3–4), and high (scores 5–6).

Before going live, we pre-tested the questionnaire on 30 BPH students (roughly 10% of the target) to spot confusing wording or unclear items; anything flagged was revised. Those 30 students were left out of the final sample of 275. The finished form went onto Google Forms and was circulated through institutional email lists, WhatsApp groups, and Facebook pages, with college representatives helping to spread the link. The opening screen presented a digital consent statement covering study purpose, voluntary participation, right to withdraw, data handling, and confidentiality; respondents had to click "I Agree" before proceeding. Collection ran for three weeks; we sent weekly reminders to push the response rate up.

Participant flow was as follows. The questionnaire link was distributed to approximately 300 eligible students across the participating institutions, that figure being the combined membership of the institutional email lists, WhatsApp groups, and Facebook pages through which it was circulated. Recruitment used a pre-specified stopping rule: the form was closed as soon as the calculated target was reached, and 275 responses were received before it closed. Because Google Forms required an answer to every item, no partially completed form could be submitted; no duplicate submissions were detected and no response was found ineligible, so none were excluded and all 275 responses entered the analysis. This gives a response rate of approximately 92% among the students reached, and a corresponding non-response rate of approximately 8%. We report the denominator as an approximation because the survey was distributed through shared links in group channels rather than by individually addressed invitation, so the number of students who actually saw the link cannot be established exactly; the true number reached may be lower than the combined membership figure, in which case the response rate quoted here is conservative.

Two features of that flow bear on how the results should be read. The high response rate means that non-response bias within the group reached is likely to be small: almost everyone who saw the link took part. The selection in this study therefore happened almost entirely at the point of who was reached, not at the point of who chose to reply. Against an estimated national population of about 2,000 BPH students, the roughly 300 reached represent a small and non-random slice, and the 275 analysed amount to approximately 14% of that population. We return to the implications in the Discussion.

Because web-based surveys are open to duplicate and low-quality submissions, several checks were applied before analysis. Google Forms was configured to restrict repeat submissions from the same account, and required responses on all items so that partially completed forms could not be submitted. Two rounds of cleaning in Excel removed duplicate and incomplete records and screened for internally inconsistent entries, such as an academic year that could not be reconciled with the reported age or university. A random manual review of a subset of completed forms checked for straight-lining and other response patterns suggesting inattentive completion. No record was removed by any of these checks. We did not use automated bot detection, IP-address screening, or attention-check items embedded in the questionnaire, so while we found no evidence of fraudulent or inconsistent responding, we cannot rule it out entirely; we note this among the limitations.

We exported the raw responses from Google Forms into Microsoft Excel as a CSV file, dropped any duplicates or incomplete entries, and coded the variables. All statistical work was done in Python (NumPy, Pandas, SciPy). We first ran the usual descriptives (frequencies, percentages, means, standard deviations) for the socio-demographic variables, for knowledge scores (overall and by domain), and for the prior-exposure items.

To check whether each independent variable was linked to knowledge level (low / moderate / high), we used Pearson's Chi-square where expected cell counts allowed it and the Fisher–Freeman–Halton Exact (FFHE) test where they did not. The switch was governed by the conventional rule that no expected count should fall below 5: the three variables analysed by Chi-square had minimum expected counts of 9.86 (gender), 7.59 (parental education), and 5.76 (educational background), while every variable analysed by FFHE had cells below that threshold, the smallest being 0.70 (prior exposure), 0.87 (university), and 1.05 (monthly family income). Because a p-value alone conveys neither the strength nor the direction of an association, we report the category-wise distribution of knowledge levels alongside every test.

The outcome variable has three levels, and we fitted it by binary logistic regression after collapsing it to two: high knowledge (>80%) coded 1, and moderate or low knowledge (≤80%) coded 0. This gave 153 events and 122 non-events. We chose dichotomisation over an ordinal or multinomial model for two reasons. First, the low-knowledge stratum contains only 24 of 275 participants, too few to support stable estimation of a third outcome level across four-category predictors, several of which are themselves sparse. Second, an ordinal model would impose the proportional-odds assumption, which we could not test adequately at these cell sizes; collapsing avoids resting the results on an assumption we cannot verify. The high-knowledge threshold was chosen as the cut point because it is the one with a substantive interpretation: it identifies students who have reached the level the modified Bloom's classification treats as adequate mastery. Only variables significant in the bivariate step entered the model: age group, monthly family income, and academic year, contributing nine dummy parameters against 122 non-events, or roughly 13.6 events per parameter, which satisfies the conventional minimum of ten without a wide margin. We report adjusted odds ratios (AOR) with 95% confidence intervals (CI). Throughout, $p < 0.05$ was the significance cut-off.

Several steps kept data quality in check: the pre-test, mandatory fields with built-in Google Forms validation, a duplicate-submission block, two cleaning rounds in Excel, standardized coding, and a random manual spot-check of completed forms. Content validity came from the expert review described above; the pre-test bolstered reliability.

The Institutional Review Committee (IRC) of Purbanchal University cleared the study (Ref. No. 11D-082/83) before we collected any data. Every respondent gave electronic informed consent. Participation was voluntary, and anyone could drop out at any point without consequence. All data were stripped of identifiers and stored on a password-protected device; nothing was shared with outside parties. We plan to share the aggregated results with Purbanchal University and other relevant stakeholders so they can feed into curriculum discussions, without revealing who said what.

Table 1. Socio-demographic characteristics of participants (n=275)

Characteristics	Frequency	Percentage
Gender		
Female	162	58.9
Male	113	41.1
Age Group		
15-19	16	5.8
20-24	194	70.5
25-29	49	17.8
30-34	16	5.8
Academic year		
First year	39	14.2
Second year	38	13.8
Third year	116	42.2
Final year	82	29.8
University		
Purbanchal	183	66.5
Madan Bhandari Academy of Health Sciences	35	12.7
Tribhuvan University	24	8.7
Karnali Academy of Health Sciences	23	8.4
Pokhara University	10	3.6
Educational Background		
+2 science	209	76.0
Diploma in Health Sciences	66	24.0
Place of residency		
Rural Municipality	65	23.6
Municipality	151	54.9
Sub-metropolitan city	30	10.9
Metropolitan city	29	10.5
Monthly family income		
<10,000	12	4.4
10,000-19,999	23	8.4
20,000-29,999	48	17.5
≥30,000	192	69.8

Table 2a: Overall knowledge level and prior exposure to digital health (n = 275)

Variable	Frequency	Percentage
Overall knowledge level		
High (>80%)	153	55.6
Moderate (50-80%)	98	35.6
Low (<50%)	24	8.7
Overall prior exposure		
Low (0-2)	251	91.3
Moderate (3-4)	16	5.8
High (5-6)	8	2.9

Table 2b. Mean percentage of items answered correctly, by knowledge domain (n = 275; five items per domain)

Domain	Items	Mean % correct
General digital health	5	90.33
Wearable devices	5	86.18
Electronic health records	5	78.98
mHealth	5	77.96
Telehealth	5	65.02
All domains	25	79.69

Table 3. Association between independent variables and level of knowledge on digital health (n = 275)

Variable	Category	High f (%)	Moderate f (%)	Low f (%)	Total	Test	Statistic	p-value
Age category (years)	15–19	2 (12.5)	11 (68.8)	3 (18.8)	16	FFHE	20.59	0.004
	20–24	115 (59.3)	67 (34.5)	12 (6.2)	194			
	25–29	29 (59.2)	12 (24.5)	8 (16.3)	49			
	30–34	7 (43.8)	8 (50.0)	1 (6.3)	16			
Monthly family income (NPR)	<10,000	4 (33.3)	3 (25.0)	5 (41.7)	12	FFHE	28.01	<0.001
	10,000–19,999	14 (60.9)	9 (39.1)	0 (0.0)	23			
	20,000–29,999	22 (45.8)	17 (35.4)	9 (18.8)	48			
	≥30,000	113 (58.9)	69 (35.9)	10 (5.2)	192			
Academic year	First year	14 (35.9)	20 (51.3)	5 (12.8)	39	FFHE	14.29	0.024
	Second year	21 (55.3)	15 (39.5)	2 (5.3)	38			
	Third year	67 (57.8)	43 (37.1)	6 (5.2)	116			
	Final year	51 (62.2)	20 (24.4)	11 (13.4)	82			
Gender	Female	98 (60.5)	54 (33.3)	10 (6.2)	162	χ^2	5.21 (df 2)	0.074
	Male	55 (48.7)	44 (38.9)	14 (12.4)	113			
University	Purbanchal University	103 (56.3)	62 (33.9)	18 (9.8)	183	FFHE	11.07	0.188
	Madan Bhandari Academy	25 (71.4)	10 (28.6)	0 (0.0)	35			
	Tribhuvan University	11 (45.8)	10 (41.7)	3 (12.5)	24			
	Karnali Academy	10 (43.5)	10 (43.5)	3 (13.0)	23			
	Pokhara University	4 (40.0)	6 (60.0)	0 (0.0)	10			
Parental education	Both secondary or higher	56 (57.7)	30 (30.9)	11 (11.3)	97	χ^2	3.53 (df 4)	0.473
	One secondary	46 (50.5)	37 (40.7)	8 (8.8)	91			
	Neither secondary	51 (58.6)	31 (35.6)	5 (5.7)	87			
Permanent residence	Rural municipality	40 (61.5)	20 (30.8)	5 (7.7)	65	FFHE	4.40	0.642
	Municipality	84 (55.6)	53 (35.1)	14 (9.3)	151			
	Sub-metropolitan city	15 (50.0)	11 (36.7)	4 (13.3)	30			
	Metropolitan city	14 (48.3)	14 (48.3)	1 (3.4)	29			
Educational background	+2 Science	111 (53.1)	77 (36.8)	21 (10.0)	209	χ^2	3.09 (df 2)	0.213
	Diploma in Health Sciences	42 (63.6)	21 (31.8)	3 (4.5)	66			
Prior exposure	Low (0–2)	144 (57.4)	88 (35.1)	19 (7.6)	251	FFHE	6.54	0.161
	Moderate (3–4)	6 (37.5)	7 (43.8)	3 (18.8)	16			
	High (5–6)	3 (37.5)	3 (37.5)	2 (25.0)	8			

Note. Percentages are row-wise within each category. χ^2 = Pearson's Chi-square test of independence; FFHE = Fisher–Freeman–Halton Exact test. FFHE was used wherever any expected cell count fell below 5; the minimum expected counts were 0.70 (prior exposure), 0.87 (university), 1.05 (monthly family income), 1.40 (age category), 2.53 (permanent residence), and 3.32 (academic year). The three variables analysed by Chi-square had minimum expected counts of 9.86 (gender), 7.59 (parental education), and 5.76 (educational background). For FFHE rows the statistic shown is the Pearson χ^2; the p-value is from the exact test. Bold indicates $p < 0.05$.

RESULTS

The 275 respondents were predominantly female (58.9%) and in the 20–24 age bracket (70.5%; mean age 23.29 ± 2.96). Third-year students made up the biggest slice (42.2%), and Purbanchal University contributed roughly two thirds of the sample (66.5%). Most had come through the +2 Science track (76.0%), and about seven in ten reported a monthly family income of NPR 30,000 or more (69.8%). Table 1 gives the full socio-demographic breakdown.

Table 2 shows on average, students answered 79.69% of items correctly (SD = 17.43), right at the top of the moderate band. It breaks down knowledge level alongside prior exposure and its three sub-components. Just over half (55.6%) scored high, yet paradoxically 91.3% reported low prior exposure. Alongside, how students did in each domain. General digital health and wearable-device items drew the highest scores; telehealth trailed behind, with EHR and mHealth falling in the middle.

Table 3 lays out the bivariate results, with the distribution of knowledge levels within each category so that the direction of each association is visible alongside its p-value. Three variables reached significance. Knowledge differed by age group ($p = 0.004$): only 12.5% (2/16) of students aged 15–19 years reached the high-knowledge category, against 59.3% (115/194) at 20–24 years and 59.2% (29/49) at 25–29 years, falling back to 43.8% (7/16) at 30–34 years; low knowledge was most common in the youngest group (18.8%, 3/16) and among those aged 25–29 (16.3%, 8/49). Monthly family income was significant ($p < 0.001$) but did not run as a simple gradient: the lowest band was the outlier, with 33.3% (4/12) high and 41.7% (5/12) low knowledge, against 58.9% (113/192) high and only 5.2% (10/192) low in the highest band; the 10,000–19,999 band recorded the largest high-knowledge share (60.9%, 14/23) and no low-knowledge students at all (0/23), though on 23 respondents. Academic year climbed steadily ($p = 0.024$): high knowledge rose from 35.9% (14/39) in first year to 55.3% (21/38) in second, 57.8% (67/116) in third, and 62.2% (51/82) in the final year, a gain of 26.3 percentage points across the programme. Gender, university, parental education, permanent residence, educational background, and prior exposure showed no significant association; the largest of these non-significant differences was for gender, where 60.5% (98/162) of women reached high knowledge against 48.7% (55/113) of men ($p = 0.074$).

Table 4 reports the three significant variables entered into a binary logistic regression together. Only age retained significance. Students aged 15–19 years had 87% lower odds of high knowledge than the 20–24 year reference group (AOR = 0.13, 95% CI 0.02–0.72, $p = 0.019$). Neither the 25–29 group (AOR = 1.12, 95% CI 0.58–2.18, $p = 0.740$) nor the 30–34 group (AOR = 0.51, 95% CI 0.17–1.50, $p = 0.220$) differed significantly from the reference, and both confidence intervals include 1. Monthly family income and academic year lost the significance they had shown bivariately. Relative to the ≥30,000 reference group, none of the income bands reached significance, although the 20,000–29,999 band came close (AOR = 0.52, 95% CI 0.26–1.01, $p = 0.054$), with the lowest band at AOR = 0.35 (95% CI 0.10–1.27, $p = 0.110$). Academic year showed a consistent upward gradient in the point estimates relative to first year: second year AOR = 1.19 (95% CI 0.42–3.37, $p = 0.742$), third year AOR = 1.23 (95% CI 0.49–3.06, $p = 0.661$), final year AOR = 1.55 (95% CI 0.60–4.02, $p = 0.369$). Every interval spans 1, though, so the apparent progression across the programme cannot be distinguished from chance once age is accounted for. The model as a whole was significant (LLR $p = 0.010$; McFadden's pseudo $R^2 = 0.057$).

DISCUSSION

The central finding of this study is a paradox, and it is worth sitting with before turning to what might explain it. BPH students in Nepal scored a mean of 79.69% (SD = 17.43) on the knowledge test, right at the top of the moderate band, and more than half (55.6%) crossed into the high-knowledge category. Yet 91.3% of these same students reported low formal exposure to digital health, meaning that almost none of this knowledge can be traced back to the curriculum, formal training, or online courses. What these future public health professionals know about digital health, in other words, they have mostly taught themselves. We are cautious about calling this "competence." A 25-item multiple-choice quiz rewards recognition of consumer-level ideas (the kind of thing any smartphone-savvy young adult absorbs without trying) and says comparatively little about whether students could actually deploy these tools in a professional setting.

The domain-level breakdown reinforces this reading (Table 2). Students scored highest on the general definition of digital health (90.33%) and on wearable devices (86.18%), both topics they encounter daily through fitness bands and health apps, and considerably lower on telehealth (65.02%), which depends less on personal gadget familiarity and more on understanding how services are actually organised and delivered at the system level. That gap is consistent with a picture in which most of this learning happens through everyday device use rather than through any structured teaching of how digital tools plug into a health system.

Why would students know this much without being taught it? Part of the answer is simply how fast Nepal's digital landscape has moved. Internet penetration reached about 52% by 2024, smartphones are now common even in smaller towns, and platforms such as YouTube, Facebook, and TikTok have become, almost by default, informal health-information channels for young people. BPH students, who are heavy smartphone users on the whole, absorb digital health ideas through fitness trackers, health apps, COVID-era video consultations, and social-media health posts, rather than through anything a lecturer formally assigns. The classroom, in short, has not kept pace with the environment surrounding it. That gap matters more than it might first appear, because self-taught knowledge of this kind tends to be wide but thin: a student may know perfectly well what a wearable device does and still have no real grasp of the data-governance rules, interoperability standards, or clinical-validation steps that a trained professional is expected to handle.

How do these students compare with others? The 79.69% mean sits in the same neighbourhood as the 70.59% digital health literacy figure reported for health workers in Lalitpur (15), and is not far from the 74.78-out-of-100 moderate literacy score found among nursing undergraduates in Hunan, China (18). It comfortably exceeds the roughly one-third correct rate seen among Austrian medical students (19), as well as the knowledge gaps documented earlier among medical and dental interns at the B.P. Koirala Institute of Health Sciences (20). Taken as a whole, Nepalese BPH students appear to be keeping pace with their regional peers, although the comparison should be read loosely: the instruments, populations, and educational systems involved differ enough that any precise ranking is not really possible.

Perhaps the most telling result of all is that formal exposure did not predict knowledge ($p = 0.1606$). This lines up with what was found among Austrian medical students, whose knowledge likewise failed to climb with year of study, leading the original authors to infer that it was being acquired outside the lecture hall altogether (19). Nepalese medical students tell a similar story of decent awareness of telemedicine but almost no formal teaching behind it (14), and Egyptian medical students showed the same combination of heavy technology use paired with weak formal evaluation skills (21). Our data add BPH undergraduates to what is now a fairly sizeable list of health-student populations whose digital health know-how appears to have formed outside the syllabus rather than because of it.

Turning to the socio-demographic predictors, the bivariate results were largely what we expected: age group ($p = 0.004$), monthly family income ($p < 0.001$), and academic year ($p = 0.024$) each showed a link with knowledge level on their own. Once the three were entered into a logistic regression together, however, the picture simplified considerably: only the youngest cohort (15–19 years) remained significant (AOR = 0.13, 95% CI 0.02–0.72, $p = 0.019$), while income and academic year both dropped out. That is not, on reflection, a surprising outcome: older students have by definition spent more years in the programme and tend to come from households that have had correspondingly more time to accumulate income, so the three variables overlap with each other far more than any of them overlaps cleanly with knowledge alone.

That overlap most likely means the model carries some degree of multicollinearity, which inflates standard errors and is the more probable explanation for why income and academic year lost significance, rather than any real absence of a relationship. In terms of power, the model is adequate for its size: nine dummy parameters set against 122 non-events works out to about 13.6 events per parameter, comfortably clearing the conventional minimum of ten. Even so, the McFadden's pseudo R^2 of 0.057 is modest, and the sparsest cells in the data (16 students aged 15–19, 12 in the lowest income band) carry correspondingly wide confidence intervals, as the 0.02–0.72 interval on the age effect makes plain. The regression is therefore best read as exploratory: it identifies age as the variable that survives adjustment without settling how large that effect truly is. Even with that caveat, the direction is consistent with Chinese and Turkish data showing that age-related digital exposure matters more than how far a student has progressed through the degree (18,22). The raw numbers do show a climb, with high-knowledge rates rising from 35.9% among first-years to 62.2% among final-years, but because that trend disappeared once age was accounted for, we read it as reflecting years of informal digital exposure accumulating, rather than anything the curriculum itself is doing.

Looking at the domains individually, the pattern holds together: consumer-facing topics top the ranking (general digital health 90.33%, wearables 86.18%), system-level topics sit at the bottom (telehealth 65.02%), and EHR (78.98%) and mHealth (77.96%) fall somewhere in between. Nepalese medical students showed a strikingly similar profile in 2022, understanding why telemedicine matters while having received almost no formal teaching on it (14), which hints at a broader hole in telehealth instruction that runs across health disciplines in this country, not just BPH. The high wearable-device scores, by contrast, match what a cross-sectional survey of university students in Lebanon found (23), and almost certainly reflect consumer familiarity rather than anything learned in a classroom.

Two features of how the sample was assembled deserve to be weighed carefully before these findings are generalised. The first concerns size. The study enrolled 275 respondents against a corrected requirement of 276, which for practical purposes is the size it set out to be. That calculation, however, rested on a finite population correction applied to an assumed pool of about 2,000 students, and that assumption is not a solid one: no national register of BPH enrolment exists, and the 2,000 figure was inferred from annual seat allocations rather than counted directly. Set the correction aside, as arguably it should be for a convenience sample that was never drawn from an enumerated frame in the first place, and the same parameters call for 319 respondents instead. The resulting shortfall does not change the direction of any finding, but it does widen the uncertainty around each one: the high-knowledge proportion of 55.6% carries a 95% confidence interval running from 49.8% to 61.5%, meaning the true value could plausibly sit anywhere from just under half to nearly two-thirds of all students. Estimates for the smaller subgroups (16 students aged 15–19, 12 in the lowest income band) are correspondingly less stable still, which is the main reason we treat the regression itself as exploratory rather than confirmatory.

The second concerns who ended up answering. Recruitment proceeded by convenience sampling through an online invitation, and both halves of that phrase pull in the same direction. A questionnaire circulated through institutional email, WhatsApp groups, and Facebook pages reaches, almost by construction, students who are already active within those channels, and reaching them in the first place requires exactly the connectivity and digital habits that the survey then goes on to measure. The students least likely to have ever seen the link are precisely those whose digital health knowledge we would expect to be lowest, which makes the mean of 79.69% more plausibly an overestimate than an underestimate of the true figure for all BPH students in Nepal. The participant flow lets us locate that bias with some precision. Of roughly 300 students reached, 275 responded, a response rate of about 92%; almost everyone who saw the questionnaire went on to complete it. The distortion in this study therefore arises almost entirely from who was reached, not from who chose to answer once reached, which makes it a coverage problem rather than a non-response problem. That distinction is not a technicality: coverage bias is not corrected by a high response rate, nor is it evidenced by one, since a study can achieve near-complete response within a narrow and unrepresentative slice of its population and show nothing for it. Roughly 300 students out of an estimated national pool of 2,000 is exactly such a slice, and the 275 students analysed here represent about 14% of that population. The institutional spread makes the pattern concrete: Purbanchal University alone supplied 66.5% of respondents, so what this study reports is better understood as a Purbanchal-weighted, multi-institution picture than as anything approaching a national one, and should be read with that caution attached. We cannot quantify the size of this bias from the data in hand; the honest position is simply that the true population value likely sits somewhat lower than what we observed here, and that the paradox at the heart of this paper, high scores sitting alongside minimal formal exposure, is, if anything, strengthened rather than weakened by that bias, since it would inflate the knowledge scores without touching the exposure finding at all.

Taken together, all of this points toward a practical opening rather than a deficit to be filled from nothing. Students are not starting from zero; they arrive with a usable, if informal, foundation already in place. What is missing is the structured depth, the critical thinking, and the hands-on practice that only a deliberate curriculum can supply. Were BPH programmes to align their syllabi with WHO's Global Strategy on Digital Health 2020–2025 (1) and with Nepal's own e-Health Strategy and Digital Nepal Framework, universities would have a genuine chance of converting that surface-level familiarity into real professional skill.

There are a few limitations to this study. Convenience sampling meant that Purbanchal University dominated the sample (66.5%), so the results are best read as a Purbanchal-led multi-institution snapshot, not a nationally representative estimate. Recruitment by online invitation compounds this: it reaches only students who are active in the email and social media channels used, and who therefore already possess the connectivity and digital familiarity the study set out to measure, so the reported scores are more likely to overstate than understate knowledge among BPH students as a whole. The questionnaire reached approximately 300 students, roughly 14% of the estimated national population, and although about 92% of those reached responded, that high response rate speaks only to the absence of non-response bias within the group reached; it does not offset the narrowness of the group itself. The sample size calculation relied on a finite population correction against an assumed population of about 2,000, a figure inferred from seat allocations rather than counted from a register; without that correction the target would have been 319 rather than 275, and the achieved precision is ±5.9 percentage points against the ±5.0 the design assumed. The prevalence figure used in the calculation (70.59%) came from health workers in Lalitpur, a different construct in a different population. Multiple-choice questions, by nature, test breadth more than depth; scenario-based or performance tasks would tell us more about real competence. We applied the modified Bloom's cut-offs (<50 / 50–80 / >80) as given and did not run a sensitivity analysis with alternative thresholds such as tertiles, so the headline classification carries that uncertainty. Our data-quality checks covered duplicates, incomplete submissions, and internal inconsistency, but did not include bot detection, IP screening, or embedded attention checks, so we cannot fully exclude inattentive or duplicated responses from different accounts. The logistic regression carries likely multicollinearity among age, income, and academic year, and rests on some sparse cells, so it should be read as exploratory. Last, because this is a cross-sectional study, we captured one moment in time and cannot say anything about how knowledge changes as students move through the program.

Table 4. Binary logistic regression of factors associated with high digital health knowledge (n = 275)

Variable	Category	AOR	95% CI	p-value
Age category (years)	20–24 (reference)	1.00	-	-
	15–19	0.13	0.02–0.72	0.019
	25–29	1.12	0.58–2.18	0.740
	30–34	0.51	0.17–1.50	0.220
Monthly family income (NPR)	≥30,000 (reference)	1.00	-	-
	<10,000	0.35	0.10–1.27	0.110
	10,000–19,999	0.92	0.37–2.28	0.859
	20,000–29,999	0.52	0.26–1.01	0.054
Academic year	First year (reference)	1.00	-	-
	Second year	1.19	0.42–3.37	0.742
	Third year	1.23	0.49–3.06	0.661
	Final year	1.55	0.60–4.02	0.369

Note. AOR = adjusted odds ratio; CI = confidence interval. Outcome: high knowledge (>80%, n = 153) versus moderate or low knowledge (≤80%, n = 122). All three variables were entered simultaneously; reference categories are 20–24 years, ≥30,000 NPR, and first year. Overall model: LLR p = 0.010; McFadden's pseudo R^2 = 0.057. Bold indicates $p < 0.05$.

CONCLUSIONS

BPH students in Nepal know more about digital health than their curricula would predict (most land in the moderate-to-high range), but that knowledge clusters around consumer-level topics and owes very little to formal teaching. As things stand, the BPH syllabus is not giving students the structured, applied skills that Nepal's national digital health plans demand. Unless that changes, the workforce the country is counting on to operationalize the Digital Nepal Framework, the e-Health Strategy, and the health-related SDG 3 targets will enter the field with breadth but not depth.

What should happen next? Universities running BPH programs have an opening right now, with the Medical Education Commission's ongoing curriculum revision, to fold in a dedicated digital health module that covers telehealth, mHealth, wearables, EHRs, and the national platforms (DHIS2, HMIS, OpenIMIS), pegged to WHO's Global Strategy on Digital Health 2020–2025 and Nepal's own e-Health Strategy. The Medical Education Commission and CTEVT ought to work with universities on a standardized competency framework that draws on international benchmarks, so every program is aiming at the same bar. On the teaching side, the smart move is to build on what students already know informally: telehealth simulations, hands-on EHR/EMR practice on OpenIMIS, and field placements at health facilities that actually run DHIS2 would all help turn surface familiarity into usable competence. Finally, future studies should move beyond cross-sectional snapshots. Longitudinal designs, mixed methods, validated instruments, and samples drawn from multiple institutions would give a much clearer picture of how digital health competencies develop as students progress through their degrees.

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Conflict of Interest

The authors declare no conflict of interest.

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