Changes in University Students' Media Use since the Introduction of ChatGPT – A Comparison across Study Domains

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App. **Directions for Future Research**

LLM Chatbots Enter the University Classroom

What We Already Know

- LLMs (e.g., ChatGPT, Claude, Gemini) have become embedded in students' everyday academic practices since late 2022 (Jo, 2024; Naznin et al., 2025)
- LLMs have the potential to support learning by providing immediate feedback, generating study material, and facilitating self-regulated learning (Jo, 2024)
- Prior digital platforms (YouTube, Wikipedia, Google) already shifted students away from textbooks, suggesting a broader pattern of technology-driven media rebalancing (Bartlett et al., 2020; Dolch et al., 2021)
- Chatbot capabilities uniquely integrate summarisation, explanation, and text generation - reducing cognitive effort vs. traditional multi-step search (Xu et al., 2023)
- Institutional responses remain fragmented: some universities restrict AI tools, others actively integrate them (Mollick & Mollick, 2023; Chirikov, 2026)

Media Shift Timeline

2005+ Rise of Wikipedia & YouTube; textbook use begins declining

2012+ MOOCs & digital newspaper use rises

2022+ ChatGPT launch new phase of AI adoption

2023-25 This study: tracking the shift

Research Gap

Longitudinal Evidence

Most existing studies are cross-sectional and capture attitudes or one-time usage snapshots. How chatbot use evolves over multiple semesters remains mostly unexplored (Schei et al., 2024; Liang et al., 2023).

Disciplinary Differences

Disciplines differ in epistemology and learning tasks, yet most studies treat students as homogeneous. Whether STEM vs. social science students adopt LLMs differently is largely untested (Qu et al., 2024).

Substitution vs. Complementarity

It is unclear whether AI tools replace or complement existing resources. The media substitution debate remains unresolved in the higher educational context (Jang & Park, 2016; Wagner & Jiang, 2025).

Individual-Level Predictors

While the Technology Acceptance Model (TAM) predicts that perceived competence and usefulness drive adoption, empirical evidence across disciplines on which students adopt most, and why, is limited (Ngo et al., 2025).

Research Hypotheses

H1 ChatGPT Uptake

Students' use of LLM chatbots has significantly increased over three academic terms across all domains (2023-2025).

H2a Media Decline (Cross-Sectional)

Use of textbooks, Wikipedia, YouTube, and online newspapers has decreased among successive cohorts over three terms.

H2b Substitution (Within-Student)

Within-student increases in ChatGPT use predict decreases in use of traditional and digital learning media.

H3 Disciplinary Differences

Usage patterns of LLM chatbots and other media differ systematically across Economics, Social Sciences, Medicine, and Physics.

H4 AI Competence & Relevance

Students with higher perceived relevance of LLMs and higher self-rated competence in using them use these tools more frequently.

H5 Language Background

Non-native German speakers use LLM chatbots more frequently, potentially due to the linguistic support they provide.

SECTION 02

Research Design

Sample · Measures · Analytical Strategy

Survey Design

- *Recruited in introductory classes at semester start via structured online surveys*
- *9 Universities across Germany*
- *4 major study domains*
- ***Longitudinal sub-sample: n = 507 matched pairs (participated at t_0 and either t_1 or t_2).***

0 1 2

t_0 Baseline

Winter 2023/24

n = 2,528

Initial chatbot landscape. Cross-sectional reference cohort

t_1 Follow-up 1

Winter 2024/25

n =1,690

First follow-up. Rapid ChatGPT diffusion period

t_2 Follow-up 2

Summer 2025

n = 674

Second follow-up. Mature adoption, broader AI landscape

Key Measures & Operationalisation

Media Use (Dependent Variables)

- Single-item 1–6 frequency scale per medium
- (1 = never · 6 = multiple times daily)
- *"On average, how often per week do you use the following media during your studies to complete assignments and search for information?"*
- Five media tracked: ChatGPT, Textbooks, YouTube, Wikipedia, Online News
- High-frequency = top 25th percentile
  → (binary robustness variable)

Predictors & Controls

- **Perceived competence** in using ChatGPT (school grades → lower = better with a range of 1-5)
- **Perceived relevance** of ChatGPT for studies (school grades → lower = better with a range of 1-5)
- Age, gender (1 = male), semester
- University entrance qualification (UEQ) grade (0.7 = best)
- Native German speaker (1 = yes)
- University fixed effects & cohort dummies: controls for institutional and timing variation

Analytical Strategy

1

Cross-Sectional OLS with t0 as Reference Group

Linear regression with university fixed effects + cohort dummies. Tests H1 (chatbot uptake over time), H2a (other media decline), H3 (domain heterogeneities), H4–H5 (individual predictors)

2

Logistic Regression (Robustness)

Converts outcome to binary high-frequency user flag (top 25th percentile). Coefficients converted to marginal effects. Validates cross-sectional OLS results for outlier group.

3

Individual Fixed-Effects* (Longitudinal)

Within-student panel models using **n = 507** matched pairs. Removes time-invariant unobserved heterogeneity. Tests H2b: whether rising chatbot use predicts declining other media use. Identifies whether chatbot gains coincide with medium-specific losses — partial vs. full substitution.

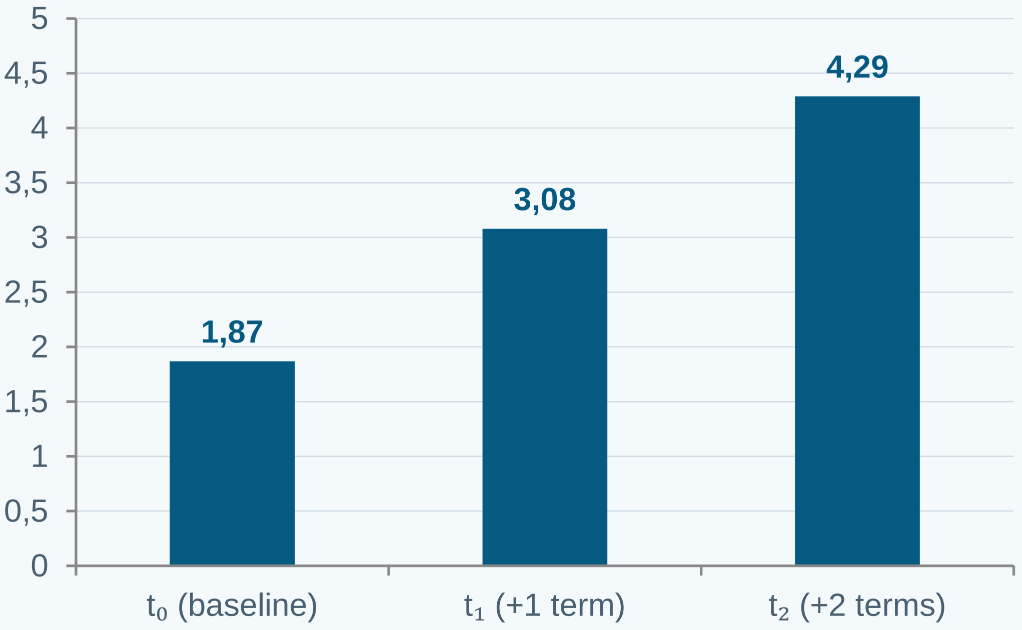
**Hausman test rejected random-effects ($p < .05$) → fixed-effects preferred. All analyses: Stata 18 (StataCorp, 2023).*

SECTION 03

Results

H1: Chatbot Adoption Increased Across Three Terms

Mean chatbot use (1–6 scale)



Key Statistics

+0.7 points

increase from t_0 to t_1 ($p < .01$)

+1.2 points

total increase from t_0 to t_2 ($p < .01$)

+15.4%

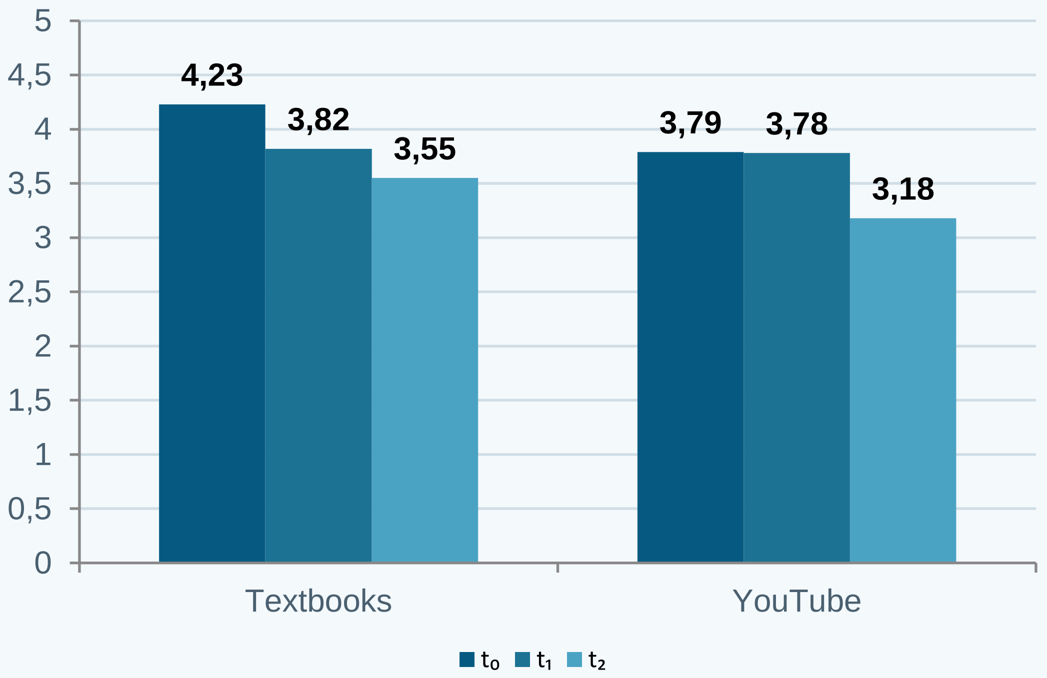
probability of high-freq use at t_1 vs. t_0 (logistic)

+29.7%

probability of high-freq use at t_2 vs. t_0 (logistic)

H1 confirmed. Consistent across all domains and both OLS and logistic models.

H2a: Textbook & YouTube Use Declined Across Cohorts



Coefficient Summary

Textbooks

t_1: −0.32* t_2: −0.61**

Significant decline at both t_1 and t_2 · Strongest decline overall

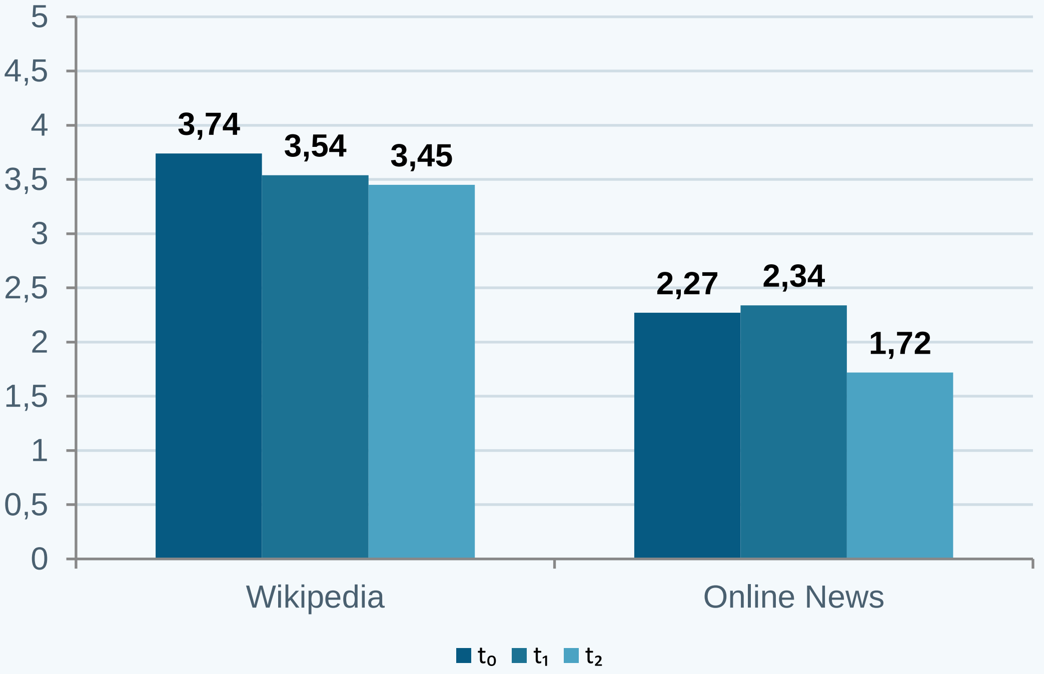
YouTube

t_1: Stable t_2: −0.27**

Stable at first · Declined by t_2 · Suggests delayed adoption effect

** p < .10 ** p < .05 (OLS estimates, university fixed effects + cohort dummies)*

H2a: Wikipedia & News Media Use Declined



Coefficient Summary

Wikipedia

t_1: −0.15 t_2: −0.28*****

Modest but consistent decline · ChatGPT's conversational lookup may replace Wikipedia's quick-fact role

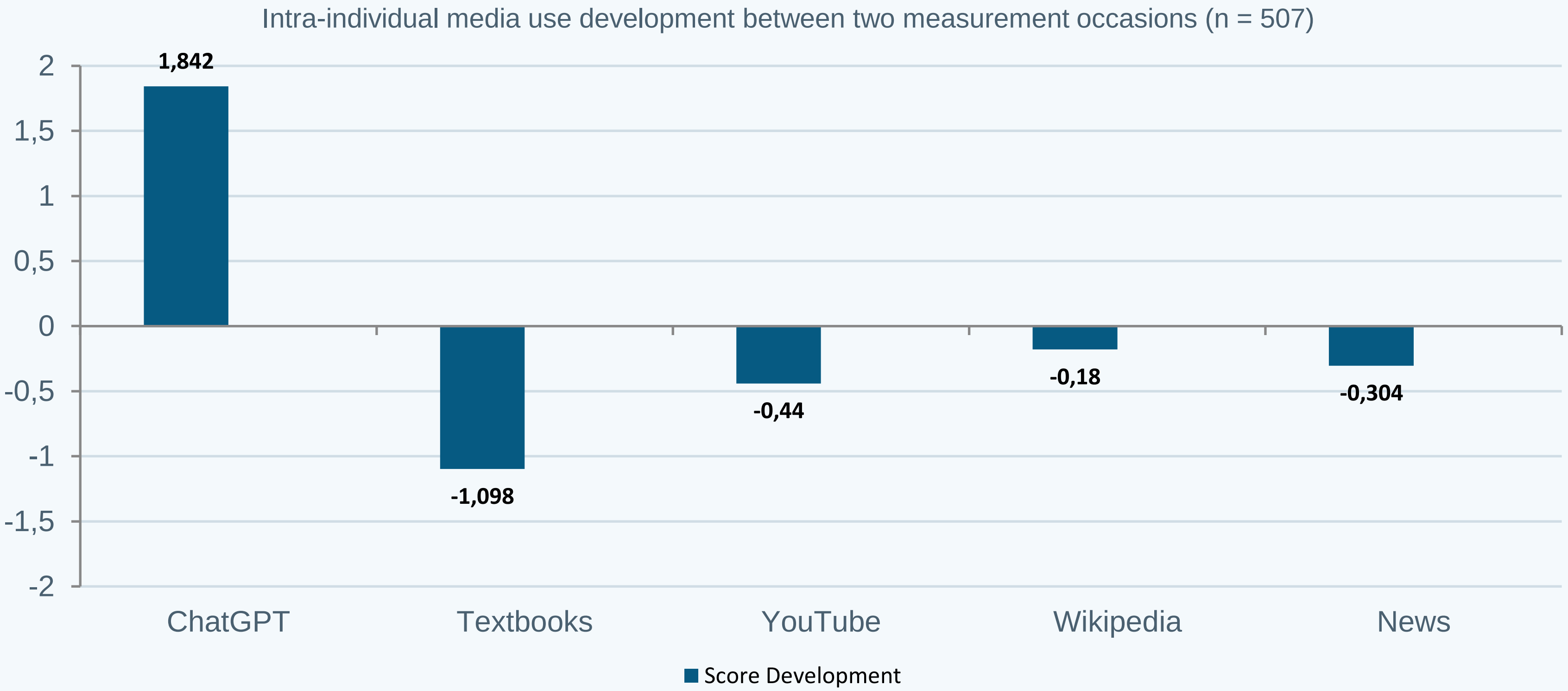
Online News

t_1: +0.08* t_2: −0.35***

Temporary uptick at t_1 (COVID news lingering?) · Strong decline by t_2

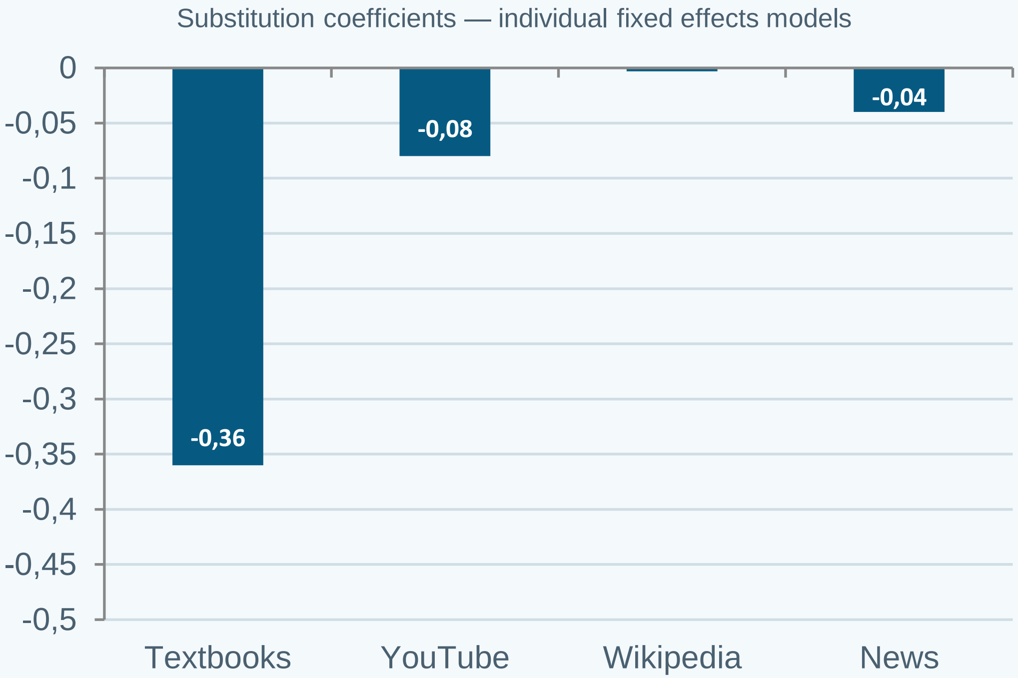
** p < .10 ** p < .05 *** p < .01; Wagner & Jiang (2025) independently document Wikipedia decline consistent with this finding.*

Within-Student Changes in Media Use



All media use developments are significant at p < .01. Overall media use constellation is reshuffling and not contracting.

H2b: Within-Student Substitution Evidence

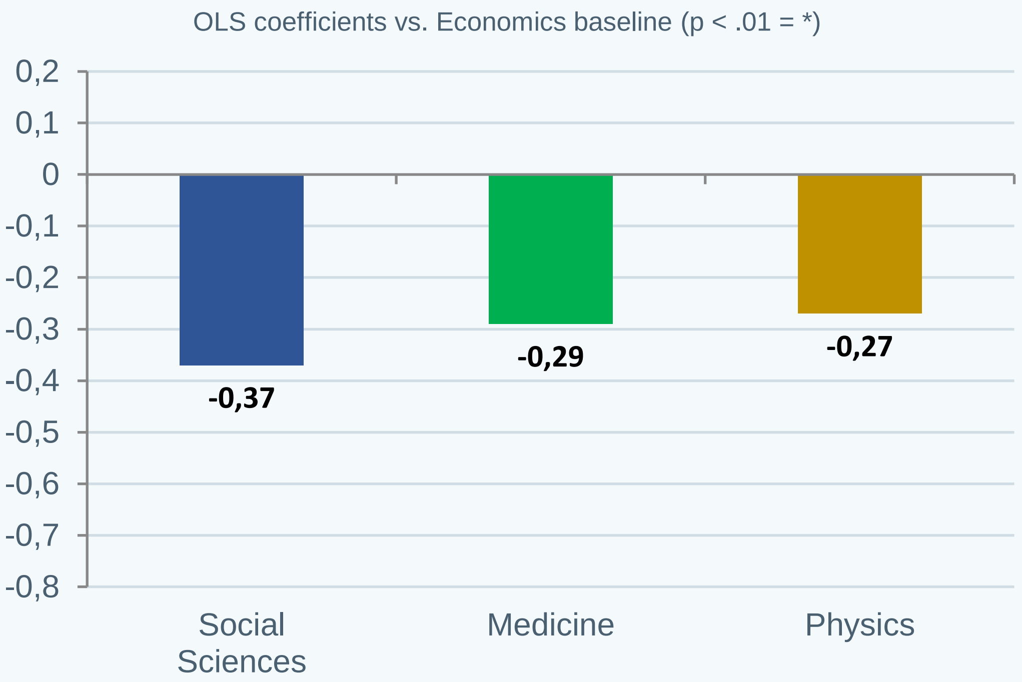


Results

- Every point increase in ChatGPT use is associated with a 0.36-point decrease in textbook use, the strongest substitution effect.
- YouTube shows a 0.08-point decline as chatbot may replace its explanation/tutorial function.
- Wikipedia use is mostly unaffected by an increase in ChatGPT use.
- News media barely affected (−0.05 ns)
- Pattern suggests function-specific partial substitution, not outright displacement (Jang & Park, 2016)

H2b confirmed. Fixed-effects models (n=507). Causal interpretation limited — alternative explanations cannot be excluded.

H3: Domain Differences in ChatGPT Use



Domain Interpretation

- Economics · Highest use (Baseline)
- Medicine · −0.29 points
- Social Sci. · −0.37 points
- Physics · −0.27 points

H3 confirmed. All three domain contrasts vs. Economics significant at $p < .01$, besides physics ($p < .1$)

H3: Disciplinary Differences Across All Media

Media	Economics	Social Sciences	Medicine	Physics
ChatGPT	Highest	Lower (−0.37***)	Lower (−0.29***)	Lower (−0.27*)
Textbooks	Baseline	Similar	Highest (+0.54**)	Similar
YouTube	Baseline	Lower (−0.26**)	Similar	Similar
Wikipedia	Baseline	Higher (+0.19*)	Higher (+0.33***)	Higher (+0.41***)
News Media	Highest (ref.)	Similar	Lower (−0.32***)	Lower (−0.72***)

**** $p < .01$ ** $p < .05$ * $p < .1$ Coefficients relative to Economics reference group.*

H4 & H5: Individual Predictors of ChatGPT Use

H4 Perceived Competence

+0.38 points

Per 1-point improvement on competence scale ($p < .01$) · +6.5% high-freq probability

H4 Perceived Relevance

+ 0.14 points

Per 1-point improvement on competence scale ($p < .01$) · +6.5% high-freq probability

H5 Non-native Speaker

+0.23 points

vs. native German speakers ($p < .01$): Potential linguistic support for paraphrasing, translation

Addition Gender

+0.20 points for male students

vs. female ($p < .01$), which is consistent with tech adoption gap (Bouzar et al., 2024; Stöhr et al., 2024)

Addition Older Students

Negative

Less frequent chatbot use for older students: technology adoption age gap (Abu-Shanab, 2011)

Addition Better UEQ Grade

Negative

Higher prior achievement → less chatbot use (Wecks et al., 2024), possibly due to higher self-efficacy without AI; consistent with regression estimates

SECTION 04

Discussion

Interpretation · Theory · Practice

Theoretical Implications

Extends TAM to LLM context

TAM (Davis, 1989)

Replicates and extends TAM in the domain of generative AI: Perceived competence and relevance drive adoption as predicted, across four disciplines and three time points. Adds temporal validity absent from prior cross-sectional studies.

Validates TIDE model predictions

TIDE (Muis et al., 2006)

Indicates that disciplinary epistemology (Becher & Trowler, 2001) shapes not just learning preferences but real changes in media use behavior.

Contributes to media substitution research

Jang & Park (2016)

Provides one of the first longitudinal tests of media substitution theory in higher education. Results are consistent with partial, function-specific substitution.

Practical Implications — Institutions & Educators

Embed AI Literacy Systematically

Institutions should move beyond ad-hoc AI policies toward systematic curricular integration of AI. This should include the evaluation of AI output quality, recognition of hallucinations, and prompt strategy (Bauer et al., 2025; Naznin et al., 2025).

Develop Critical Online Reasoning

Students need structured training in Critical Online Reasoning (COR) skills to evaluate ChatGPT-generated content for accuracy, source credibility, and epistemic status (Nagel et al., 2024; Oates & Johnson, 2025).

Redesign Instructional Contexts

Instructors should design learning environments that harness AI efficiency for routine tasks while preserving structured opportunities for deep engagement, critical analysis, and reasoning (Sailer et al., 2024; Mollick & Mollick, 2023).

Address Equity Gaps Proactively

Male, younger, and higher-achieving students adopt LLMs more readily. Institutions should target AI competence support for older students, female students, and those from lower-resourced backgrounds (Wang et al., 2024; Arum et al., 2025).

Thanks for your attention!

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