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Technology and Electronic Media Use in Education: Patterns, Predictors, and Effects on Learning Outcomes and Digital Well-Being among Higher Secondary School Students in Kerala

Jayachithra C, Research Scholar, Mar Theophilus Training College, Thiruvananthapuram

Abstract

This study examined whether Active Academic Media Use (AAMU), Digital Literacy (DL), and Non-Academic Screen Time (NAST) predict Academic Achievement (ACH) and Digital Well-Being (DWB) among higher secondary school students in Kerala. A cross-sectional survey design was employed with a sample of 384 students. Measures included a seven-day time-use diary for AAMU and NAST, the 25-item Student Digital Literacy Scale (SDLS-25), the 25-item Digital Well-Being Scale (DWB-25), and ACH drawn from school records. Data analysis was conducted using EDUSTAT software. Multiple linear regressions addressed two research questions: whether the three technology-use variables jointly predict ACH and DWB. Findings indicated that greater AAMU and higher DL were associated with higher ACH and better DWB, whereas higher NAST was associated with lower scores on both outcomes. The results highlight the importance of building students' digital literacy and increasing the academic share of media use while bounding leisure screen time. Implications for classroom practice, school policy, and parental guidance are discussed.

Keywords: *Active Academic Media Use; Digital Literacy; Non-Academic Screen Time; Academic Achievement; Digital Well-Being; Educational Technology; Higher Secondary Education*

Introduction

Digital technologies are now woven into secondary classrooms, yet their impact depends on instructional alignment and students' competencies. Meta-analytic syntheses report small-to-moderate average benefits of educational technology on achievement when integrated with sound pedagogy (Tamim et al., 2011), and multimedia learning research explains why design choices (e.g., signalling, segmenting) matter for understanding (Mayer, 2009). At the same time, assumptions that today's "digital natives" are naturally information-savvy or can learn effectively while multitasking are not supported; rather, students need explicit digital-literacy instruction and focused task design (Kirschner & De Bruyckere, 2017; Ophir et al., 2009). Building on this backdrop, the present study distinguishes Active Academic Media Use (purposeful, study-oriented media activity), Digital Literacy, and Non-Academic Screen Time

(recreational use) and examines how these relate to Academic Achievement and Digital Well-Being among higher secondary school students in Kerala.

Beyond achievement, evidence on adolescents' digital well-being suggests nuance: large-scale analyses typically find very small average links between overall screen time and well-being (Orben & Przybylski, 2019), with potential benefits at moderate levels and differences by timing/type of use (Przybylski & Weinstein, 2017). However, specific patterns—especially evening or bedtime use—are frequently associated with shorter sleep duration, which is itself linked to mood, attention, and school functioning (Cain & Gradisar, 2010; Lund et al., 2021). These mixed but theoretically coherent findings motivate a focused test of whether Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time jointly predict both Academic Achievement and Digital Well-Being in this context.

Background of the Study

Over the past decade, secondary schooling has seen rapid integration of digital tools—learning management systems (LMS), e-textbooks, video lessons, and collaborative apps—expanding access to content and opportunities for active learning. Research shows, however, that technology's benefits depend less on mere availability and more on quality of use and learner competencies. Meta-analytic work reports small-to-moderate positive effects when technology is aligned with sound pedagogy (Tamim et al., 2011), and multimedia learning research explains how design features such as signalling and segmenting enhance comprehension (Mayer, 2009). Two cautions are also well established: the belief that "digital natives" learn effectively without explicit instruction is not supported (Kirschner & De Bruyckere, 2017), and multitasking during study impairs cognitive control and learning (Ophir et al., 2009). Together, these strands indicate that Active Academic Media Use (purposeful, study-oriented use) and Digital Literacy (skills for finding, evaluating, creating, and safely managing information) are likely to matter for learning outcomes more than overall screen exposure.

A parallel literature addresses adolescents' Digital Well-Being. Large-scale analyses typically find very small average links between total screen time and well-being, implying that the type and timing of use may be more consequential than hours alone (Orben & Przybylski, 2019; Przybylski & Weinstein, 2017). Specific patterns—especially evening or bedtime use and entertainment multitasking—are frequently associated with shorter sleep and reduced daytime functioning, with implications for mood, attention, and school performance (Cain & Gradisar, 2010; Lund et al., 2021). These findings motivate the present study's focus on a lean set of predictors—Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time—and two outcomes of direct educational value—Academic Achievement and Digital Well-Being—among higher secondary school students in Kerala. By modelling these predictors jointly, the study addresses a practical evidence gap: whether purposeful academic use and digital literacy are associated with higher achievement and better well-being even when everyday leisure screen time is taken into account.

Research Questions

1. To what extent do Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time collectively predict Academic Achievement among higher secondary school students in Kerala?
2. To what extent do Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time collectively predict Digital Well-Being among higher secondary school students in Kerala?

Objectives

1. To examine whether Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time are significant predictors of Academic Achievement among higher secondary school students in Kerala.
2. To examine whether Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time are significant predictors of Digital Well-Being among higher secondary school students in Kerala.

Hypotheses

1. Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time are significant predictors of Academic Achievement among higher secondary school students in Kerala.
2. Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time are significant predictors of Digital Well-Being among higher secondary school students in Kerala.

Methodology

Research design

The study adopted a cross-sectional survey design to examine whether Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time jointly predict Academic Achievement and Digital Well-Being among higher secondary school students. This design suited the objective of estimating relationships between clearly defined continuous variables using parametric statistics.

Population and sampling

The study was conducted in higher secondary schools in Kerala, India. The population comprised students enrolled in Classes XI–XII in recognised government, aided, and unaided schools. A stratified random sampling strategy ensured representation across school type (government, aided, unaided) and school locale (urban/rural) within Thiruvananthapuram district. Within each stratum, classes were randomly selected and all present, consenting students were invited to participate.

Sample size determination and sample

The required sample size was calculated using the modified Cochran's formula (Cochran, 1963) with a 95% confidence level, 5% margin of error, and an assumed proportion $p = .50$. The target sample was N = 384, and the achieved sample equalled N = 384 higher secondary school students from Thiruvananthapuram district, Kerala.

Inclusion and exclusion criteria

Inclusion criteria covered currently enrolled Class XI–XII students who regularly used electronic media for study and leisure. Students with incomplete questionnaires or missing achievement records were excluded listwise from the predictive analyses.

Variables and operational definitions

- **Active Academic Media Use (AAMU):** percentage of total daily media time devoted to academic activities (e.g., LMS modules, digital textbooks, simulations, assignment creation, live online classes).

- **Digital Literacy (DL):** skills for locating, evaluating, creating, and safely managing digital information, including self-regulatory behaviours for focused study.
- **Non-Academic Screen Time (NAST):** average daily hours spent on social networking, gaming, OTT/short-video, and related leisure activities.
- **Academic Achievement (ACH):** most recent standardised examination or term-end percentage (0–100) obtained from school records.
- **Digital Well-Being (DWB):** positive functioning in digital contexts—sleep quality, attention control, perceived control of media, mood/stress, minimal interference with study/relationships, and privacy/safety practices—where higher scores indicated better well-being.

Tools Used for Data Collection

7-Day Media Time-Use Diary (AAMU and NAST)

Students completed a structured seven-day diary, entering at the end of each day the minutes devoted to academic and non-academic media use across all devices. All figures were self-reported; no device-generated analytics were used. Indices were computed as:

- AAMU (%) = 100 × [academic minutes ÷ (academic minutes + non-academic minutes)]
- NAST (hours/day) = (total non-academic minutes over 7 days) ÷ (7 × 60) *(AAMU = Active Academic Media Use; NAST = Non-Academic Screen Time.)*

Student Digital Literacy Scale (SDLS-25)

A 25-item questionnaire with 5-point Likert-type items (1 = Strongly Disagree to 5 = Strongly Agree) spanning five subdomains: Information Search; Evaluation & Ethics; Content Creation & Productivity; Communication & Collaboration; Self-Regulation & Troubleshooting. After reverse-coding the negatively keyed items, responses were summed to a total score (25–125; higher = better digital literacy).

Digital Well-Being Scale (DWB-25)

A 25-item questionnaire with 5-point Likert-type items (1–5) across five subdomains: Sleep & Rest; Attention & Focus; Control & Habits; Mood & Social Impact; Privacy & Safety. Nine items were negatively keyed; after reverse-coding, responses were summed to a total score (25–125; higher = better digital well-being).

Academic Achievement Proforma

A single field recorded each student's most recent standardised examination/term percentage from school records or verified report cards.

Tool development, validity, and reliability

Items for the SDLS-25 and DWB-25 were drafted from current literature and higher-secondary curricular expectations. Content validity was established through expert review by three specialists (educational technology, psychology, and higher-secondary pedagogy). Using the Content Validity Index, all retained items met the item-level criterion (I-CVI ≥ .78), and the scale-level average (S-CVI/Ave) exceeded .90 for both tools. A pilot with 20 students was conducted to check clarity, completion time, and preliminary reliability, leading to minor wording refinements. In the main sample (N = 384), internal consistency was satisfactory: Cronbach's alpha was > .80 for the total scales and ≥ .70 for all subscales.

Data collection procedure

Institutional permission was obtained in advance. On scheduled days, the investigator personally administered all tools in classroom settings. The purpose of the study and confidentiality safeguards were explained, and informed consent/assent procedures were completed as per school policy. Students first completed the SDLS-25 and DWB-25 (approximately 15–20 minutes). They were then issued the 7-Day Media Time-Use Diary with instructions to record, at the end of each day, the minutes devoted to academic and non-academic media use across all devices. All figures were self-reported; no device-generated analytics were used. Diaries were collected by the investigator after seven days during a scheduled follow-up visit. Academic Achievement percentages were obtained from school records with administrative approval. Participation was voluntary, and students could withdraw at any time without penalty.

Data management and preparation

Completed forms were checked for completeness prior to coding. Data were entered into a master sheet with double-entry verification for a random 10% subsample. For the SDLS-25 and DWB-25, negatively keyed items were reverse-coded and item responses were summed to produce total (25–125) and subscale scores. Descriptive statistics (mean, standard deviation, skewness, kurtosis) were generated for all variables. Cases with substantial missing data were excluded from subsequent analyses; otherwise, listwise deletion was applied for the regression models.

Data analysis

All analyses were carried out using EDUSTAT software. Descriptive statistics summarised the distributions of AAMU, DL, NAST, ACH, and DWB. The hypotheses and research questions were tested using multiple linear regression with two models: Model 1 used Academic Achievement as the dependent variable with AAMU, DL, and NAST as predictors; Model 2 used Digital Well-Being as the dependent variable with the same predictors. For each model, the overall F-test, R^2 and adjusted R^2 were reported to indicate the extent of prediction, and coefficient statistics were presented for each predictor (unstandardised B, standard error, *t*, *p*, and 95% confidence interval). Standardised coefficients (β) were also reported. Statistical significance was evaluated at $\alpha = .05$ (two-tailed).

Ethical considerations

The study complied with institutional and school-level ethical guidelines. Prior permission was obtained from school authorities. Parental consent and student assent were secured as required. Participation was voluntary and could be discontinued at any time without penalty. Data were anonymous and confidential, with results reported only in aggregate.

Delimitations and methodological limitations

The study focused on Classes XI–XII in Kerala and on a concise set of technology-use predictors; findings are therefore delimited to this context and variable set. The cross-sectional design restricts causal inference, and self-reported time-use entails some recall bias despite the seven-day logging protocol. Even so, careful instrumentation, expert review, piloting, and consistent data-handling procedures enhanced the rigour of the study.

Data Analysis and Interpretation

Descriptive Statistics

This section deals with the descriptive analysis of the variables used in the study.

Table 1

Descriptive Statistics of the Main Study Variables

Variable	Scale / Units	Mean (M)	Standard Deviation (SD)	Minimum	Maximum	Skewness	Kurtosis
Active Academic Media Use (AAMU)	% of total media time	42.70	17.90	4.00	92.00	–0.14	–0.56
Digital Literacy (DL)	25–125 (sum of 25 items)	87.00	14.00	46.00	123.00	–0.21	–0.12
Non-Academic Screen Time (NAST)	hours/day	3.10	1.39	0.40	7.20	0.61	0.08
Academic Achievement (ACH)	% (exam/term)	72.40	10.60	41.00	95.00	–0.38	–0.19
Digital Well-Being (DWB)	25–125 (sum of 25 items)	84.00	14.50	43.00	122.00	–0.10	–0.34

On average, students devoted 42.7% of their total media time to academic purposes (AAMU), which indicates that less than half of screen use was study-oriented. The dispersion is sizeable (SD = 17.9; range 4–92%), showing substantial heterogeneity—some students used very little media for study while others used a great deal. The slight negative skew (–0.14) and modestly flat kurtosis (–0.56) suggest an approximately symmetric, broad spread around the mean.

Digital Literacy (DL) totals averaged 87 on a 25–125 scale, sitting above the midpoint (75) by 12 points, which reflects generally good literacy levels. Variation was moderate (SD = 14), with scores spanning 46–123. The distribution was near-symmetric (skew –0.21, kurtosis –0.12).

Students reported Non-Academic Screen Time (NAST) of 3.10 hours/day on average (SD = 1.39; range 0.40–7.20 hours). The positive skew (0.61) indicates a tail of heavy leisure users, while kurtosis near zero (0.08) points to a roughly mesokurtic (normal-like) shape.

Academic Achievement (ACH) averaged 72.4% (SD = 10.6; range 41–95%). The slight negative skew (–0.38) suggests a modest clustering towards the higher end of performance, with no strong ceiling effect.

Digital Well-Being (DWB) totals averaged 84 (on 25–125), also above the midpoint (75), indicating generally favourable well-being. Dispersion was moderate (SD = 14.5; range 43–122), and the distribution was close to symmetric (skew –0.10, kurtosis –0.34).

Overall, the sample shows (i) ample variability across all variables for meaningful modelling, (ii) AAMU below the 50% mark on average alongside ~3 hours/day of leisure screen time, and (iii) generally good levels of digital literacy and digital well-being. These patterns are consistent with the expectation that greater academic use and higher literacy are associated with better achievement and well-being, while higher leisure screen time tends to relate to poorer outcomes.

Hypotheses Testing

This section deals with the testing of hypotheses formulated for the study using appropriate statistical techniques.

Testing of Hypothesis 1

Table 2

Regression Model Summary for Predicting Academic Achievement

R	R^2	Adjusted R^2	F(3, 380)	p-value
0.56	0.31	0.30	56.91	< .001

The multiple regression model with Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time as predictors shows a moderate-to-strong overall fit:

- R = 0.56 indicates a moderate correlation between the observed Academic Achievement scores and the scores predicted by the model.
- R^2 = 0.31 means the three predictors jointly explain 31% of the variance in Academic Achievement; 69% remains unexplained by this model.
- Adjusted R^2 = 0.30 suggests that, after adjusting for the number of predictors and sample size (df = 3, 380; N = 384), the model would be expected to explain about 30% of variance in similar samples—indicating good generalisability.
- The F(3, 380) = 56.91, p < .001 shows the model is statistically significant overall; taken together, the predictors improve prediction of Academic Achievement beyond chance.

Table 3

Regression Coefficients for Predicting Academic Achievement

Predictor	B	SE B	β (Std.)	t	p-value	95% CI for B (Lower, Upper)
(Constant)	52.70	2.96	–	17.80	< .001	46.90, 58.50

Active Academic Media Use (AAMU, %)	0.14	0.03	0.24	5.02	< .001	0.09, 0.20
Digital Literacy (DL, 25–125)	0.204	0.030	0.27	6.80	< .001	0.145, 0.263
Non-Academic Screen Time (NAST, h/day)	–1.30	0.37	–0.17	–3.51	< .001	–2.03, –0.57

All three predictors are statistically significant ($p < .001$) and their confidence intervals exclude zero, indicating reliable unique associations with Academic Achievement (ACH).

- Active Academic Media Use (AAMU) shows a positive association with ACH ($B = 0.14$; $\beta = 0.24$). Practically, a 10-percentage-point increase in the share of media time devoted to academic purposes is associated with about +1.4 percentage points in exam/term score, holding Digital Literacy and Non-Academic Screen Time constant.
- Digital Literacy (DL) also relates positively to ACH ($B = 0.204$; $\beta = 0.27$). A 10-point rise on the 25–125 DL scale corresponds to roughly +2.0 percentage points in ACH, net of AAMU and NAST. Among the three, DL has the largest standardised effect.
- Non-Academic Screen Time (NAST) relates negatively to ACH ($B = –1.30$; $\beta = –0.17$). Each additional hour/day of leisure screen use is associated with about –1.3 percentage points in ACH, controlling for AAMU and DL.
- The intercept ($B = 52.70$) is the model's baseline when predictors are zero and is not substantively interpreted. Overall, higher Digital Literacy and a greater academic share of media use are linked with higher achievement, whereas more leisure screen time is linked with lower achievement within this sample. These are associations, not proof of causation.

Tenability of the Hypothesis

$H_0 1$: *Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time are not significant predictors of Academic Achievement among higher secondary school students in Kerala.*

The multiple regression model was statistically significant, $R = 0.56$, $R^2 = 0.31$, Adjusted $R^2 = 0.30$, $F(3, 380) = 56.91$, $p < .001$, indicating that the predictor set explains 31% of the variance in Academic Achievement. Coefficient tests showed significant unique contributions from all three predictors: Active Academic Media Use *($B = 0.14$, $SE = 0.03$, $t = 5.02$, $p < .001$)*, Digital Literacy *($B = 0.204$, $SE = 0.030$, $t = 6.80$, $p < .001$)*, and Non-Academic Screen Time *($B = –1.30$, $SE = 0.37$, $t = –3.51$, $p < .001$)*.

Decision: At $\alpha = .05$, both the overall (omnibus) null and the coefficient-level nulls are not tenable. $H_0 1$ is rejected, supporting the alternative that these variables significantly predict Academic Achievement.

Testing of Hypothesis 2

Table 4

Regression Model Summary for Predicting Digital Well-Being

R	R^2	Adjusted R^2	F(3, 380)	p-value
0.59	0.35	0.34	68.21	< .001

The multiple regression model using Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time to predict Digital Well-Being shows a moderate-to-strong overall fit:

- R = 0.59 indicates a solid multiple correlation between the observed Digital Well-Being scores and those predicted by the three-predictor model.
- $R^2 = 0.35$ means the predictors collectively explain 35% of the variance in Digital Well-Being; 65% remains due to other factors and random error.
- Adjusted $R^2 = 0.34$ (only slightly below R^2) suggests stable explanatory power after accounting for model complexity and sample size (df = 3, 380).
- The model is statistically significant overall, $F(3, 380) = 68.21$, $p < .001$, confirming that, taken together, the predictors improve prediction beyond chance.

Table 5

Regression Coefficients for Predicting Digital Well-Being

Predictor	B	SE B	β (Std.)	t	p-value	95% CI for B (Lower, Upper)
(Constant)	44.25	5.50	–	8.05	< .001	33.44, 55.06
Active Academic Media Use (AAMU, %)	0.175	0.050	0.19	3.33	.001	0.075, 0.275
Digital Literacy (DL, 25–125)	0.45	0.05	0.43	8.33	< .001	0.34, 0.56
Non-Academic Screen Time (NAST, h/day)	–2.25	0.50	–0.22	–4.29	< .001	–3.25, –1.25

All three predictors are statistically significant ($p \leq .001$) and their 95% confidence intervals exclude zero, indicating reliable unique associations with Digital Well-Being (DWB).

- Active Academic Media Use (AAMU) shows a positive association with DWB (B = 0.175; β = 0.19). Practically, a 10-percentage-point increase in the share of media time devoted to academic purposes is associated with about +1.75 points on the DWB total (25–125), holding Digital Literacy and Non-Academic Screen Time constant.
- Digital Literacy (DL) also relates positively to DWB (B = 0.45; β = 0.43). A 10-point rise on the 25–125 DL scale corresponds to about +4.5 points in DWB, net of AAMU and NAST. Among the three, DL has the largest standardised effect.

- Non-Academic Screen Time (NAST) relates negatively to DWB (B = −2.25; β = −0.22). Each additional hour/day of leisure screen use is associated with about −2.25 points on DWB, controlling for AAMU and DL.
- The intercept (B = 44.25) is the model's baseline when predictors are zero and is not substantively interpreted. Overall, higher Digital Literacy and a greater academic share of media use are linked with better digital well-being, whereas more leisure screen time is linked with poorer digital well-being within this sample. These are associations, not proof of causation.

Tenability of the Hypothesis

$H_0$2: *Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time are not significant predictors of Digital Well-Being among higher secondary school students in Kerala.*

The multiple regression model was statistically significant, $R = 0.59$, $R^2 = 0.35$, Adjusted $R^2 = 0.34$, $F(3, 380) = 68.21$, $p < .001$, indicating that the set of predictors explains 35% of the variance in Digital Well-Being. Coefficient tests showed that each predictor had a significant unique contribution: Active Academic Media Use *($B = 0.175$, $SE = 0.050$, $t = 3.33$, $p = .001$)*, Digital Literacy *($B = 0.45$, $SE = 0.05$, $t = 8.33$, $p < .001$)*, and Non-Academic Screen Time *($B = –2.25$, $SE = 0.50$, $t = –4.29$, $p < .001$)*.

Decision: At $\alpha = .05$, the omnibus null and the coefficient-level nulls are not tenable. $H_0$2 is rejected, and the alternative—that these variables significantly predict Digital Well-Being—is supported.

Discussion of the Results

This study examined whether Active Academic Media Use, Digital Literacy, and Non-Academic Screen Time jointly predict Academic Achievement and Digital Well-Being among higher secondary school students in Kerala. Both regression models were statistically significant and explained a meaningful share of variance—31% for Academic Achievement and 35% for Digital Well-Being—considered substantial for a three-predictor field study with N = 384.

Across both models, Digital Literacy was the strongest unique predictor. Controlling for the other variables, higher Digital Literacy was associated with better Academic Achievement and higher Digital Well-Being. In practical terms, a 10-point increase on the 25–125 Digital Literacy scale corresponded to about a 2.0-point gain in Achievement (percentage score) and a 4.5-point gain in Digital Well-Being, underscoring the importance of evaluating information, managing privacy and safety, producing academic work, and regulating attention online.

Active Academic Media Use also showed a consistent, though smaller, positive association with both outcomes. A 10-percentage-point increase in the share of media time devoted to academic purposes related to roughly +1.4 points in Achievement and +1.75 points in Digital Well-Being, holding the other factors constant. This pattern highlights that how students use media—not simply how much—matters for performance and well-being.

By contrast, Non-Academic Screen Time related inversely to both outcomes. Each additional hour per day of leisure screen use was associated with about −1.3 points in Achievement and −2.25 points in Digital Well-Being after adjustment, effects that are small to moderate but educationally meaningful—especially for students near grade thresholds or struggling with attention and sleep routines.

Taken together, the findings point to clear, actionable implications. Strengthening Digital Literacy through explicit instruction and guided practice, and structuring classroom tasks that promote purposeful, production-oriented technology use, are likely to yield gains in both learning and well-being. Complementary self-management strategies that bound leisure screen time—particularly in the evening—may further protect outcomes. While the cross-sectional design and self-reported time-use limit causal inference, the results provide concise, evidence-based guidance: build digital literacy, increase the academic share of media use, and manage leisure screen time to support students in Kerala's higher secondary schools.

Implications of the Study

The findings suggest that classrooms should prioritise active, production-oriented technology use—writing, problem-solving, simulations, and data work—so that a larger share of students' screen time directly serves learning. Embedding short, graded digital-literacy micro-modules (source evaluation, referencing, privacy/safety, attention control) within regular subject tasks can lift both achievement and digital well-being without adding separate workload.

For teachers, the results point to professional development on designing low-distraction activities and LMS layouts, using focus modes and clear task scaffolds, and giving feedback that rewards thoughtful online research and original outputs. Routine classroom practices—brief "notification-off" intervals, eye/posture breaks, and explicit planning for online tasks—can further increase the academic share of media use.

For students and families, a self-management approach is indicated: simple weekly planning of leisure screen time, device-off routines before bedtime, and occasional seven-day self-logs to reflect on habits. The aim is not zero leisure use, but bounded, purposeful use that does not crowd out study or sleep—practices that the data associate with stronger achievement and better well-being.

At the school level, leadership can support these shifts with consistent norms and infrastructure: reliable access to learning devices and connectivity, brief termly checks of digital literacy and digital well-being to identify support needs, and integration of screen-time and sleep check-ins within counselling and pastoral care. At a system level, policymakers can back schools with funding for teacher PD and curriculum-embedded digital-literacy initiatives, while encouraging data-informed monitoring that respects privacy.

Conclusion

This study shows that how higher secondary students in Kerala use technology matters: greater emphasis on Active Academic Media Use and stronger Digital Literacy are associated with higher Academic Achievement and better Digital Well-Being, while heavier Non-Academic Screen Time relates to poorer outcomes on both fronts. Taken together, these findings underscore that the quality and purpose of media engagement—not simply the number of hours—are central to educational value. Practically, curriculum-embedded digital-literacy instruction and classroom routines that promote purposeful, production-oriented technology use can support learning and health, complemented by simple self-management strategies that bound leisure screen time, especially in the evenings. While the cross-sectional design and self-reported time-use limit causal claims, the results offer clear, actionable guidance for teachers, school leaders, and families seeking to make technology work for students. Future research can extend this work using longitudinal designs and device/LMS logs to validate patterns over time and across contexts.

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