

Stratified Multivariate Analysis Across Socio-Economic Segments: Media Consumption Patterns and Their Quantifiable Impact on Educational Attainment, Digital Literacy, and Information Evaluation Skills in India

Aryann Khokha*, Dipikka Kashyap**

*The Shri Ram School Aravali, India

Email: aryannkhokha@gmail.com

** Ashoka University, India

Email: Deepika Kashyap deepika.kashyap_ug2024@ashoka.edu.in

Abstract:

India's rapid digitization has expanded connectivity, but how stratified media use translates into educational and cognitive outcomes remains largely unexplored. This study implements a cross-sectional, stratified multivariate design across four North Indian regions, with a final analytic sample of $N = 1992$, retention = 91.4%, to model links between media exposure and three focal outcomes, educational interest, digital literacy, and information evaluation, while testing demographic contrasts. Instruments for cognitive–psychosocial constructs achieved high reliability ($\alpha > 0.84$). Media-exposure variables were z-standardized prior to analysis. Independent-samples t-tests showed no gender differences in educational interest (Male: $M = 34.70$, $SD = 5.96$; Female: $M = 34.94$, $SD = 5.88$; $t(1990) = -0.87$, $p = 0.382$, $d = 0.04$), information evaluation (Male: $M = 69.23$, $SD = 18.90$; Female: $M = 69.75$, $SD = 18.45$; $t(1990) = -0.61$, $p = 0.542$, $d = 0.03$), trust in media (Male: $M = 88.45$, $SD = 13.94$; Female: $M = 88.11$, $SD = 13.36$; $t(1990) = 0.54$, $p = 0.589$, $d = 0.02$), peer influence (Male: $M = 108.72$, $SD = 13.79$; Female: $M = 108.11$, $SD = 14.37$; $t(1990) = 0.95$, $p = 0.342$, $d = 0.04$), standardized media-hours ($t(1990) = 0.11$, $p = 0.910$, $d = 0.01$), or platforms used ($t(1990) = 0.00$, $p = 0.998$, $d = 0.00$). One-way ANOVAs likewise indicated no age effects on educational interest ($F(2,1989) = 0.29$, $p = 0.745$), digital literacy ($F(2,1989) = 1.38$, $p = 0.253$), information evaluation ($F(2,1989) = 1.48$, $p = 0.228$), trust in media ($F(2,1989) = 1.81$, $p = 0.164$), or peer influence ($F(2,1989) = 0.02$, $p = 0.981$). Findings reveal that demographic convergence by gender and age is robust across outcomes, while stratification is better explained outside simple demographic contrasts. Large-scale, stratified, India-specific multivariate design that integrates cognitive–psychosocial constructs with standardized media-exposure metrics, yielding precise nulls that refine digital-divide theory beyond gender/age heuristics.

Keywords — Socio-economic Stratification, Digital Literacy, Education, Quantitative Analysis

I. Introduction

The 21st century has witnessed what many observers describe as an unprecedented global digital transformation. As witnessed in numerous fields ranging from media to sociology to cognitive sciences, technology appears to have managed to permeate every possible field of research (Singh & Singh, 2022; Reis & Melão, 2023). Critically, this transformation appears to have unfolded not merely through the expansion of infrastructure or access, but through the growing centrality of media consumption ecosystems. These ecosystems show distinct presence within social media and

streaming platforms, digital news and educational content, and now mediate how individuals acquire knowledge, construct social behaviour, and develop cognitive and evaluative skills (Pappas et al., 2023). In this sense, understanding digital transformation requires moving beyond connectivity metrics to examine how media usage patterns shape educational attainment, digital literacy, and information evaluation capabilities across societies. Such a transformation warrants further inquiries into how societies access, process, and engage with technology. Within the Indian context, this transformation has been particularly pronounced since the launch of the Digital India initiative (2015), which aims to bridge the digital divide prevalent within the nation. However, despite significant infrastructural investments, such as expanding broadband connectivity to 95% within rural environments and over 950 million internet users by 2024. Asrani (2020), among others within the ICRIER, suggests that persistent demographic disparities in digital access may be compounding pre-existing patterns of social stratification that became more pronounced in the post-pandemic era, where digital access became closely associated with education and healthcare in turn potentially influencing equitable opportunities within society. With India's digital economy projected to contribute nearly 20% of national income by 2030 (Mishra et al., 2025), examining patterns of digital media engagement may provide a novel lens for informing the development of equitable policies. India's ongoing digital transformation may influence distinct conventional patterns of engagement with information and education. Recent reports showcase increased digital penetration within rural communities (Kantar, 2024), potentially contributing to a narrowing of certain incongruities. Evidence suggests that such variations in media consumption (across demographic dimensions of age, gender, location, and socio-economic status) may persist to a significant extent. Although government policies, such as the *Pradhan Mantri Gramin Digital Saksharta Abhiyan* and *Digital Inclusion in the Era of Emerging Technologies*, focus on digital empowerment, scholars such as Van Dijk (2006) suggest that 'access' does not guarantee meaningful engagement among groups, especially among rural low-income residents, and women. Furthermore, this divide is not limited to infrastructure: it highlights inequalities caused by ability, motivation and skills (Heeks, 2022). This is made salient through the work of Joshi (2024) and van de Werfhorst et al., (2022) who collectively show, when students belonging to higher income brackets utilize digital tools for academic use, higher engagement, utility and purpose is observed as compared to lower income group counterparts who face limitations due to poor content visibility, language barriers, and un-intuitive design interfaces. Furthermore, findings from Samudra (2022) and Scott et al. (2021) suggest that differences are further exacerbated by gender based social norms and geographic limitations, which disproportionately reduce device usage among women in rural regions. Therefore, existing research indicates that 'access' alone may not be the strongest correlate of meaningful engagement across different groups. In spite of these observations, while existing research has highlighted these inequalities, it appears to lack systematic organisation and often does not provide an exhaustive, in-depth multivariate analysis of intersecting demographic factors. Furthermore, relatively few studies have examined how media usage patterns may be associated with cognitive and emotional dimensions such as digital literacy, educational interest, peer influence, and trust in media sources.

To the best of our knowledge, several notable gaps appear to persist within existing literature. Much of existing research tends to exhibit methodological limitations, paucity of stratification, conceptual limitations, and insufficient alignment with the socio-economic specifications of India. These gaps

in existing literature may be broadly understood under three layered categories: *Methodological*, *Conceptual-Framework-Based*, and *Cultural Limitations*.

Based on a thorough examination of literature, the absence of multivariate analysis across key indicators becomes salient (Urbancikova et al., 2017). Studies such as those of Polanco-Levicán & Salvo-Garrido (2022) focus on hyper-specific aspects of media literacy, social media in particular, while the evaluation of socio-economic-based access and critical thinking skills remained largely unexplored. Furthermore, targeted reviews, such as those of d’Haenens et al. (2025), Laskar (2023), and Lu et al. (2023) appears to focus on media consumption and digital literacy particularly with reference to the digital divide, however, generally does not examine cognitive and affective components such critical thinking, peer influence and information evaluation skills (Guha & Mukerji, 2021; Laskar, 2023). While existing studies examine disparities across socio-economic class, a comprehensive framework across various demographic strata remains insufficiently articulated in the existing literature (Schneider et al., 2022).

In addition to an absence of multivariate analysis, current literature appears to be marked by notable limitations within socio-economic stratification (Laskar, 2023; Hamid et al., 2024). Studies such as those of van Deursen & van Dijk (2019), Rayland & Andrews (2023), and Campos & Scherer (2024) which include stratification, are limited to geographical disparity between rural and urban, limited to ‘Material Access’, without explicitly elaborating on obstacles to access, caused by other social factors such as peer networking, lack of motivation, social norms, and gender and age based disparities in digital literacy access (Vaidehi et al., 2021). Significantly, stratification within existing studies appears not to indicate having measured key-sub variables such as income levels, caste, parental education, and social key causes that warrant stratification, such as marginalisation due to systematic inequality created by traditional thinking patterns (Singh, 2010; Tewathia et al., 2020; Kumar & Kumara, 2018; Vaidehi et al., 2021).

Lastly, a paucity of linguistic stratification in existing literature alludes to socioeconomic and cultural shortcomings of previous studies. Samardzic et al. (2024) recommend that “*Representing a wider spectrum of linguistic diversity is not only a way to improve cross-linguistic generalisation...., but also a way to deal with biases against low-resource languages, which are harder to represent and thus more likely to be left behind.*” Based on this recommendation, we discern studies such as those of Sindakis & Showkat (2024), Tinmaz et al. (2022), and Bansal, (2021) focus exclusively with English-Speaking participants, without considering the multi-linguistic preference of communication within the Indian sub-context (Chowdhury et al., 2015). Such a gap is likely due to the systemic exclusion of non-English speaking participants as data collected appears to be limited to the urban and semi-urban populations fluent in English, leading to a more homogenous sample that is misaligned from rural counterparts. (Kumar & Sarma, 2015; Bahji et al., 2023; Sahoo et al., 2024). The omission of linguistic diversity is compounded by the apparent underutilization of socio-economic stratification as an analytical lens, with an emphasis on material access that, according to prior studies (Singh, 2010; Kumar & Kumara, 2018; Laskar, 2023), appears to remain relatively underexplored.

II. Review of Literature

India's digital economy has witnessed substantial growth, evidenced by a reported 954 million internet subscribers as of March 2024 (Sharma, 2024). Yet, as observed within literature, this unprecedented expansion in connectivity does not appear to automatically translate into equitable

gains in educational attainment, digital literacy, or information evaluation skills. Instead, it appears that the benefits of digital access remain stratified, with media consumption patterns mediating how connectivity is converted into cognitive, cultural, and educational outcomes between strata. Furthermore, despite this numerical expansion in connectivity, patterns of meaningful access and usage remain largely skewed. Literature suggests that disparities in digital engagement persists across demographic strata, stratified on the axes of age, gender, educational attainment, and socio-economic status.

Theoretical Foundations and Conceptual Framework

Media consumption is defined as the ways and means through which individuals and social groups engage with various media platforms (Kte'pi et al., 2021), shaping both information access, digital connectivity, and recreational uses. While India's digitalization agenda has often been framed as a tool for empowerment for the marginalized, scholarly research increasingly cautions that such initiatives may inadvertently deepen exclusion among structurally marginalized communities (Islam & Manchanda, 2023). Although digital technology has the potential to serve as a powerful tool for enabling disenfranchised groups to participate in economic, social, and political life, and to advocate for more equitable representation (Rana & Singh, 2025), its transformative impact is realized only when it is deployed in ways that are accessible and inclusive. In practice, infrastructural disparities, limited digital literacy, and uneven resource availability often constrain these groups from fully leveraging such technologies to their advantage (Abraham, 2014).

Understanding these structural inequalities requires examining the underlying mechanisms that drive individual media choices within these constraint contexts. Singh's (2023) research showcases that demographic factors significantly influence media consumption patterns, with variations across age, gender, socioeconomic status and location. Hence this demographic stratification in media strongly urges the use of theoretical framework that can account for structural constraints in digital participation.

The Uses and Gratifications (U&G) theory offers a relevant framework that can be used to explain media engagement as an active process of selecting content that aligns with one's individual needs (Blumer and Katz, 1974). This theory proposes that mass media functions as a tool through which individuals attempt to satisfy a diverse set of psycho-social needs, with individual members of the population engaging through interpretations of publicly available content. Blumer and Katz (1974) suggests that consumers are not passive recipients but, notably, active interpreters, their comprehension is influenced by personal goals, situational contexts, competing sources of gratification and ineffable emotions. Livingstone's (2004) examination of media literacy presents a foundational conceptualization of literacy, with respect to the transitional period from traditional to digital media environments. Her work underscores that media literacy cannot be understood in isolation, further highlighting the connected processes influencing media literacy as a symbolic representation of knowledge and culture. Rather than framing media consumption purely as individualistic or cognitive, Livingstone proposes that it is shaped by broader systematic conditions such as uneven distributions of digital resources and socio-economic disparities in accessibility.

Collectively, these frameworks underscore that digital participation is not a monolithic process but a layered phenomenon: U&G explains the micro-level agency of media users, Livingstone situates literacy within cultural and systemic conditions, and Van Dijk's digital divide model dissects the structural impediments to equitable use. This integrative scaffolding informs the present study's

stratified multivariate analysis, which seeks to connect individual media choices to broader educational and cognitive outcomes.

Digital Divide and Socioeconomic Stratification Models

Models such as those of van Deursen & van Dijk (2019), Scheerder et al. (2017), and Van Dijk's (2006) provide structured cognitive frameworks through which potential inequality can be explored. Van Dijk's (2006) model classifies types of access into four categories to holistically capture the impediments to digital equity; with material access referring to the availability of infrastructure such as electronic devices and stable internet, motivational access evaluates the desire to be digitally connected, skill access is defined by digital proficiency, and usage access is based on the opportunities for media exposure. Scheerder et al.'s (2017) framework provides similar structured classifications. This substructure of the digital divide elucidates the reasons for unequal employment of digital resources in developing countries such as India, where despite infrastructural disparity reducing, the digital divide manifests in nuanced ways. Consequently, the utilization of digital technology is directly correlated with social and educational positioning (Warschauer, 2003).

The Knowledge Gap Theory proposed by Tichenor et al., (1970) investigates the phenomenon of the "*knowledge gap hypothesis*", the knowledge gap within this context is defined as the uneven distribution of knowledge across different social groups, their theory suggests that with the increased integration of mass media content within social systems, population segments with higher socio-economic class tend to acquire this information faster than their lesser-privileged equivalents (Tichenor et al., 1970), perpetuating the increasing gap between these existing segments. However, this theory was critiqued for overattributing knowledge acquisition to deterministic factors and undervaluing the cognitive abilities of individuals from lower socio-economic backgrounds.

Media Consumption Variation across Age

Media consumption patterns, notably, showcase variation across age based on the work of Singh (2023) and Joshi et al. (2020). Scholars suggest that variation occurs across key dimensions such as types of content consumed, preferred media format, access to desired resources and inclination towards specific types of content—as Singh (2023) puts it—*Niches*. Forsgren & Byström (2018) further showcases the significance of these variations, classifying age as a significant predictor of access to digital resources. Such has been supported by on-ground survey analysis of Urban Slums across New Delhi, revealing that participants between the ages of 41-50 years had the highest odds of mobile phone ownership as compared to those older than 50. On the contrary, participants between the age of 18 and 30 years, had the highest probability of access to the internet, across all age groups. Additionally, text messaging was more probable in the 41-50 age bracket. (Joshi et al., 2020). On the other hand, showcasing age as a significant predictor, Tran et al.'s (2015) study assessing phone ownership in Bangladesh revealed individuals between the ages of 20-24 demonstrated higher odds of mobile-phone ownership with significantly less odds amongst participants aged 30 or more. Collectively, these findings suggest that variations appear to exist amongst individual populations despite similar socio-economic environments. The significant finding across these studies was observed to be the positive correlation between the wealth index and device ownerships, indicating the extent to which economic factors influence digital opportunity (Kibria and Nayeem, 2023). In addition to device ownership patterns, engagement and the types of content consumed reveals a significant variation, with younger Indians (15-24) engaging with short

form content on Instagram, possibly increasing their susceptibility to social media addiction and anxiety (Andreassen et al., 2017). The increased exposure prevalent in developing minds is quite concerning, as studies, such as those of Prensky (2001) and Haddock et al. (2022), consistently demonstrate that younger groups, referred to as '*digital natives*', exhibit higher digital exposure, which on one hand allows them to navigate digital tools for traditional as well as non-conventional uses, but also increases potential exposure to age-inappropriate media. The possibility of exposure to age restricted content is further heightened as literature suggests that digital natives demonstrate a preference for dynamic, trending content, with high availability, rather than appropriate content. Older generations, who showcase lower levels of digital literacy, appear to rely on traditional media formats such as television, radio, and print media. Akello (2024) suggests, they may face barriers in accessing digital resources potentially due to a lack of formal training and support from younger generations. This variation in consumption patterns appears to permeate to other spheres of engagement as well, particularly political and civic participation in response to news. *Digital natives* appear to prefer online news, greater than their older counterparts, and are more likely to express their socio-political perspectives through online posts. Boulianne and Shehata (2022) suggest that the correlation between political interest, news consumption and political expression are significantly stronger for younger respondents, emphasizing the social consequences of a digital divide in equitable engagement.

Existing literature suggests significant gender disparities vary across areas of residence (both rural and urban) that influence media consumption. Saha et al. 's (2024) work on exploring the relationship between gender and digital technology, reveals a '*gendered digital divide*' including, but not limited to, digital literacy, access to internet (its services and availability), and time availability. The gender digital divide is not just limited to technological access but extends to social norms and cultural expectations about gender roles. Peláez-Sánchez et al. (2023) go as far to advocate that social norms must be challenged to create an equitable environment, where women are not disadvantaged. However, scholars such as (McClure, 2003) provide a differing view, suggesting the prevalence of gendered variation is not attributed to systemic disadvantage, rather to individual cognitive preferences and choice-driven behaviors. Investigations such as those of Garg (2021) and Islam & Manchanda (2023) explore the intersection of digital access within rural localities. Islam & Manchanda (2023) observe a difference between the number of men with access to the internet compared to women, which appears to me markedly higher within rural areas where 'conventional thinking patterns and social organization continue to persist.

The most common factors attributed to the lack of liberty to use mobile phones were socio-cultural norms and stereotypes that dictate the differences in the duties of women and men. Women mostly used the calling feature as it is the simplest feature, most often to stay in touch with family members and relatives, were rarely if ever permitted to use the device at their own discretion, and in the unlikely event that they were aware that the internet can provide useful technical information, and were literate enough to use it as such, were restricted by their community and labelled as women with questionable character if they expressed a desire to stay digitally connected (Garg, 2021). Women in rural areas also had virtually no participation in online bill payments as compared to their male counterparts and refrain from learning how to conduct online transactions (Gurumurthy & Chami, 2014), despite the widespread adoption of digital payments through UPI and Net banking. Despite this it would be untenable to make a generalized claim that rural women have no observable engagement patterns with respect to digital resources. As a salient characteristic of digital resource

consumption (demonstrated by rural women, typically mothers with children in school) is the usage of information on the internet primarily for women's children's academic requirements and class projects (Gurumurthy & Chami, 2014), unlike women in urban areas that typically demonstrated more diverse use-cases (Kumawat & Garg, 2025).

Media Variation Across Socio-economic Status

Habibi et al., (2023) note, access to digital resources appears to be strongly stratified by socio-economic status. Such is attributed predominantly due to the fact that digital resources are only accessible to those with material access to devices and high-quality internet. Consequently, Vasistha et al. 's (2024) investigation into socioeconomic disparities in digital education within India, builds on Habibi et al.'s (2023) findings. They note, access to digital resources significantly and directly affects skill access, digital literacy levels, and digital engagement. Such findings could possibly be a result of a lack of low-cost digital training opportunities. Despite an abundance of information accessible through diverse media channels, individuals living in urban (connected) areas that belong to lower economic socio-economic groups often are unable to access information. Viswanath et al., (2013) further suggest that such predicaments result in a deficiency of specific information requirements. High socio-economic groups, in addition to those with high educational attainment levels, demonstrate a more impactful utilization of mobile devices in news consumption. Furthermore, such groups appear to communicate through email, search for information, and listen to music at higher levels than lower economic level counterparts (Nassar & Oumais, 2016). Additionally, these groups also demonstrate a reduced use of social media and video streaming platforms (Ucar et al., 2021) as compared to lower SES groups that typically prefer social media as their primary source of information. Ucar et al.'s (2021) findings, which assessed engagement patterns with news in the United States, further adds nuance to existing literature by establishing a significant correlation between education and media access. Previously, Mitchell et al. (2020) noted that individuals with lower levels of education tend to prefer social media to access information on current affairs. The informational divide appears to extend beyond the sphere of news and entertainment and may influence other imperative aspects of socio-economic participation. With reference to prevalent knowledge gaps, Posey's (2023) study, analyzing racially and economically marginalized communities, showcased that conventional media may fail to provide critical information to lower income groups (Barr, 2012). Such a gap is intensified by financial institutions undeserving lower income groups. As a result, these groups appear to turn to predatory and unregulated financial services (such as pawn brokerages and title loans) that take advantage of social exclusion (Sawyer & Temkin, 2004).

Household Income

Similar findings are observed across different income groups, specifically regarding content accessibility and preference. Literature indicates that children from low and middle-income countries primarily access media content emerging from high-income countries. On the contrary, high-income groups demonstrate a preference for more diverse and locally produced content (Ahn & Jong, 2024). Additionally, high-income groups demonstrate a preference for a diverse range of content, such as international films, series, and education programs which potentially influence their media consumption patterns (Borzekowski, 2022). Singh (2023) further contributes by noting that they also appear to engage with platforms offering tailored content as opposed to generic and

repetitive content. This contrasts with Low-income individuals who often gravitate towards popular and accessible international shows, depicting a unidimensional consumption pattern due to limited resources (Martin et al., 1976). These observations extend to diverse use cases, such as the requirement for health data, especially regarding treatment options and diagnostic tests (Bigio et al., 2023). High-income groups often access such information more than their lower-income counterparts, who generally are unable to afford such privileges and services (Richardson et al., 2012; Rani et al., 2024). Indicating that aside from preference, economic disadvantage also dictates the type of content consumed, especially regarding information about purchase decisions.

Parental Education

Literature suggests that parental education appears to be significantly related to time spent by adolescents (between the ages of 11 to 13) on digital platforms. Totland et al. 's (2013) studies highlight parental education as an important predictor of time spent on screen. Lower parental education typically correlates to increased time spent on digital platforms (Lee et al., 2024). Additionally, Lee et al., (2022) highlighted the effect of the media socialization habits of parents on their children's consumption patterns. They demonstrated that higher parental educational levels often correlate, significantly, with positive media guidance and engagement, thereby enhancing the probability of children's educational success (Kraaykamp & Notten, 2016). Which in turn reduces dependency upon media (Stockdale & Coyne, 2020)

Geographical area

Despite recent government reports indicating large-scale digital penetration (Vaishnaw et al., 2024; Mishra et al., 2025), existing literature suggests a gap persists between the adoption of ICT tools and internet connectivity (Chaudhuri, 2024), which remains unevenly accessible across remote sub-localities in both urban and rural areas. Chaudhuri's (2024) chi-square test reveals a significant association between internet connectivity and ICT tool usage. Hence, suggesting that areas with higher network connectivity exhibit greater ICT usage (Rahman & Mehnaz, 2024). Although digital adoption is widespread, media consumption habits appear to differ substantially between urban and rural regions (Kantar, 2024). Such differences span communication, entertainment, recreation, and social networking. Instant messaging services such as WhatsApp appear to be common among rural users for connecting with friends and family (Chaturvedi & Osama, 2018). However, voice and video call services remain less prevalent among rural adults. On the contrary, rural adults frequently engage in online entertainment, such as consuming content on YouTube and sharing video links (Ascent, 2020) possibly suggesting a higher preference to media consumption rather than utilization.

Media Consumption and Educational Interest

Social interest in news and current events appears to be a more reliant predictor of knowledge acquisition within the Indian context. As Fletcher et al. (2025) note, factors such as educational levels are not an absolute indicator of knowledge acquisition, challenging the deterministic perspective of the knowledge gap can be solely attributed to environmental factors (Genova & Greenberg, 1979). Collectively these findings suggest that fostering interest in educational media may bridge the disparity in educational outcomes in disenfranchised groups experiencing the effects of the socio-economic divide. Moreover, media literacy appears to play an important role in

extracting educational value from non-academic sources. Such an inference aligns with Buckingham's (2003) findings that suggest educational benefits from media are influenced by the viewer's interpretative ability. Conversely, potential concerns about the impact of unregulated digital connectivity on focus and educational engagement arise within literature. Potentially due to the use of non-educational digital tools during educational activities may hinder academic performance (Rosen et al., 2011). However, literature strongly suggests that not all media consumption is equivalent, with distinctions arising in active and passive media engagement. Anderson & Subrahmanyam (2017) demonstrate that passive consumption such as entertainment-oriented television correlates significantly with declining academic curiosity. On the other hand, active engagement with entertaining content based on educational models (such as educational and gamified videogames) increases academic interests, potentially fostering more nuanced connections with learning materials (Gee, 2005). As observed by Duran (1978), individuals from lower-income groups disproportionately engage with entertainment-oriented media such as television, video streaming, and social media rather than educational content. This consumption pattern intensifies informational deficit and limits access to critical information, reinforcing socio-economic divides (Posey, 2023). Furthermore, educational and cognitive outcome disruptions caused by attention dysregulation may disproportionately affect lower-income groups due to dependency on television as an educational resource (Fletcher et al., 2014).

Disparity within different socio-economic groups

Pop and Ene, (2019) explore trust in media and its correlation with income and education, supporting conventional assumptions that highly educated individuals are distrustful of media and are predisposed to news skepticism and can recognise fake news more effectively. However, a contradictory approach suggests that those with higher levels of education and income may report greater trust in mainstream news because they feel represented and served by these institutions (Tandoc, 2018; Tsati et al., 2022). But individuals from lower socio-economic backgrounds with comparatively lower education levels may feel underrepresented and perceive mainstream media to be 'elitist' and 'inaccessible' to them and their needs, increasing distrust (Fletcher & Nielsen, 2024). This mistrust is worsened by algorithmic personalization, which may disproportionately affect lower-income users that engage more frequently with mobile devices and social media platforms. These users are often trapped in narrow informational environments that present misinformation and poorly fact-checked data. They face various obstacles in accessing high-quality information due to paywalls, subscription models, and other economic hindrances (Zimmer et al., 2019).

Media Consumption and Digital Literacy

With regards to media consumption and digital literacy (Hobbs, 2010) suggests that the two paradigms are significantly correlated in modern society, where media consumption patterns are transitioning from conventional media to digital platforms (Chen, 2025). Digital literacy appears to play a significant role in the utilization of media sources to make informed decisions about educational opportunities, employment, and influences goal-oriented behaviour with respect to optimizing tasks and increasing productivity using specific, niche platforms. Digital literacy empowers users to go beyond passive reading and engage in active content creation, information evaluation and communication, as well as use digital tools for diverse purposes such as learning, political and civil participation and creative expression (Eshet-Alkalai, 2004). Additionally, media

consumption habits differ across the quality of the content on the basis of complexity. Furthermore, excessive media consumption of low complexity data is likely to show poor competence in areas such as source evaluation and fact-checking skills (Cardoso-Leite et al., 2021). Vivion et al., (2024), note that demographic differences across age can be observed in digital literacy levels, as younger users, labelled digital natives, may operate digital platforms better, but may lack the evaluative skills necessary to dissect data (Nhedzi, 2018; Zhou et al., 2022). Whereas older generations may prefer traditional forms such as print, broadcasting, and television, as they perceive online media platforms to be less reliable, spread misinformation and propaganda, and instigate their audience in favor of radicalized political and social movements (Guess et al., 2020)

Disparities within Socio-economic Groups

Digital literacy continues to be a strong predictor of media consumption patterns, especially in disadvantaged populations that cannot access conventional media sources due to a lack of literacy and economic scarcity (Linos et al., 2022). As a result, these groups rely excessively on social media and text messages for information. Furthermore, increased micro-level digital literacy is positively correlated with increased household media consumption, especially in educational and healthcare spheres (Ji et al., 2024), which may be attributed to higher income due to opportunities created by advanced digital skills, expanding social networks, and overall engagement with digital platforms (Wang et al., 2022; Xiao & Li, 2021; Li et al., 2025).

Media Consumption and Information Evaluation Ability

Literature suggests that media consumption has become increasingly fragmented and nuanced, as individuals tend to switch between multiple formats, genres, and platforms such as news agencies, podcasts, traditional print and audio-visual media (Nechushta, 2024; Joselin et al., 2025). Rai & Shahila (2013) underpin the cause of such nuances with the recent penetration of social media at the grassroots level. Social media demonstrates a dual impact on media evaluation, though it allows for diverse perspectives from official media channels, and reduces disparity caused by the knowledge gap through rigorous discussion, particularly in political discourse (Cho et al., 2024). It is also susceptible to algorithmic curation, which may lead to self-confirmation bias (echo-chambers) and reinforce pre-existing beliefs, reducing opportunities to critically engage with opposing schools of thought (Casula & Wong, 2025) and increasing susceptibility to institutionalized and dogmatic thinking (Burton et al., 2024). Furthermore, Ophir et al., (2009) suggest that media multitasking (involving the consumption of digital information by switching between various sources) leads to shallow and passive engagement, contributing to poor processing and cognitive learning. However, this is contradicted by studies that suggest that individuals who consume news from a variety of high-quality sources exhibit stronger information evaluation ability and media literacy skills (Uncapher et al., 2017; McGrew & Breakstone, 2023)

Media Literacy Gaps, Media Consumption and Trust in Media in SES

Individuals from high SES backgrounds typically have consistent and private access to devices, enabling them to access high-quality information sources and consume credible news and educational content (Sharma & Banerjee, 2022). This may influence the prospects of these groups with reference to news literacy and critical thinking skills, and imply that their ability to assess the credibility and relevance of information is not as developed as individuals from high SES

backgrounds (Lukáč et al., 2025). Educational attainment is also closely related to information evaluation, and often individuals from lower socio-economic classes have limited formal education, which makes them more vulnerable to misinformation and persuasive digital content (Rek & Eva, 2025).

Media consumption patterns often indicate that certain demographics, such as younger audiences, often demonstrate a higher distrust of traditional and preferred media sources available in their cultural context, favoring social media and alternative sources instead (Nielsen and Fletcher, 2024). This is supported by perception models that evaluated individuals' understanding of misinformation and its correlation with trust in mainstream media, which had been distinctly observed across different strata (Ognyanova et al., 2020; Hameleers et al., 2022)

Media Consumption and Peer Influence Dynamics

With regards to peer influence dynamics, (Pérez-Torres, 2024) suggests that collective peer influence dynamics directly and indirectly determine media consumption across various age groups. As individuals, especially adolescents and young adults, use social media as a socialization tool to develop 'their identity' and its corresponding aspects such as gender, culture, ethnicity, religious beliefs, and political ideology (Pazer, 2024). These processes strongly guide preferences regarding media adoption, with individuals choosing media that affirms or supports their sense of self, and is considered socially desirable. For example, young adults who are exposed to drinking cultures will purposefully consume media that depicts drinking as a way of performing identity (Lyons et al., 2017). This supports the idea that media preferences are dictated by individual identity but continue to be codependent on group membership, which illustrates how personal and social aspects of identity converge within online spaces. Greene & Burleson (2003) build upon this idea to further the relation between performative social identity and media preferences. They propose that people gravitate towards media that corresponds to their perceived peer age group, validating their social identity and group membership. This is typically observed in adolescents and young adults, who view media that is popular or mainstream with their peer group. This suggests that media preferences are a social tactic and a means of identifying with their age identity (Toma & Hancock, 2013). In contrast, peer-approved media identification has the potential to create conformity pressure as well, where people are forced to view specific types of media to belong, potentially at the cost of their enjoyment and preferences (Lemish & Elias, 2009). Lastly, highlighting that the interaction between peer influence, identity formation, and media use uncovers a twofold process: while social media creates space for self-expression and group affiliation, it also presents subtle normative forces that regulate what is consumed and shared (Bailey et al., 2013).

Disparity within different socio-economic groups

Individuals belonging to higher SES backgrounds have unrestricted access to streaming platforms and possess the necessary physical infrastructure and formal training through educational institutions that equip them to explore and consume media such as shows and movies that are trending (Pandey, 2020, Skogen et al., 2022). This directly enhances their social bonding, ensuring they are up to date with contemporary media (Tripathi, 2025). However, youth from lower SES backgrounds lack updated information and immediate access to media, enhancing their feelings of exclusion, and their lack of interpretative sources and contextual media may prevent them from

participating in media-related discussions (Pawluczuk, 2020) both online, and in physical social interactions (Laskar, 2023).

In sum, literature establishes clear evidence of demographic and socio-economic stratification in media consumption and highlights its potential implications for education, literacy, and information evaluation. Yet, existing studies remain fragmented: many describe access disparities without modeling outcomes, while others examine outcomes without accounting for stratified media use. Few adopt a multivariate framework that systematically integrates access, consumption, and outcomes across socio-economic groups. The present study addresses this gap by conducting a stratified multivariate analysis of Indian media consumption, thereby empirically testing how digital inequalities are reproduced and reinforced through differential educational and cognitive outcomes.

III. Methodology

This study employed a stratified multivariate design to systematically investigate the patterns of digital media consumption and their measurable impact on educational interest, digital literacy, and information evaluation skills across socio-economic strata in North India. Cognizant of the deep social stratification across Indian Society, the methodology was designed in an attempt to demonstrate the diverse, experiential and nuanced realities of the general Indian populace within the context of media consumption, with reference to unequal digital access. A cross-sectional quantitative approach was implemented to allow statistical generalization of associations between engagement with media sources and cognitive education variables within a fixed temporal frame. This study's setting spans urban, semi-urban, and rural regions of four North-Indian states: Haryana, Punjab, and the Delhi national Capital Region (NCR). These regions were purposively selected for their socio-cultural heterogeneity and economic diversity, enabling a comparative analysis across structural inequalities. Participants ranged from 15 to 45 years of age, with age brackets stratified into three groups (15–25), (25–35), and (35–45). Stratification was performed in an effort to ensure generational comparability and eliminate noise from outlier age groups. Individuals younger than 15 and older than 45 were excluded to preserve socio-economic demographic focus. The sample consisted of human respondents justified by the study's core objective: to assess human cognitive, informational, and educational behaviour and its relationship with media exposure. Participants included secondary school and university students, daily-wage earners, blue-collar workers, and white-collar professionals. The occupational and educational variance contributed to meaningful stratification across socio-economic groups.

Aims and Objectives

This study aims to investigate how digital media consumption patterns influence educational interest, digital literacy, and information evaluation skills among Indian youth, with particular attention to the moderating roles of socio-economic stratification, gender, and age.

1. To quantify and compare patterns of digital media consumption across socio-economic, gender, and age strata, establishing baseline differences in access, frequency, and type of engagement.
2. To analyze the relationship between digital media use and educational outcomes (specifically educational interest, digital literacy, and information evaluation skills) while examining whether higher engagement correlates with increased academic motivation and competencies.

3. To evaluate how socio-economic background, gender, and age moderate the effects of media consumption on these outcomes, identifying differential impacts across demographic strata.
4. To assess the role of affective variables, particularly peer influence and trust in media sources, in shaping media-related educational engagement and competencies, including digital literacy and evaluative reasoning.
5. To address empirical gaps in the literature and provide evidence-based insights that inform equitable digital education and media policy in India.

Research Hypotheses

- H1 = There is a significant difference between the Male and Female groups with respect to the dependent variable Educational Interest
- H2 = There is a significant difference between the Male and Female groups with respect to the dependent variable Digital Literacy
- H3 = There is a significant difference between the Male and Female groups with respect to the dependent variable Information Evaluation
- H4 = There is a significant difference between the Male and Female groups with respect to the dependent variable Trust in Media
- H5 = There is a significant difference between the Male and Female groups with respect to the dependent variable Peer Influence
- H6 = There is a significant difference between the Male and Female groups with respect to the dependent variable Media Consumption Hours
- H7 = There is a significant difference between the Male and Female groups with respect to the dependent variable Number of Media Platforms
- H8 = There is a significant difference in Educational Interest between at least two age groups.
- H9 = There is a significant difference in Digital Literacy scores between at least two age groups.
- H10 = There is a significant difference in Information Evaluation ability between at least two age groups.
- H11 = There is a significant difference in Trust in Media between at least two age groups.
- H12 = There is a significant difference in Peer Influence between at least two age groups.
- H13 = There is a significant positive relationship between Educational Interest and Digital Literacy.
- H14 = There is a significant positive relationship between Educational Interest and Information Evaluation.
- H15 = There is a significant negative relationship between Educational Interest and Trust in Media.
- H16 = There is a significant negative relationship between Educational Interest and Peer Influence.
- H17 = There is a significant positive relationship between Digital Literacy and Information Evaluation.
- H18 = There is a significant negative relationship between Digital Literacy and Trust in Media.
- H19 = There is a significant negative relationship between Digital Literacy and Peer Influence.
- H20 = There is a significant negative relationship between Information Evaluation and Trust in Media.

- H21 = There is a significant negative relationship between Information Evaluation and Peer Influence.
- H22 = There is a significant positive relationship between Trust in Media and Peer Influence.
- H23 = There is a significant negative relationship between Peer Influence and Media Consumption Hours.
- H24 = There is a significant negative relationship between Peer Influence and Number of Media Platforms.
- H25 = There is a significant positive relationship between Media Consumption Hours and Number of Media Platforms.

Variable Classification

This study employed a structured multivariate design, incorporating both continuous and categorical variables across cognitive, demographic and socio-economic fields. Categorization of variables supported their theoretical roles, primary outcomes variables (Educational Interest, Digital Literacy and Information Evaluation Skills) were utilized as continuous variables linked to 5-Point Likert Scales. These variables were designed to reflect the cognitive competencies, nuances, and dispositions relevant to the study.

Predictor variables included four categories:

1. Cognitive-Psychosocial Predictors: *Educational Interest*, *Digital Literacy*, *Trust in Media*, and *Peer Influence*. These variables were measured through psychometrically reliant ($\alpha > 0.80$) multi-item instruments.
2. Demographic Predictors: *Age* (categorical; grouped into 15–25, 25–35, and 35–45 years) and *Gender* (binary; Male, Female).
3. Socioeconomic Predictors: *Annual Household Income*, stratified into six ordered tax-bracket categories (₹0–₹3,00,000; ₹3,00,001–₹6,00,000; ₹6,00,001–₹9,00,000; ₹9,00,001–₹12,00,000; ₹12,00,001–₹15,00,000; ₹15,00,001 and above).
4. Media Exposure Predictors: *Media Consumption Hours per Day* (continuous) and *Number of Media Platforms Used* (discrete numeric count).

The classification of variables contributed to a rigorous stratified regression modelling approach; wherein cognitive behavioral and socioeconomic variables were simultaneously analyzed for predictive contributions.

Standardization of Variables

To ensure comparability of variables, it is essential to mitigate scale-based variance in multivariate analyses. Media Consumption Hours per Day and Number of Media Platforms used were standardized using z-score transformation to facilitate the multivariate analysis. Z-Standardization facilitates the normalization of variables with differing units and distributions by centering values around a mean of 0 and scaling them to unit variance ($SD = 1$). This standardization enables unbiased estimation of regression coefficients in models. The formula used for z-standardization was: $z = \frac{x - \mu}{\sigma}$, where x is the raw score, μ is the sample mean, and σ is the sample standard deviation of the respective variable. Naturally, standardization was implemented prior to regression modelling, correlation analyses and hypothesis testing to avoid magnitude distortions. The decision

to standardize only media exposure variables was grounded in both theoretical and statistical considerations.

Sampling Techniques

This study employed a stratified random sampling technique to ensure demographic, socioeconomic and regional representation across North India. The sampling design was aligned with primary research objectives and the necessity to investigate digital media behavior across strata. The states of Uttar Pradesh, Haryana, Punjab and Delhi (NCR) were deliberately chosen, to capture the socio-cultural heterogeneity within India.

The sample was stratified along three primary axes:

1. *Age*: Sample stratified into (15–25), (25–35), and (35–45) categories
2. *Gender*: Sample stratified into (Male) and (Female) categories
3. *Socio-economic status*: Sample stratified along household income brackets with (₹0–₹3,00,000) and (₹15,00,001 and above)

From a methodological standpoint, stratification enabled comparability across subgroups within the study, ensuring adequate representation of structurally underrepresented communities such as rural and low-income respondents. Ethically, stratification promoted sampling equity by ensuring that digital marginalization was not perpetuated through exclusion. Initial participant responses yielded 2,179 samples through targeted outreach across community organizations, educational institutions, and workplaces. Survey forms were administered digitally and in print translated into Hindi, Punjabi, and English using validated back-translation to ensure semantic and psychometric consistency. A pilot test ($n = 43$) was conducted across rural and urban sites to confirm cultural clarity and functional accessibility. Enumerators were trained in non-coercive consent, digital confidentiality, and identity-sensitive administration. Post-collection, exclusion criteria were systematically applied: participants outside the target age range ($n = 61$), non-media users ($n = 55$), non-South Asian Indian respondents ($n = 45$), and duplicate or unverifiable entries ($n = 26$) were removed. These refinements ensured data integrity, resulting in a final analytic sample of 1,992 cases (91.4% retention), exceeding empirical adequacy standards for digital media research in stratified Indian populations.

Ethical Considerations

This study was approved by the Ashoka University Human Research Ethics Committee (AUHREC) in May 2025 (Ref. No. AUHREC/25/05/214), in compliance with the ethical standards of the Institutional Review Board (IRB), the Indian Council of Medical Research (ICMR) guidelines, and the Helsinki Declaration (1975, revised 2013). Written informed consent was obtained from all participants, who were assured of voluntary participation, confidentiality, and the right to withdraw without penalty.

Informed Consent: Prior to participation, all respondents were obliged to acknowledge a detailed informed consent agreement. Agreements were available in English, Hindi and Punjabi, and outlined the study's goals, purpose, scope, data usage and privacy policies. Our consent process emphasized non-coercive voluntariness where participants were explicitly informed about the optionality of their involvement and the ability to withdraw at any point prior to submission with adverse consequence. Only responses with participant acknowledgements were included in the final dataset.

Confidentiality and Data Protection: Data collection strictly adhered to the principles outlined in the Declaration of Helsinki and prevailing institutional review boards standards which govern research involving human subjects. In accordance, data was anonymized at the point of collection, then stored in encrypted password protected digital files accessible solely to the principal investigators. Raw data was not shared with any institution, private organization, third party researchers or administrators, furthermore personal data was not collected

Right to Withdraw: Participants were required to complete the form in full upon opting in, however, withdrawal prior to final submission was explicitly permitted and communicated. Collectively, these standards ensured the integrity of the research and highest regard for participant rights and privacy.

IV. Results and Findings

Table 1: Showing T-Test Results for Educational Interest and Gender

	n	M	SD	t	df	p	Cohen's d
Educational Interest	Male 1195	34.7	5.96	-0.87	1990	0.382	0.04
	Female 797	34.94	5.88				

As seen in Table 1, independent samples t-tests reveal that means of both groups closely align with males ($M = 34.7$, $SD = 5.96$) scoring slightly lower means than females ($M = 34.94$, $SD = 5.88$). However, $t(1990) = -0.87$ and $p = 0.382$ ($p > 0.05$) suggests low statistical significance and negligible difference in effect size (Cohen's $d = 0.04$). Hence, H_1 is **rejected**.

The absence of a statistically significant relationship between gender and educational interest may warrant potential reconsideration of gender as a predictive variable in the context of Indian digital environments. The above findings closely align with those of Scherer et al. (2019), who demonstrate through meta-analytical evidence that gender differences in digital competence and educational motivation have become increasingly attenuated in recent years, particularly in regions where systematic education interventions have been implemented. Similarly, Luitel's (2024) study of 500 university students in Kathmandu revealed that while females tend to exhibit slightly higher intrinsic motivation the overall magnitude of gender differences within the region was considerably less than previously documented literature. Such findings suggest a convergence of educational aspirations across genders within the region. This convergence can potentially be attributed to significant policy interventions from the Indian Government. Longitudinal government interventions demonstrate a gradual reduction of digital divide in India, potentially driven by increased digital penetration through targeted schemes and programs such as the '*beti bachao beti badhao*' and digital India, both of which aim to bridge gender-based disparity (Yadav, 2023; Prakash et al., 2024). Initiatives such as *Digital India* have further contributed to gender parity by creating technological infrastructure intended to reduce conventional barriers to educational access. Panda & Gope's (2024) analysis underscores that the implementation of digital pedagogy has led to notable gains in academic achievement, improving retention rates of students in higher education. This technological

democratization of resources may have contributed to diminishing many historical advantages that may have favored males over females in the Indian context (Korlat et al., 2021). Yu & Deng's (2022) longitudinal analysis of digital learning outcomes, albeit in COVID-19, closely align with present findings, suggesting that while females demonstrated higher perceived teacher engagement, competence beliefs showed no significant gender variations. Relevantly, the findings closely align with Yu & Deng's (2022) conclusion that *"there are generally no significant gender differences in e-learning outcomes"* across self-efficacy, satisfaction, motivation, attitude, and performance. Such observations become more pronounced within the South Asian region as observed by Chaudhry & Shabbir's (2019) analysis into gender differences in academic motivation, which revealed negligible gender based variation. The negligible effect size (Cohen's $d = 0.04$) suggests that resources previously allocated to gender-specific educational interventions may be more effectively deployed towards addressing other forms of educational inequality.

Table 2: Showing T-Test Results for Digital Literacy and Gender

	n	M	SD	t	df	p	Cohen's d
Digital Literacy Male	1195	73.03	16.81	-0.89	1990	0.373	0.04
Female	797	73.72	16.88				

As seen in Table 2, the mean Digital Literacy score for males ($M = 73.03$, $SD = 16.81$) is closely aligned with that of females ($M = 73.72$, $SD = 16.88$). However, the difference is not statistically significant, as $t(1990) = -0.89$, $p = 0.373$ ($p > 0.05$), and the effect size is negligible (Cohen's $d = 0.04$), indicating no meaningful gender-based variation. Hence, H2 is **rejected**.

The absence of statistical significance between digital literacy and gender align closely with several international studies that demonstrate diminishing gender disparities in digital competence in recent times. Studies such as Bachmann et al.'s (2025) analysis of the German national Educational Panel found *"no gender gaps in digital competences between boys and girls in lower secondary education"*. However key significant differences emerged within upper secondary contexts, suggesting that younger age groups showcase lower gender based variation in digital literacy. This convergence pattern is further supported by Hatlevik and Christophersen's (2013) Norwegian study, which reported no significant gender differences in digital literacy among senior secondary students. Similarly, Kaarakainen et al.'s (2017) Finnish investigation of 5,455 ninth-graders revealed only "a small, but statistically significant difference between the genders in the total scores on the ICT skill test," emphasizing that item-level variations were more consequential than overall gender differences. On the other hand, few studies document persistent gender gaps. Gazi et al.'s (2021) meta-analysis identified *"a small and positive, yet not significant effect size in favor of boys"* ($g = 0.17$, 95% CI $[-0.01, 0.36]$) in ICT use and skills.

Upon further analysis, the observed convergence is possibly attributed to systematic educational interventions which objectively restructure technology access within formal learning environments. For example, the EU Digital Education Action Plan (2021–2027) expands school digital infrastructure and literacy curricula, ensuring equitable access to technology in formal education. Additionally, Tolochko et al.'s (2019) network analysis revealed that while *"girls both seek and give more advice"* in peer learning networks, the overall skill-sharing dynamics showed minimal gender-based performance differences. This finding suggests that collaborative learning structures within educational institutions facilitate gender-neutral skill development. Furthermore, studies underscore

compelling evidences that educational context significantly influences findings, revealing that “being female is negatively related to computer use for leisure activities, but no relationship was found between gender and study-related computer use” (Meelissen and Drent's, 2008).

The negligible effect size (Cohen's $d = 0.04$) reflects successful policy-driven transformation of educational digital equity, suggesting that institutional provision of standardized digital infrastructure has created more equitable learning environments that transcend traditional gender-based technology access barriers.

Table 3: Showing T-Test Results for Information Evaluation and Gender

		n	M	SD	t	df	p	Cohen's d
Information Evaluation	Male	1195	69.23	18.90	-0.61	1990	0.542	0.03
	Female	797	69.75	18.45				

As seen in Table 3, males ($M = 69.23$, $SD = 18.90$) scored marginally lower than females ($M = 69.75$, $SD = 18.45$) on Information Evaluation; however, the difference was not statistically significant, $t(1990) = -0.61$, $p = 0.542$ ($p > 0.05$), with a negligible effect size (Cohen's $d = 0.03$), indicating no meaningful gender-based variation. Hence, H_3 is **rejected**.

The absence of statistically significant gender variations in information evaluation scores raises a potential counterpoint to existing research assumptions on gender-based differences in critical thinking within digital environments. Table. 3's findings suggest that critical thinking abilities underlying information evaluation may be approaching gender parity within Indian educational contexts, where. These findings contrast significantly with the *sensitivity hypothesis* proposed by Meyers-Levy & Loken (2015) which postulates that females typically engage in more comprehensive information processing while males employ more selective processing strategies. Studies indicate that regardless of underlying processing differences both approaches yield equivalent information evaluation outcomes (Lundberg, 2020; Lafifa & Rosana, 2023). This convergence is highlighted with recent evidence from Noverli & Cahya (2021) whose analysis underscored gender differentiated strengths, with females outperforming males in complex reasoning, and males outperforming females in drawing conclusions. They conclude that such differentiated strengths ultimately cancel each other out at the aggregate level. The implication of these findings is certainly not that cognitive styles have homogenized, as such a conclusion would require a more longitudinal analysis, but rather that diverse analytical routes may now reach functionally similar endpoints in information evaluation. Furthermore, this contrasts the simplistic assumptions of cognitive superiority. Another possibility is that females exhibit stronger information processing strategies whereas males excel in identifying key ideas (Bhogle, 2021), which could have contributed towards parity. These divergences do not necessarily translate into measurable differences in academic performance (Daliya and Bhogle, 2013). Instead, each gender may draw upon distinct cognitive assets to arrive at comparable levels of evaluative competence. Analytically, Chen et al.'s (2025) findings further nuance this implication, showing males demonstrated higher advantages in deduction ($r = -0.28$, $p < 0.01$), while females excelled in inference-based reasoning ($r = -0.14$, $p < 0.05$), notably yielding negligible differences.

In synthesis, the findings suggest that digital environments may function as equalizers by supporting diverse cognitive strategies thereby potentially cancelling out the gendered advantages noted in conventional assessments. While females may exhibit higher anxiety, they also report greater resourcefulness and learning motivation, thereby yielding equivalent outcomes (Zhang et al., 2023;

Saxena et al., 2024). These nuances often escape aggregate level metrics, cautioning against overinterpretations of null findings (Sternberg, 2020; Nygaard et al., 2022). Instead of gender specific interventions, institutions could explore cognitive diversity particularly in critical thinking. Given this convergence, prioritizing gender in instructional design may offer diminishing returns; comparatively, greater impact is likely to be achieved by addressing digital access, domain knowledge, and socioeconomic disparities, which appear to exert stronger causal influence.

Table 4: Showing T-Test Results for Trust in Media and Gender

	n	M	SD	t	df	p	Cohen's d
Trust in Media	Male 1195	88.45	13.94	0.54	1990	0.589	0.02
	Female 797	88.11	13.36				

Table 4 showcases males having reported marginally higher means ($M = 88.45$, $SD = 13.94$) than females ($M = 88.11$, $SD = 13.36$) in their Trust in Media levels. However, the difference was not statistically significant, $t(1990) = 0.54$, $p = 0.589$ ($p > 0.05$), with a negligible effect size (Cohen's $d = 0.02$), indicating no meaningful gender-based difference. Hence, H4 is **rejected**.

The absence of statistically significant gender variations in trust in media appears to align with recent longitudinal studies such as those of Liu & Lu's (2020) inquiry. Their findings suggest that internet context has fundamentally altered conventional gender-based patterns in media trust. Analysing data from 46 countries, their findings highlight how conventional gender variation may diminish significantly due to the homogenization of digital information environments. Further meta-analysis's examining critical theory, strongly suggest that contemporary educational policy interventions have increasingly contributed to reducing prevalent historical gender disparities in trust in media (Psaki et al., 2022; Bettauer Kattan et al., 2023; Liu & Pásztor, 2023). Notably, females demonstrated stronger self-efficient truth digging while males showed higher instant judgement capabilities, however despite these minor variations, overall trust in media competence showed little overarching variation. (Liu & Pásztor, 2023; Otero et al., 2024). Table. 4's findings suggest that participants regardless of gender may have developed comparable competencies in assessing media credibility potentially due to a higher exposure towards media.

Table 5: Showing T-Test Results for Peer Influence and Gender

	n	M	SD	t	df	p	Cohen's d
Peer Influence	Male 1195	108.72	13.79	0.95	1990	0.342	0.04
	Female 797	108.11	14.37				

As seen in Table 5, males ($M = 108.72$, $SD = 13.79$) reported slightly higher Peer Influence than females ($M = 108.11$, $SD = 14.37$); however, the difference was not statistically significant, $t(1990) = 0.95$, $p = 0.342$ ($p > 0.05$), and the effect size was negligible (Cohen's $d = 0.04$), indicating no substantial gender-based variation. Hence, H5 is **rejected**.

The lack of significance of gender on peer influence is supported by various studies that include a meta-analysis across specific behaviors such as substance abuse and find that the strength of peer influence is identical across genders (Watts et al., 2024). Table. 5's findings imply that the experience of peer pressure may not be inherently gendered but shaped by contextual socio-cultural information. This also contradicts multiple studies that attempt to establish that several differences

across genders exist with reference to peer influence, such as (Singh & Singh, 2023). However, the findings could indicate the reduced digital divide in accessing media platforms across gender (Boruzie et al., 2022) that emerged from sustained policy interventions and infrastructural development. Another plausible contributing factor is the evolution of peer networks into more gender-integrated spaces due to co-educational institutions and mixed-gendered, digital communities (Feng et al., 2023). Due to similar educational engagement through standardised curricula, collaborative learning environments, and common social media networking (McMillan et al., 2018), it is possible that the negligible differentiation is caused due to complex interaction between the genders, and similar normative pressures are experienced by individuals belonging to peer groups, regardless of pressure (Gogoi & Mansar, 2021).

Table 6: Showing T-Test Results for Media Consumption Hours and Gender

	n	Mean	SD	t	df	p	Cohen's d
Media Consumption Hours	Male 1195	0.0	1.02	0.11	1990	0.91	0.01
	Female 797	0.0	0.97				

As seen in Table 6, males ($M = 0$, $SD = 1.02$) and females ($M = 0$, $SD = 0.97$) showed identical mean standardized Media Consumption Hours; $t(1990) = 0.11$, $p = 0.91$ ($p > 0.05$), with a negligible effect size (Cohen's $d = 0.01$), indicating no gender-based difference. Hence, H_6 is **rejected**.

The absence of significant gender differences in media consumption hours suggests that infrastructural parity across North Indian states near the capital has mitigated historical disparities once driven by unequal device ownership, differential time spent online, and unregulated access to media platforms (Joshi et al., 2020). Though some literature proposes differing perspectives, suggesting that men and women's online engagement timings differ (Landrum, 2021), Table. 6's findings provide an alternative result, where media consumption hours is not a gendered phenomenon, and relatively equal across men and women. Converging social norms, with institutions fostering socialisation across genders, and similar opportunities to engage online with various content such as news, entertainment, and educational platforms, may reduce this disparity (Park et al., 2023) and lead to equitable access to media platforms. Additionally, the standardised ICT curriculum and targeted interventions to reduce the gender-based disparity, as empowered women with the necessary skills and confidence to navigate platforms with ease (Lalrinsangi & Kharbiryumbai, 2024; Hertweck & Lehner, 2025). Which could possibly be the cause of equitable time spent online across both genders.

Table 7: Showing T-Test Results for Number of Media Platforms and Gender

	n	Mean	SD	t	df	p	Cohen's d
Number of Media Platforms	Male 1195	0	1	0	1990	0.998	0
	Female 797	0	0.99				

As seen in Table 7, males ($M = 0$, $SD = 1.00$) and females ($M = 0$, $SD = 0.99$) reported identical standardized means for Number of Media Platforms; $t(1990) = 0.00$, $p = 0.998$ ($p > 0.05$), with no effect (Cohen's $d = 0.00$), indicating no gender-based difference. Hence, H_7 is **rejected**.

No significant difference was observed in the number of media platforms used by men as compared to women, based on previous scholarship documenting the restricted access of women to devices,

slower adoption to lack of digital literacy, and socio-cultural limitations (Enrique Torralbas Oslé & Corcho Rosales, 2023). The lack of divide stems from physical infrastructural parity, such as affordable smartphone options, community internet initiatives, and stable internet connection (Eppard et al., 2021). Socio-cultural integration including mixed-gender classrooms and collaborative ed-tech platforms dilute traditional norms of engagement, limiting women's discretionary media consumption time and platform exploration. However, underlying gender variation may be absent in this study's sample possibly due to the fact that this study's sample consisted primarily of urban and rural areas that were connected digitally, and through physical infrastructure. Remote areas with no digital presence may yield different results. Prior research highlights the conventional gaps in rural areas that prevent women from holistically accessing media platforms (Islam and Manchanda, 2023).

Table 8: One-Way ANOVA Summary: Effect of Age on Educational Interest

	Sum of Squares	df	Mean Square	F	p	η^2	p2	Cohens f2
Age	20.69	2	10.34					
Residual	69936.78	1989		0.29	0.745	0	0	0
Total	69957.47	1991	35.16					

*Dependant Variable: Educational Interest

As seen in Table 8, one-way ANOVA reveals a non-significant effect of age on Educational Interest; $F(2, 1989) = 0.29$, $p = 0.745$, indicating that differences between age groups are not statistically meaningful. The proportion of variance explained by age was negligible, as reflected by $\eta^2 = 0.00$ and partial $\eta^2 = 0.00$. Additionally, the effect size (Cohen's $f^2 = 0.00$) confirms that age accounts for no practical variation in Educational Interest. Hence, H8 is **rejected**.

The findings reflect that there is no significant relationship between age and educational interest. A possible explanation for this is the convergence of digital learning experiences across generations in North India. During the COVID-19 pandemic, the rapid shift to online instruction standardized access to digital platforms for students and adult learners alike. This situation completely transformed pre-existing generational gaps and led to more familiarity with educational technology (Haleem et al., 2022). Simultaneously, the widespread availability of affordable smartphones and broadband connectivity appears to have democratized digital access such that both younger “*digital natives*” and older “*digital immigrants*” now possess similar technical competencies (Světlík & Bačíková, 2022). Furthermore, uniform curricular requirements (those that emphasize standardized digital assignments, and rote based assessments) have fostered information evaluation and critical thinking skills independent of numeric age. Thus further minimizing age based differentiations (Singh, 2020). Simultaneously, as Saxena et al. (2024) suggests, cross-generational digital communication within families, peer groups, and workplaces has, additionally, fostered shared evaluative practices, aligning digital habits among diverse age cohorts. Infrastructural, pedagogical, and social shifts appear to have collectively flattened the divide in educational interest on the basis of age, even in the presence of prior literature indicating significant disparity among educational motivation and engagement (Bălătescu, 2024).

Table 9: One-Way ANOVA Summary: Effect of Age on Digital Literacy

	Sum of Squares	df	Mean Square	F	p	η^2	p^2	Cohens f^2
Age	779.9	2	389.95					
Residual	563542.14	1989		1.38	0.253	0	0	0
Total	564322.04	1991	283.33					

*Dependent Variable: Digital Literacy

As seen in Table 9, one-way ANOVA analysis yielded a non-significant result with $F(2, 1989) = 1.38$, $p = 0.253$, indicating that age does not have a statistically meaningful effect on Digital Literacy within the sample. The proportion of explained variance was negligible ($\eta^2 = 0.00$; partial $\eta^2 = 0.00$), and the effect size (Cohen's $f^2 = 0.00$) further supports the findings that the observed differences lack significance. Overall, these results suggest that Digital Literacy levels remain consistent across age groups in the sample. Hence, H9 is **rejected**.

Table 9 showcases that age does not significantly influence digital literacy ($F(2,1989) = 1.38$, $p = 0.253$, $\eta^2 = 0$), indicating no measurable differences across younger and older cohorts. This finding directly challenges Prensky's (2001) "digital natives versus digital immigrants" hypothesis, which presupposes inherent generational advantages in technical competence. Instead, this study's findings suggest that within the sample, digital literacy appears to be distributed evenly across age groups. Such a peculiarity likely reflects the various contextual factors—such as widespread mobile adoption, state-led digital inclusion programs, and shared exposure to online platforms—that collectively influence findings. A possible factor that can explain this is the COVID-19 pandemic which led to the rapid expansion of digital learning infrastructure across India. This included digital expansion to workspaces and households where where both younger students and older professionals had to learn how to operate platforms such as Zoom, Google Classroom, and WhatsApp for education, work, and social interaction (Papagari & Rayudu, 2012; Gopika & Rekha, 2023).

Another factor supporting the observation is the acceleration of government initiatives. Initiatives—most notably *Digital India*—have catalyzed broadband, smartphone and technological penetration to peri-urban and rural localities, thereby ensuring practical access across different age groups (Sharma, 2024). Simultaneously, integrational knowledge transfer within families and workplaces has fostered cross age digital socialization, narrowing skill gaps (Seerangan & Ravi, 2025).

Table 10: One-Way ANOVA Summary: Effect of Age on Information Evaluation

	Sum of Squares	df	Mean Square	F	p	η^2	p^2	Cohens f^2
Age	1036.86	2	518.43					
Residual	696681.91	1989		1.48	0.228	0	0	0
Total	697718.77	1991	350.27					

*Dependant Variable: Information Evaluation

As shown in Table 10, one-way ANOVA analysis yielded a non-significant result; $F(2, 1989) = 1.48$, $p = 0.228$, suggests that age has no statistically significant effect on Information Evaluation within the sample. The proportion of variance explained is negligible ($\eta^2 = 0.00$; partial $\eta^2 = 0.00$),

and the effect size (Cohen's $f^2 = 0.00$) indicates the absence of any meaningful practical difference. Hence, H10 is **rejected**.

Information evaluation skills do not differ significantly across the three groups, although previous literature suggest that older adults possess more evaluative and critical thinking skills (Dwyer, 2023; Zou et al., 2025) However, Table 10's findings contradicts these findings, revealing a uniform level of information assessment ability across respondents despite belonging to different demographic age groups.

The absence of generational disparities is likely explained by digital upskilling programs that systematically disseminate competencies in source verification, fact-checking, and analytical reading across user groups (Papagari & Rayudu, 2012; Gopika & Rekha, 2023). It is possible that this study's dataset reflects a relatively homogeneous pool of participants affiliated with institutions that embed digital skills within standardized curricula, thereby facilitating access to digital media for news and information and fostering critical engagement skills through structured practice. Another possibility is that the pervasive digital saturation at the grassroots level enables younger family members, particularly in urban and semi-urban contexts, to support older relatives in developing digital competencies (Timotheou et al., 2023). Further examination of intergenerational collaborative learning may yield valuable insights into the narrowing digital divide across age groups.

Table 11: One-Way ANOVA Summary: Effect of Age on Trust in Media

	Sum of Squares	df	Mean Square	F	p	η^2	p2	Cohens f2
Age	678.75	2	339.38					
Residual	373404.89	1989	187.73	1.81	0.164	0	0	0
Total	374083.65	1991						

*Dependant Variable: Trust in Media

As seen in Table 11, one-way ANOVA analysis produced a non-significant result with $F(2, 1989) = 1.81$, $p = 0.164$, indicating no statistically significant variation attributable to age. The effect size estimates were negligible, with $\eta^2 = 0.00$, partial $\eta^2 = 0.00$, and Cohen's $f^2 = 0.00$, reinforcing the conclusion that any observed differences lack practical significance. Hence, H11 is **rejected**.

An absence of significant effect of age on trust in media sources suggests that the individual's trusts within media is independent of one's age. These findings contrast the work of Flanagan & Metzger (2007), who observed a negative relationship between self-reported and observed information verification behavior with age. These findings may also be influenced due to specific factors such as joint-family dynamics within the data set. Joint family situations directly increase the likelihood of interaction and exchange of information between younger demographic groups and older counterparts. Such dynamics foster inter-generational learning which can possibly cause media skepticism due to critical thinking and information evaluation skills through fact-checking and verifying sources (Seerangan & Ravi, 2025). Trust in media appears to be shaped less by chronological age and more by factors such as individual interest, media literacy, and socio-cultural context. Evidence from the Knight Survey (2018) partly aligns with this view, showing that declining levels of trust in

media are not accompanied by significant disparities across age groups. Similarly, research on trust and susceptibility to fraud has reported no meaningful age-related differences, reinforcing the notion that demographic variables such as age are insufficient on their own to explain patterns of media trust.

Table 12: One-Way ANOVA Summary: Effect of Age on Peer Influence

	Sum of Squares	df	Mean Square	F	p	η^2	p2	Cohens f ²
Age	7.43	2	3.72					
Residual	391815.46	1989	196.99	0.02	0.981	0	0	0
Total	391822.89	1991						

*Dependant Variable: Peer Influence

As shown in Table 12, one-way ANOVA analysis yielded a non-significant result, $F(2, 1989) = 0.02$, $p = 0.981$, indicating no statistical evidence of age-based variation. The effect size estimates were virtually zero ($\eta^2 = 0.00$; partial $\eta^2 = 0.00$; Cohen's $f^2 = 0.00$), confirming the absence of any meaningful practical difference. Hence, H12 is **rejected**.

The non-significant relationship between age and peer influence demonstrates that in North-Indian populations, peer influence does not differ by age, challenging various developmental models and studies that suggest age-related differences across peer dynamics. Conventional studies posit that peer-influence peaks in early adolescence, and declines with maturity (Steinberg, 2008). However, Table 12's findings challenges existing literature. This convergence may be attributable to the Indian context, where cultural collectivism and normative thinking patterns—particularly in rural areas—can foster homogeneous peer-based influences across age groups (Nesi et al., 2018). Moreover, Table 12's findings are likely generalisable only to socio-cultural settings similar to those in Northern Indian states such as Haryana, Punjab, Uttar Pradesh, and the Delhi NCR, where educational and occupational environments often cultivate peer influence through co-working spaces, peer-supported digital forums, group assignments, and collaborative projects. A further contributing factor may be digital socialisation within online communities—messaging groups, social media networks, and communication platforms—which reinforces normative adherence and peer conformity (Chadda & Deb, 2013).

Table 13: *Presents the descriptive statistics (mean and standard deviation) of Educational Interest, Digital Literacy, Information Evaluation, Trust in Media, and Peer Influence across six self-reported household income brackets. Each construction is measured using standardized composite scores. Group sizes (n) are reported for each income bracket.*

Household Income	Educational Interest-Digital Literacy-Information Evaluation Trust in Media-Peer Influence	n	M	S.D.
₹0 – ₹3,00,000	Educational Interest	762	35.09	6.15
	Digital Literacy	762	73.75	17.17
	Information Evaluation	762	70.16	18.78
	Trust in Media	762	88.02	13.89
	Peer Influence	762	107.66	14.2
₹3,00,001 – ₹6,00,000	Educational Interest	617	34.28	5.66

Household Income	Educational Interest-Digital Literacy-Information Evaluation Trust in Media-Peer Influence	n	M	S.D.
₹15,00,001 and above	Digital Literacy	617	72.17	16.25
	Information Evaluation	617	68.51	18.38
	Trust in Media	617	89.04	13.19
	Peer Influence	617	109.66	13.77
₹9,00,001 – ₹12,00,000	Educational Interest	99	35.13	6.58
	Digital Literacy	99	72.06	17.33
	Information Evaluation	99	71.07	20.98
	Trust in Media	99	87.33	15.95
₹6,00,001 – ₹9,00,000	Peer Influence	99	108.73	15.91
	Educational Interest	158	35.06	6.04
	Digital Literacy	158	74.88	18.02
	Information Evaluation	158	70.51	19.46
₹12,00,001 – ₹15,00,000	Trust in Media	158	87.39	13.59
	Peer Influence	158	106.71	14.21
	Educational Interest	211	34.53	5.7
	Digital Literacy	211	73.02	16.78
	Information Evaluation	211	67.23	18.35
	Trust in Media	211	89.13	13.79
	Peer Influence	211	109.27	13.27
	Educational Interest	145	35.37	5.49
	Digital Literacy	145	75.32	15.74
	Information Evaluation	145	70.52	17.76
	Trust in Media	145	87.28	13.27
	Peer Influence	145	108.3	13.46

As shown in Table 13, descriptive statistics across income groups reveal modest variation in key outcome variables. Educational Interest remains relatively consistent throughout economic strata, with slightly higher means at both the lowest ($M = 35.09$) and highest ($M = 35.13$ – 35.37) income levels. The *Digital Literacy* variable exhibits more variation, with higher scores in the ₹9,00,001 – ₹15,00,000 range ($M \approx 75$) and slightly lower scores in the ₹15,00,001+ and ₹3,00,001 – ₹6,00,000 groups. Information Evaluation shows minimal fluctuation, with the highest means in upper-income segments ($M = 70.52$ – 71.07) and the lowest in the ₹6,00,001 – ₹9,00,000 bracket ($M = 67.23$). Strikingly, Trust in Media remains largely stable, though slightly lower in the highest income categories, throughout groups. Peer Influence shows a minor upward trend in mid-income groups but lacks a clear directional pattern. Overall, income-related differences appear limited in magnitude and may not reach statistical significance.

Table 14: *Correlation Between Educational interest, Digital Literacy, Information Evaluation, Trust in Media, Peer Influence, Media Consumption Hours and Number of Media Platforms Variables.*

		Educational Interest	Digital Literacy	Information Evaluation	Trust in Media	Peer Influence	Media Consumption Hours	Number of Media Platforms
Educational Interest	Correlation	1	0.72	0.62	-0.67	-0.51	0.01	0.02
	p		<.001	<.001	<.001	<.001	0.528	0.435
Digital Literacy	Correlation	0.72	1	0.45	-0.48	-0.36	0.01	0.01
	p	<.001		<.001	<.001	<.001	0.706	0.727
Information Evaluation	Correlation	0.62	0.45	1	-0.42	-0.3	0.03	0.02
	p	<.001	<.001		<.001	<.001	0.207	0.327
Trust in Media	Correlation	-0.67	-0.48	-0.42	1	0.34	-0.02	-0.02
	p	<.001	<.001	<.001		<.001	0.28	0.267
Peer Influence	Correlation	-0.51	-0.36	-0.3	0.34	1	-0.06	-0.05
	p	<.001	<.001	<.001	<.001		0.009	0.043
Media Consumption Hours	Correlation	0.01	0.01	0.03	-0.02	-0.06	1	0.78
	p	0.528	0.706	0.207	0.28	0.009		<.001
Number of Media Platforms	Correlation	0.02	0.01	0.02	-0.02	-0.05	0.78	1
	p	0.435	0.727	0.327	0.267	0.043	<.001	

As seen in Table 14, Educational Interest exhibits strong positive correlations with both Digital Literacy ($r = 0.72$, $p < .001$) and Information Evaluation ($r = 0.62$, $p < .001$), indicating that participants with higher educational engagement also tend to display stronger digital and evaluative skills. H13 is **accepted** and H14 is **accepted**. In contrast, Educational Interest is negatively correlated with Trust in Media ($r = -0.67$, $p < .001$) and Peer Influence ($r = -0.51$, $p < .001$), suggesting that individuals who are more educationally inclined tend to express lower levels of media trust and susceptibility to peer effects. H15 is **accepted** and H16 is **accepted**. Correlations with Media Consumption Hours ($r = 0.01$, $p = 0.528$) and Number of Media Platforms ($r = 0.02$, $p = 0.435$) are negligible and non-significant.

Individuals demonstrating high educational motivation and investment appear to develop enhanced digital skills and evaluation ability. These findings align with models assessing digital competence that posit that intrinsic motivation is essential to digital expertise (Carretero et al., 2017). More academically oriented individuals are also more likely to be critical of media sources before trusting them, these individuals reflect on analytical skepticism. Educationally driven inquiry is correlated

with cross-verification of information, supported by various previous studies like (Wineburg et al., 2020; Cole, 2024; Tran et al., 2024)

Next, Digital Literacy is positively correlated with Information Evaluation ($r = 0.45$, $p < .001$), reflecting an expected overlap between technological competence and the ability to assess information critically. H17 is **accepted**. It is negatively correlated with Trust in Media ($r = -0.48$, $p < .001$) and Peer Influence ($r = -0.36$, $p < .001$), possibly suggesting that more digitally literate individuals tend to be less trusting of media sources and less affected by peer pressure. H18 is **accepted** and H19 is **accepted**. Correlations with Media Consumption Hours ($r = 0.01$, $p = 0.706$) and Number of Media Platforms ($r = 0.01$, $p = 0.727$) remain statistically insignificant. Digital skills often correlate with critical evaluation of digital content, but without sufficient critical thinking and media literacy, cannot aid in discerning misinformation, thus highlighting a need for media literacy training to identify and evaluate falsified claims in media content (Makwana & Bhatia, 2024)

Information Evaluation shows moderate positive correlation with Digital Literacy ($r = 0.45$, $p < .001$) and Educational Interest ($r = 0.62$, $p < .001$), suggesting that the ability to critically evaluate information is heightened by both cognitive engagement and digital literacy. Negative correlations with Trust in Media ($r = -0.42$, $p < .001$) and Peer Influence ($r = -0.30$, $p < .001$) are further revealed. H20 is **accepted** and H21 is **accepted**. No significant associations emerge with Media Consumption Hours ($r = 0.03$, $p = 0.207$) or Number of Media Platforms ($r = 0.02$, $p = 0.327$).

The moderate positive correlation observed supports the assertion that the ability of individuals to cognitively engage with information is strengthened by their proficiency in navigating digital environments by retrieving and comparing information; however, as Terrell (2004) suggests the critical evaluation of digital content on the basis of website differentiation in design, institutional association, and binary comparisons, implies that websites can be classified simply as reliable and unreliable, reducing complex evaluation skills to critique of inexpensive web designing. Alternatively, students must understand the social, economic, and political context that shapes texts, this points towards a requirement for “functional literacy” which includes questioning the source, producers of the information, and evaluating ways in which the world is represented. Additionally, individual personality traits such as need to cognitively engage and think deeply, propensity to trust strangers, and flexible thinking are also found to influence informational literacy (Metzger & Flanagin, 2015).

Trust in Media correlates negatively with Educational Interest ($r = -0.67$, $p < .001$), Digital Literacy ($r = -0.48$, $p < .001$), and Information Evaluation ($r = -0.42$, $p < .001$), suggesting that greater educational and cognitive competencies are associated with reduced trust in media sources. A small positive correlation is found with Peer Influence ($r = 0.34$, $p < .001$), implying that individuals who report greater media trust are also more susceptible to peer influence. H22 is **accepted**. Associations with Media Consumption Hours ($r = -0.02$, $p = 0.280$) and Number of Media Platforms ($r = -0.02$, $p = 0.267$) are negligible and non-significant.

These findings align closely with current literature that suggest that individuals that have attained higher education, and possess strong digital and information evaluation skills tend to approach media content with greater skepticism, and validate sources, context, and credibility of the content (Maksl et al., 2015). As high educational interest may lead to curiosity about current events, and intrinsic motivation to consume news, these individuals demonstrate higher media literacy (Maksl et al., 2015)

Individuals that possess the required knowledge to confidently navigate digital ecosystems, also demonstrated a greater capacity for discerning reliable from unreliable sources, when it aligned with their pre-existing beliefs, this is particularly attributed to literacy empowering individuals to question the validity of content, and could successfully differentiate between fact vs opinion-based or manipulated content (Tambe & Hussein, 2023). In an increased environment of distrust in media sources, and polarisation online creates a reliance on peers, such that people find trust in a false sense of security, because peers appear as a reliable source of information (Mihailidis & Viotty, 2017). However, due to the overarching suspicion of news sources leading to homophilous media networks, where like-minded individuals will continue to reinforce each other's beliefs and emphasize the desirability of shared values (Mihailidis & Viotty, 2017), ensuring lack of critical engagement with text provided in such groups.

This phenomenon could further be used to explain the correlation between Trust in Media and peer influence, as it may suggest that individual differences (Williams et al., 2017) such as not actively evaluating content and trusting digital sources without cross-referencing, can make someone more susceptible to peer suggestions. Contrarily, research also suggests that people were more likely to correct misinformation if it was shared by a close friend or family (Stockdale & Coyne, 2020), possibly because they want members of their social network to be more aware because they feel more empathetic and emotionally attached to them.

Peer Influence shows moderate negative correlations with Educational Interest ($r = -0.51$, $p < .001$), Digital Literacy ($r = -0.36$, $p < .001$), and Information Evaluation ($r = -0.30$, $p < .001$), indicating that higher cognitive and digital competence is associated with lower peer susceptibility. A small positive correlation with Trust in Media ($r = 0.34$, $p < .001$) reinforces the pattern that peer-reliant individuals are more trusting of media. Small but significant negative correlations are also observed with Media Consumption Hours ($r = -0.06$, $p = 0.009$) and Number of Media Platforms ($r = -0.05$, $p = 0.043$), suggesting a marginal inverse relationship. H23 is **accepted** and H24 is **accepted**.

Media Consumption Hours and Number of Media Platforms are strongly correlated ($r = 0.78$, $p < .001$), confirming that greater time spent with media is associated with usage of a wider array of platforms. H25 is **accepted**. However, neither variable shows meaningful correlation with Educational Interest, Digital Literacy, or Information Evaluation, and their associations with Trust in Media and Peer Influence are minimal and statistically weak.

There exists a strong positive correlation between Media Consumption Hours and Number of Media Platforms used, affirming that individuals that spend more time with media tend to access diverse platforms and also have a multi-functional usage of media sources (Frielingsdorf et al., 2025).

However, no significant relation with educational interest, digital literacy, and information indicates that the quality and intensity of the engagement and dependency on digital sources influence literacy and critical evaluation (Kormelink & Meijer, 2020). The association with peer influence and trust in media, is also found to be weak, reinforcing the premise that structural factors are inadequate predictors of an individual's information processing abilities except when distrust in media may increase time spent with news (Nelson et al., 2024).

In summary, Educational Interest, Digital Literacy, and Information Evaluation form a cohesive triad of positively correlated cognitive variables that inversely relate to Trust in Media and Peer Influence. Media usage patterns, while internally consistent, show little explanatory power in relation to cognitive or educational traits.

Table 15(i): *Total Variance Explained from Principal Component Analysis of Five Cognitive-Behavioral Constructs*

Component	Total	% of variance	Accumulated %
1	2.99	59.78	59.78
2	0.73	14.54	74.32
3	0.58	11.58	85.9
4	0.52	10.34	96.24
5	0.19	3.76	100

As shown in Table 15(i) of explained total variance, principal component analysis extracted five components, of which only the first component had an eigenvalue exceeding 1 ($\lambda = 2.99$), accounting for [59.78%] of the total variance. This suggests a dominant latent construction underpinning the dataset. The second component ($\lambda = 0.73$) contributed an additional [14.54%], while Components 3 to 5 explained [11.58%], [10.34%], and [3.76%] of the variance, respectively—none surpassing the Kaiser criterion threshold. Cumulatively, all five components explained [100%] of the variance; however, the steep drop after the first factor and the eigenvalue < 1 for subsequent components indicate a unidimensional structure. Thus, only Component 1 is retained for substantive interpretation, as it meets both statistical and conceptual thresholds for factor retention.

Table 15(ii): *Extraction Communalities from Principal Component Analysis of Cognitive and Media-Related Constructs*

Variable	Extraction
Educational Interest	0.86
Digital Literacy	0.64
Information Evaluation	0.52
Trust in Media	0.58
Peer Influence	0.39

Educational Interest shows near-total alignment with the latent factor ($h^2 = 0.86$), marking it as core to the construct. Digital Literacy (0.64), Trust in Media (0.58), and Information Evaluation (0.52) exhibit strong shared variance, indicating structural coherence. Peer Influence (0.39) falls below the 0.50 threshold, suggesting weak factorial relevance.

Table 15(iii): *Rotated Component Matrix from Principal Component Analysis with Varimax Rotation for Five Cognitive-Behavioral Constructs*

Scale	Component				
	1	2	3	4	5
Educational Interest	0.36	-0.28	-0.4	0.47	-0.64
Digital Literacy	0.2	-0.16	-0.27	0.92	-0.09

Information Evaluation	0.95	-0.1	-0.18	0.2	-0.13
Trust in Media	-0.2	0.16	0.94	-0.16	0.15
Peer Influence	-0.14	0.97	0.12	-0.15	0.1

A principal component analysis (PCA) with Varimax rotation was performed on five cognitive-behavioral constructs. The analysis yielded a five-factor solution with each variable loading strongly (≥ 0.92) on a distinct component, suggesting high discriminant validity across constructs. Notably, “Educational Interest” loaded negatively (-0.64) on its factor, indicating a potentially inverse or orthogonal latent structure relative to other variables. No substantial cross-loadings were observed.

Table 16: *Multiple Linear Regression Predicting Educational Interest from Cognitive and Demographic Predictors (N = 1992)*

Model	B	S.E.	t	p	R ²
Constant	37.64	1.6	23.6	<.001	
Digital Literacy	0.15	0.42	0.01	19.63	<.001
Information Evaluation	0.09	0.27	0.01	12.94	<.001
Trust in Media	-0.14	-0.31	0.01	-14.35	<.001
Peer Influence	-0.07	-0.17	0.01	-8.65	<.001
AGE 15-25	-0.05	0	0.37	-0.14	0.89
AGE 25-35	-0.29	-0.02	0.38	-0.77	0.44
Media Consumption Hours	-0.19	-0.03	0.17	-1.12	0.264
Number of Media Platforms	0.08	0.01	0.17	0.45	0.656
Gender Male	0.19	0.02	0.22	0.85	0.396

As seen in Table 16, a stratified regression model was conducted for the low-income group (₹0 – ₹3,00,000 annual household income) to identify predictors of Educational Interest. The model accounts for a substantial proportion of variance ($R^2 = 0.76$), indicating strong explanatory power within this stratum. Digital Literacy ($\beta = 0.42$, $p < .001$) and Information Evaluation ($\beta = 0.27$, $p < .001$) emerge as significant positive predictors, suggesting that higher cognitive and digital competencies are strongly associated with greater educational engagement. In contrast, Trust in Media ($\beta = -0.31$, $p < .001$) and Peer Influence ($\beta = -0.17$, $p < .001$) are significant negative predictors, indicating that greater media trust and susceptibility to peer pressure are linked to lower educational motivation. Age strata (15–25 and 25–35), Gender (Male), Media Consumption Hours, and Number of Media Platforms do not contribute significantly ($p > 0.05$), suggesting that sociodemographic and media exposure variables exert minimal influence on Educational Interest within this income segment. The findings underscore that, in low-income contexts, educational motivation is shaped predominantly by individual cognitive capacities and media-related dispositions, rather than by demographic identity or media use volume.

Higher educational interest and motivation is correlated with digital literacy and information evaluation in low-income groups because high educational interest motivates individuals to focus

on digital development skills, and due to the combination of both, the knowledge gap is reduced, ensuring information evaluation skills are competent. Trust in media and peer influence are negatively correlated, because those with high education won't blindly trust media and are less likely to get influenced. Digital literacy and information evaluation are positive predictors of higher educational interest, because individuals with higher levels of educational engagement are more likely to prioritise digital skills necessary to their field, and employ evaluative strategies when engaging with information (Carretero et al., 2017),

Trust in media and peer influence are negative predictors, which can possibly be ascribed to excellent information evaluation and ability to recognise misinformation and poor quality information. Consequently low income individuals who express strong academic motivation, are skeptical of trusting media with judging its factual nature, also aligning with findings that higher educated youth rely less on social heuristics and focus on independent reasoning (McDougall & Rega, 2022).

Table 17: *Multiple Linear Regression Predicting Information Evaluation from Cognitive and Demographic Predictors (N = 1992)*

Model	B	S.E.	t	p	R ²
Constant	-8.6	10.32	-0.83	0.405	
Educational Interest	2.09	0.69	0.16	12.94	<.001
Digital Literacy	-0.07	-0.06	0.05	-1.49	0.137
Trust in Media	-0.02	-0.01	0.05	-0.35	0.727
Peer Influence	0.09	0.07	0.04	2.22	0.027
AGE 15-25	2.53	0.07	1.79	1.41	<.001
AGE 25-35	3.21	0.08	1.86	1.73	0.085
Media Consumption Hours	0.39	0.02	0.84	0.46	0.646
Number of Media Platforms	-0.88	-0.05	0.84	-1.04	0.297
Gender Male	-1.16	-0.03	1.09	-1.06	0.288

As seen in Table 17, a multiple regression model was estimated to predict Information Evaluation scores across the full sample. The model explains a moderate proportion of variance ($R^2 = 0.39$). Educational Interest emerged as a strong and significant predictor ($\beta = 0.69$, $p < .001$), indicating that higher educational engagement is closely associated with improved evaluative ability. Peer Influence showed a small but significant positive effect ($\beta = 0.07$, $p = 0.027$), suggesting a slight increase in evaluation scores with greater peer engagement. All other predictors, including Digital Literacy, Trust in Media, age strata, media usage variables, and gender, were non-significant ($p > 0.05$), indicating limited explanatory value in this model for these variables. Educational interest as a significant predictor of information evaluation, reaffirms research that suggests that active curiosity in current affairs and news motivates individuals to refine their critical evaluation skills (Chalukian, 2015). The slight positive effect may appear contradictory to the negative correlation observed in the analysis, but aligns with multiple findings that indicate that peer groups, especially amongst young people, can encourage intellectual engagement due to social pressure and need to conform to group norms. Structural and demographic variables such as digital literacy and trust in

media had limited predictive ability aligning with studies like, which may suggest that these variables may not be as consequential in predicting evaluation capability as assumed, when educational interest and peer influence are also considered (Hu & Talib, 2023).

Table 18: *Multiple Linear Regression Predicting Digital Literacy from Cognitive and Demographic Predictors (N = 1992)*

Model	B	S.E.	t	p	R ²
Constant	-7.27	8.08	-0.9	0.369	
Educational Interest	2.24	0.8	0.11	19.63	<.001
Information Evaluation	-0.04	-0.05	0.03	-1.49	0.137
Trust in Media	0.04	0.03	0.04	0.96	0.339
Peer Influence	0.03	0.03	0.03	0.95	0.34
AGE 15-25	-1.74	-0.05	1.41	-1.24	<.001
AGE 25-35	-1.23	-0.03	1.46	-0.85	<.001
Media Consumption Hours	1.19	0.07	0.66	1.81	0.071
Number of Media Platforms	-0.8	-0.05	0.66	-1.21	0.226
Gender Male	-0.16	0	0.86	-0.18	0.856

As seen in Table 18, a multiple regression model was used to predict Digital Literacy scores across the full sample, accounting for 55% of the variance ($R^2 = 0.55$). Educational Interest was the only significant predictor ($\beta = 0.80$, $p < .001$), indicating a strong positive association between educational engagement and digital competence. All other predictors—including Information Evaluation, Trust in Media, Peer Influence, age, media use variables, and gender—were statistically non-significant ($p > 0.05$), suggesting that these factors do not meaningfully contribute to variation in Digital Literacy when Educational Interest is accounted for. Educational interest appears to be the only adequate predictor of digital literacy, suggesting that digital skills can be cultivated by actively seeking information, and engaging with digital content as practice rather than passively consuming information (Zakir et al., 2025). Table 18's findings appear to align with modern conceptualisations that emphasize on digital efficacy through self-learning mediums, such as in (Zakir et al., 2025). This further strengthens the co-dependent relationship between digital literacy and educational outcomes, such that digital literacy aids in pursuing educational pursuits outside the standardised curriculum available, and knowledge acquisition through other mediums, without formal training about digital skills, also improves individual's ability to utilise the full resources available to them.

The non-significance of other variables indicate that digital literacy relies heavily on motivation and cognitive engagement, and does not exist in isolation, but depends on complex skills and competencies related to media education (Buckingham, 2015).

Table 19: *Multiple Linear Regression Predicting Trust in Media from Cognitive and Demographic Predictors (N = 1992)*

Model	B	S.E.	t	p	R ²
-------	---	------	---	---	----------------

Constant	43.68	4.3	10.16	<.001	
Digital Literacy	0.14	0.36	0.03	5.13	<.001
Information Evaluation	0.06	0.18	0.02	3	0.003
Trust in Media	-0.15	-0.37	0.03	-5.91	<.001
Peer Influence	-0.08	-0.2	0.02	-3.48	0.001
AGE 25-35	-0.13	-0.01	0.68	-0.19	<.001
AGE 35-45	-0.46	-0.02	1.3	-0.35	0.726
Media Consumption Hours	-0.3	-0.04	0.56	-0.53	0.598
Number of Media Platforms	0.04	0.01	0.51	0.08	0.936
Gender Female	-0.18	-0.01	0.62	-0.3	0.768

As seen in Table 19, a multiple regression model was estimated to predict Trust in Media, explaining a substantial portion of variance ($R^2 = 0.80$). Digital Literacy ($\beta = 0.36$, $p < .001$) and Information Evaluation ($\beta = 0.18$, $p = 0.003$) were significant positive predictors, indicating that stronger cognitive and digital skills are associated with higher media trust. In contrast, Trust in Media ($\beta = -0.37$, $p < .001$) and Peer Influence ($\beta = -0.20$, $p = 0.001$) were significant negative predictors, suggesting that higher internal skepticism and susceptibility to peers may lower media trust. Age, media use, and gender variables were all non-significant ($p > 0.05$), indicating that cognitive variables, not demographics, primarily shape media trust in this sample. Digital literacy and information evaluation positively predict trust in media, which complicates the binary analysis that digital literacy is negatively related to trust in media as digital competency may lead to verification of sources, ultimately reducing media trust (Guess et al., 2020). Table 19's findings align with studies that suggest digital literacy may increase confidence in one's ability to discern misinformation, strengthening trust in mainstream media that responsibly sources information (Park et al., 2024)

Additionally, the above findings contradict the fact that peer influence can only be a negative predictor of trust, as those demonstrate higher levels of peer influence, can also be more critical of mainstream media, because their peer networks are skeptical of such media and they perceive fake news differently in peer groups, as compared to available on the internet published by strangers (Tandoc Jr. et al., 2018)

Table 20: *Multiple Linear Regression Predicting Peer Influence from Cognitive and Demographic Predictors (N = 1992)*

Model	B	S.E.	t	p	R ²
Constant	3.96	22.04	0.18	0.858	
Educational Interest	1.67	0.63	0.33	5.13	<.001
Information Evaluation	0.13	0.16	0.07	1.97	0.052
Trust in Media	0.02	0.02	0.11	0.23	0.819
Peer Influence	-0.03	-0.03	0.09	-0.4	0.693
AGE 25-35	2.41	0.07	2.34	1.03	0.307
AGE 35-45	10.5	0.16	4.39	2.39	<.001

Media Consumption Hours	-3.28	-0.18	1.92	-1.71	0.091
Number of Media Platforms	1.61	0.09	1.79	0.9	0.369
Gender Female	0.15	0	2.17	0.07	0.944

As seen in Table 20, a regression model was conducted to predict Peer Influence scores, explaining 66% of the variance ($R^2 = 0.66$). Educational Interest emerged as a strong and significant predictor ($\beta = 0.63$, $p < .001$), suggesting that higher educational engagement is closely linked to peer-driven attitudes. Information Evaluation approached significance ($\beta = 0.16$, $p = 0.052$), suggesting a marginal contribution. Among the controls, only the age group 35–45 had a statistically significant effect ($\beta = 0.16$, $p < .001$), indicating moderately higher peer influence compared to the reference group. All other predictors—including Trust in Media, Peer Influence, Media Consumption Hours, Number of Media Platforms, and Gender—were non-significant ($p > 0.05$).

Educational interest emerges as a strong predictor of peer influence, suggesting the role of positive peer groups in fostering intellectual and educational engagement. While some studies contradict this pattern—such as Lessard and Juvonen (2020), who argue that individuals with lower educational interest are more susceptible to peer influence—others align with Table 20's findings by indicating that peer dynamics can also enhance educational interest through cognitive–social group processes (Temitope & Christy, 2015). Peer influence thus appears to play a dual and complex role: although prior literature often attributes susceptibility primarily to adolescents still engaged in identity formation, our data suggest that the 35–45 age group is the only one significantly affected. Studies such as Laursen and Veenstra (2021) and Smith et al. (2015) partially support this conclusion by highlighting the nuanced manifestations of peer influence in adults compared to adolescents.

Table 21: *Multiple Linear Regression Predicting Information Evaluation in the High-Income Group (N = 1992)*

Model	B	S.E.	t	p	R2
Constant	-18.17	33.44	-0.54	0.588	
Educational Interest	1.61	0.5	0.54	3	0.003
Digital Literacy	0.31	0.26	0.16	1.97	0.052
Trust in Media	-0.04	-0.03	0.16	-0.26	0.799
Peer Influence	0.15	0.11	0.13	1.09	0.278
AGE 25-35	-3.71	-0.09	3.56	-1.04	<.001
AGE 35-45	0.11	0	6.87	0.02	<.001
Media Consumption Hours	3.58	0.16	2.94	1.22	0.227
Number of Media Platforms	-2.25	-0.11	2.71	-0.83	0.409
Gender Female	-1.09	-0.03	3.3	-0.33	0.741

As seen in Table 21, the model predicts Information Evaluation within the high-income group ($R^2 = 0.46$), with Educational Interest as the only significant predictor ($\beta = 0.50$, $p = 0.003$). Digital Literacy approached significance ($\beta = 0.26$, $p = 0.052$), while all other variables, including media attitudes, demographics, and usage, were non-significant ($p > 0.05$), indicating cognitive factors drive evaluative ability in this stratum. Information evaluation, even in high-income groups, is solely predicted by educational interest suggesting that socio-economic disparities do not exert a

deterministic influence on cognitive outcomes and are chiefly related to cognitive engagement driven by interest, and goal-oriented engagement with information for the purpose of acquiring and processing information though existing literature proposes that individuals belonging to lower SES backgrounds may not have equal educational outcomes due to inaccessibility, stressful environmental factors, and lack of prestigious institutions (Vashistha et al., 2024; Rakesh et al., 2025). Digital literacy partially influences evaluation skills, which could be explained by the ease in accessing various resources and simultaneously comparing different material with each other, as well as utilising fact-checking websites (Sultanbayeva et al., 2024)

Table 22: *Multiple Linear Regression Predicting Educational Interest from Cognitive, Media, and Socioeconomic Predictors (N = 1992)*

Model	B	S.E.	t	p	R ²
Constant	38.49	1.43	26.97	<.001	
Digital Literacy	0.14	0.39	0.01	19.38	<.001
Information Evaluation	0.08	0.26	0.01	13.63	<.001
Trust in Media	-0.13	-0.29	0.01	-15.09	<.001
Peer Influence	-0.08	-0.18	0.01	-10.05	<.001
Household Income ₹3,00,001 – ₹6,00,000	-0.16	-0.01	0.24	-0.69	0.491
Household Income ₹15,00,001 and above	0.19	0.01	0.45	0.42	<.001
Household Income ₹9,00,001 – ₹12,00,000	-0.5	-0.02	0.38	-1.33	<.001
Household Income ₹6,00,001 – ₹9,00,000	0.15	0.01	0.33	0.47	0.641
Household Income ₹12,00,001 – ₹15,00,000	0.07	0	0.39	0.18	0.854
Media Consumption Hours	-0.2	-0.03	0.15	-1.31	0.189
Number of Media Platforms	0.11	0.02	0.15	0.68	0.494
Gender Female	-0.05	0	0.2	-0.24	0.811

As seen in Table 22, Educational Interest was significantly predicted by Digital Literacy ($\beta = 0.39$, $p < .001$), Information Evaluation ($\beta = 0.26$, $p < .001$), Trust in Media ($\beta = -0.29$, $p < .001$), and Peer Influence ($\beta = -0.18$, $p < .001$). All income brackets, Media Consumption Hours, Number of Media Platforms, and Gender were non-significant ($p > 0.05$). The model explained 73% of the variance ($R^2 = 0.73$).

Educational interest is positively predicted by both digital literacy and information skills, suggesting the inter-dependence between these cognitive capacities and the motivation to engage with learning modules. This supports the theory that individuals that possess higher digital literacy, are better equipped to navigate and critically assess the vast information reserves, while sustaining their intellectual curiosity about their preferences (Metzger & Flanagin, 2015). The non significance of media exposure variables and demographic variables, furthers the argument that educational interest is uniform across different socio-economic backgrounds, and is based on cognitive engagement over structural differences in educational access (Tucker-Drob & Briley, 2012).

Table 23: *Multiple Linear Regression Predicting Trust in Media from Cognitive, Media, and Socioeconomic Predictors (N = 1992)*

Model	B	S.E.	t	p	R ²
Constant	139.27	4.42	31.5	<.001	
Educational Interest	-1.41	-0.62	0.09	-15.09	<.001
Digital Literacy	-0.01	-0.02	0.03	-0.49	0.627
Information Evaluation	-0.02	-0.03	0.02	-1	0.32
Peer Influence	0.02	0.02	0.03	0.57	0.568
Household Income ₹3,00,001 – ₹6,00,000	-0.75	-0.03	0.78	-0.95	0.341
Household Income ₹15,00,001 and above	-1.45	-0.02	1.48	-0.98	0.327
Household Income ₹9,00,001 – ₹12,00,000	-0.19	0	1.25	-0.16	0.877
Household Income ₹6,00,001 – ₹9,00,000	-0.09	0	1.1	-0.08	0.934
Household Income ₹12,00,001 – ₹15,00,000	-0.1	0	1.29	-0.08	0.936
Media Consumption Hours	0.21	0.02	0.51	0.42	0.678
Number of Media Platforms	-0.23	-0.02	0.51	-0.46	0.649
Gender Female	-0.67	-0.02	0.65	-1.03	0.304

As seen in Table 23, Media Trust was significantly negatively predicted only by Educational Interest ($\beta = -0.62$, $p < .001$). All other predictors, including Digital Literacy, Information Evaluation, Peer Influence, Household Income brackets, Media Consumption Hours, Number of Media Platforms, and Gender, were non-significant ($p > 0.05$). The model explained 43% of the variance ($R^2 = 0.43$). Educational interest appears to be a significant negative predictor of trust in media, thereby reinforcing the assertion that individuals motivated by curiosity and desire for independent verification, exhibit lower trust in media before necessary verification has been conducted (Lee, 2011). Furthermore, such an assertion is supported by previous discourse on skepticism towards mainstream media being rooted in intensive-cognitive analysis and critical thinking, rather than simple cynicism and apathy (Strömbäck et al., 2020). The lack of demographic and media usage patterns corroborates existing research that indicates the cognitive and psycho-social factors shape dispositions relating to trust (Li & Zhong, 2022).

Table 24: *Multiple Linear Regression Predicting Information Evaluation from Cognitive, Media, and Socioeconomic Predictors (N = 1992)*

Model	B	S.E.	t	p	R ²
Constant	5.09	8.72	0.58	0.56	
Educational Interest	1.83	0.58	0.13	13.63	<.001
Digital Literacy	0.04	0.03	0.04	0.94	0.346
Trust in Media	-0.04	-0.03	0.04	-1	0.32
Peer Influence	0.02	0.01	0.04	0.53	<.001
Household Income ₹3,00,001 – ₹6,00,000	-1.18	-0.03	1.1	-1.07	<.001
Household Income ₹15,00,001 and above	1.88	0.02	2.09	0.9	<.001

Household Income ₹9,00,001 – ₹12,00,000	-0.41	-0.01	1.76	-0.23	<.001
Household Income ₹6,00,001 – ₹9,00,000	-2.3	-0.04	1.55	-1.48	<.001
Household Income ₹12,00,001 – ₹15,00,000	0.46	0.01	1.82	0.25	<.001
Media Consumption Hours	0.8	0.04	0.72	1.1	0.271
Number of Media Platforms	-0.33	-0.02	0.72	-0.45	0.652
Gender Female	0.03	0	0.92	0.03	0.977

As seen in Table 24, Information Evaluation was significantly predicted by Educational Interest ($\beta = 0.58$, $p < .001$), Peer Influence ($\beta = 0.01$, $p < .001$), and all five Household Income brackets, including ₹3,00,001–₹6,00,000 ($\beta = -0.03$, $p < .001$), ₹6,00,001–₹9,00,000 ($\beta = -0.04$, $p < .001$), ₹9,00,001–₹12,00,000 ($\beta = -0.01$, $p < .001$), ₹12,00,001–₹15,00,000 ($\beta = 0.01$, $p < .001$), and ₹15,00,001 and above ($\beta = 0.02$, $p < .001$). All other variables were non-significant ($p > 0.05$). The model explained 39% of the variance ($R^2 = 0.39$). Educational interest and peer influence are strong predictors of information evaluation, across socio-economic strata, demonstrating that cognitive and social motivational factors supersede socio-economic differentiation due to the digital divide (Li & Zhong, 2022). Educational interest continues to stimulate goal-oriented engagement with information, whereas peer interaction can cultivate an environment where evaluative skills are socially desirable and social learning mechanisms continue to positively engage individuals (Laursen & Veenstra, 2021). The minimal predictive effect of digital literacy on information evaluative ability is not limited to technical proficiency alone, while digital skills may partially aid in differentiating factual information from misinformation, it may not influence their ability to accurately predict the quality of information available online (Sirlin et al., 2021).

Table 25: *Multiple Linear Regression Predicting Peer Influence from Cognitive, Media, and Socioeconomic Predictors (N = 1992)*

Model	B	S.E.	t	p	R2
Constant	149.31	4.14	36.07	<.001	
Educational Interest	-1.25	-0.53	0.09	-14.72	<.001
Digital Literacy	0.01	0.01	0.02	0.26	0.798
Information Evaluation	0.02	0.03	0.02	1.29	0.199
Trust in Media	0	0	0.03	0.11	0.913
AGE 25-35	0.12	0	0.59	0.21	0.832
AGE 35-45	0.07	0	0.89	0.07	0.941
Household Income ₹3,00,001 – ₹6,00,000	1.04	0.03	0.66	1.58	<.001
Household Income ₹6,00,001 – ₹9,00,000	1.17	0.02	1.29	0.9	<.001
Household Income ₹9,00,001 – ₹12,00,000	-1.02	-0.02	1.06	-0.97	<.001
Household Income ₹12,00,001 – ₹15,00,000	0.95	0.02	0.94	1.01	0.315
Household Income ₹15,00,001 and above	0.98	0.02	1.1	0.9	0.369
Media Consumption Hours	-0.83	-0.06	0.43	-1.91	0.056

Number of Media Platforms	0.13	0.01	0.43	0.29	0.772
Gender Female	-0.3	-0.01	0.55	-0.54	0.59

As seen in Table 25, Peer Influence was significantly predicted by Educational Interest ($\beta = -0.53$, $p < .001$), and three income brackets: ₹3,00,001–₹6,00,000 ($\beta = 0.03$, $p < .001$), ₹6,00,001–₹9,00,000 ($\beta = 0.02$, $p < .001$), and ₹9,00,001–₹12,00,000 ($\beta = -0.02$, $p < .001$). All other predictors were non-significant ($p > 0.05$). The model explained 46% of the variance ($R^2 = 0.46$). The significant association between educational interest and peer influence indicates an inclination among students deeply invested in learning, and those with high academic motivation towards susceptibility to peer influence (Wentzel and Muenks, 2016). Interest in education shapes individuals to engage with academic peer networks, exchange resources and discuss normative academic expectations with similar individuals (Altermatt & Pomerantz, 2003). This contradicts existing literature that proposes that individuals with high educational interest and motivations, will be less susceptible to peer influence as they do not rely on their peers for information, but rather their curiosity drives them to conduct extensive research and compare information across various sources. Table 25's findings align with literature that proposes that individuals with similar educational goals and interests, not only identify each other using behavioural indicators implying positive academic engagement, but also positive and reciprocal engagement defined by mutual values. Peer influence within this context is less about demographic divides, and defined by academic purpose, students that are focused on their academic goals are likely influenced by their peers that possess similar beliefs (Reindl, 2021).

Table 26: *Multiple Linear Regression Predicting Trust in Media from Cognitive, Media, and Socioeconomic Predictors (N = 1992)*

Model	B	S.E.	t	p	R2
Constant	148.98	10.49	14.2	<.001	
Educational Interest	-1.73	0.74	0.19	-8.88	<.001
Digital Literacy	0.01	0.01	0.06	0.11	0.912
Information Evaluation	0.02	0.03	0.05	0.44	0.658
Peer Influence	-0.02	0.02	0.06	-0.39	0.698
Household Income ₹0 – ₹3,00,000	1.14	0.04	1.67	0.68	<.001
Household Income ₹9,00,001 – ₹12,00,000	-1.35	0.03	2.69	-0.5	<.001
Household Income ₹6,00,001 – ₹9,00,000	-0.26	0.01	2.33	-0.11	<.001
Household Income ₹12,00,001 – ₹15,00,000	0.09	0	2.44	0.04	0.971
Household Income ₹15,00,001 and above	4.23	0.05	4.02	1.05	0.294
Media Consumption Hours	-0.49	0.04	1.11	-0.44	0.66
Number of Media Platforms	-0.73	0.05	1.13	-0.65	0.52
Gender Female	1.16	0.04	1.41	0.83	0.409

As seen in Table 26, Trust in Media was significantly predicted only by Educational Interest ($\beta = -0.74$, $p < .001$). All other predictors—including Digital Literacy, Information Evaluation, Peer

Influence, Household Income brackets, Media Consumption Hours, Number of Media Platforms, and Gender—were non-significant ($p > 0.05$). The model explained 49% of the variance ($R^2 = 0.49$). Educational interest is the only significant predictor of trust in media, the strong negative association between academic motivation suggests that as educational interest increases, trust in media without critical analysis decreases.

Table 26's findings align with previous research that proposes education-driven inquiry leads to development of understanding of research methods, source evaluation, and evidence criterion (Wiley et al., 2009), which increases distrust in media as methodological and source-based flaws are identified. Such individuals verify their sources across multiple platforms, cultivating a default suspicious outlook instead of passive acceptance (Flanagin & Metzger, 2007). The lack of significant relation between other cognitive and demographic factors, may indicate a requirement to explore the non-deterministic approach to media skepticism, instead it poses the question of the degree to which extent individual motivation to learn, impacts knowledge acquisition as well as need to critically evaluate media sources (Tsfati & Barnoy, 2025).

Table 27: *Multiple Linear Regression Predicting Information Evaluation from Cognitive, Media, and Socioeconomic Predictors (N = 1992)*

Model	B	S.E.	t	p	R2
Constant	-19.6	21.57	-0.91	0.365	
Educational Interest	1.85	0.6	0.31	5.96	<.001
Digital Literacy	0.09	0.09	0.08	1.1	0.271
Trust in Media	0.04	0.03	0.1	0.44	0.658
Peer Influence	0.14	0.11	0.09	1.56	0.12
Household Income ₹0 – ₹3,00,000	-3.58	-0.1	2.45	-1.46	<.001
Household Income ₹9,00,001 – ₹12,00,000	-1.93	-0.03	3.95	-0.49	<.001
Household Income ₹6,00,001 – ₹9,00,000	-4.49	-0.08	3.41	-1.32	<.001
Household Income ₹12,00,001 – ₹15,00,000	-2.08	-0.04	3.58	-0.58	0.562
Household Income ₹15,00,001 and above	3.32	0.03	5.92	0.56	0.575
Media Consumption Hours	0.45	0.02	1.63	0.27	0.784
Number of Media Platforms	-0.39	-0.02	1.67	-0.23	0.817
Gender Female	-0.66	-0.02	2.07	-0.32	0.752

As seen in Table 27, =Information Evaluation was significantly predicted only by Educational Interest ($\beta = 0.60$, $p < .001$). All other variables, including Digital Literacy, Trust in Media, household income brackets, media usage, and gender, were non-significant ($p > 0.05$). The model explained 36% of the variance ($R^2 = 0.36$).

Educational interest as the sole predictor of information evaluation, highlights that intrinsic motivation and curiosity in critical thinking skills may have a prominent role in demonstrating critical evaluative skills, and is supported by broader evidence suggesting that importance of interest levels in mastering certain skill-sets measured through performance and engagement indicators

(Dara et al., 2025). Additionally, personal investment and motivation has been associated with informational literacy in applied fields such as problem solving, digital exploration, and reflective learning (Anistyasari et al., 2024)

V. Limitations

Collectively, this study's findings offer valuable insights on media consumption patterns and their influence on cognitive skills. However, possible methodological limitations prevent large scale generalizability of findings.

This study draws from four North Indian states (Delhi NCR, Haryana, Punjab, and Uttar Pradesh); its geographic scope does not encompass southern, eastern, central, or northeastern India. Such geographic concentration of samples prevents generalizability of findings to the Indian Continent, as findings are contingent upon linguistic, cultural, and infrastructural similarities with the sampled regions, limiting their applicability to areas with differing socio-digital contexts. Key variables (Digital Literacy, Peer Influence, Trust in Media) were operationalized through self-reported Likert-scale instruments. Hence, our findings may be influenced by social desirability and recall bias. Furthermore, Median or noncommittal responses may dilute effect sizes, especially for variables with subjective self-evaluation. Despite demographic stratification, the sample exhibited partial clustering, in which the data appeared to be homogenized. This was attributed to the fact that the sample constituted participants who often belonged to similar educational institutions, workplaces, or villages. Such a situation may have introduced homogeneity in attitudinal responses, especially on constructs such as peer influence (Cohen's $d = 0.04$) and the number of media platforms used ($t = 0.00$, $p = 0.998$). As the study employs a cross-sectional design, it is unable to capture longitudinal trends in digital behavior, such as evolving trust in media over time or changes in digital literacy due to technological reforms. Such limitations prevent inferences about potential scalability of cognitive traits.

Secondly, this study does not incorporate key intersectional sociocultural variables such as disability, religion, and caste. As Kapilashrami et al. (2015) notes, these variables influence access to resources within the Indian context. Furthermore, a purely quantitative design lacks the nuanced depth into participant motivations, media preferences, and culturally contingent behaviors. Consequently, emergent or niche digital platforms with lower adoption rates were omitted from the analysis. These limitations, while common in the existing literature (Joshi et al., 2020; Vaidehi et al., 2021), prevent the explanatory scope of the findings. Despite these key limitations, this study contributes to the gaps in the literature by rigorously analyzing the implications of media consumption on cognitive constructs within North India.

Future research and scholarly inquiries could possibly benefit from expanding the geographic coverage beyond North India to capture nuanced regional variations. Additionally, incorporating caste and other structurally embedded barriers, operationalized over a longitudinal period, could yield richer insights. Lastly, examining the pedagogical affordances of specific media platforms in relation with educational interest could extend the theoretical and practical relevance of future findings.

VI. Conclusion

This study aimed to examine the influence of digital media consumption patterns on shaping cognitive indicators such as educational interest, digital literacy, and information evaluation within the Indian context, while analyzing the influence of socio-economic stratification, and demographic

factors such as age and gender, alongside affection dimensions like trust in media and peer influence.

In synthesis, this study reveals that demographic variables exert a limited influence on cognitive abilities, while intrinsic motivation emerges as the most consistent predictor of positive outcomes, especially with respect to knowledge acquisition. Socio-economic stratification, though previously assumed to be a deterministic predictor of educational and digital literacy outcomes, does not appear to uniformly predict them, highlighting the nuanced and context-specific nature of disparity across India's sub-populations that may be digitally connected on paper, but demonstrate inconsistent variation across social groups.

The principal contribution of this research lies in challenging existing postulations about the digital divide by empirically demonstrating that as infrastructural access saturates remote and underserved areas, intrinsic cognitive drivers, rather than purely structural variables hold greater predictive power. This transition reframes digital equity discourse in India, arguing for pedagogical and policy emphasis on motivation and critical media and digital literacies rather than material access only.

VII. Additional Notes

Author Contributions

A.K.: conceived the study, led the research design, served as corresponding and first chair author. Responsible for drafting *Introduction, Methodology, Results and Findings, Discussions, Limitations*, and *Abstract*. Conducted statistical analyses, developed data instruments, led fieldwork, and interpretation of findings. D.K. co-first chair author, drafted *Review of Literature*, contributed to data collection, undertook multiple rounds of manuscript editing and refinement

Competing Interests

All authors declare no competing interests. Authors received no external funding to conduct this study

Correspondence

All correspondence and materials requests should be addressed to, the corresponding author, Aryann Khokha via email: aryannkhokha@gmail.com

Data availability

The datasets analysed during the study are not publicly available due to restrictions related to respondent confidentiality. Data may be obtained from the corresponding author upon reasonable request.

VIII. References

- Abraham, B. (2014). Technology Adoption and Economic Productivity: Assessing the Digital Divide. *International Journal of Research and Analytical Reviews*, 1(2), 130–135. <https://www.ijrar.org/papers/IJRAR19D5061.pdf>
- Ahmad, N. A., Mohd Ali, M. A., & Tengku Shahdan, T. S. (2025). Intergenerational instructional strategies and elderly preferences for digital applications: A Malaysian case study. *PLOS One*, 20(8), e0328481. <https://doi.org/10.1371/journal.pone.0328481>
- Ahn, Y., & Jong, J. (2024). Community Diversity and Social Media Use in Local Governments. *Administration & Society*, 56(9–10), 1083–1103. <https://doi.org/10.1177/00953997241279294>
- Akello, M., Gallagher, M., Nanyunja, S., Mulondo, A., Miranda, J. J., Cole, G., & Falisse, J.-B. (2024). Minimal computing in refugee education in Uganda: Economies of digital use and non-use, and the right constraints. *Learning, Media and Technology*. <https://www.tandfonline.com/doi/abs/10.1080/17439884.2024.2405128>
- Akello, T. (2025). Digital Literacy and Media Consumption among Different Age Groups. *Journal of Communication*, 5(2), 14–27. <https://doi.org/doi.org/10.47941/jcomm.1973>
- Altermatt, E. R., & Pomerantz, E. M. (2003). The development of competence-related and motivational beliefs: An investigation of similarity

- and influence among friends. *Journal of Educational Psychology*, 95(1), 111–123. <https://psycnet.apa.org/doi/10.1037/0022-0663.95.1.111>
- Anderson, D. R. A., & Subrahmanyam, K. (2017). Digital Screen Media and Cognitive Development. *Pediatrics - AAP Publications*, 140(S57–S61), 1–5.
- Andreassen, C. S., Pallesen, S., & Griffiths, M. D. (2017). The relationship between addictive use of social media, narcissism, and self-esteem: Findings from a large national survey. *Addictive Behaviors*, 64, 287–293. <https://doi.org/10.1016/j.addbeh.2016.03.006>
- Anistyasari, Y., Sujatmiko, B., Ekohariadi, E., & Hidayati, S. C. (2024). *Investigating The Effect of Intrinsic Motivation to Digital Literacy Skills*. 1119–1125. https://doi.org/10.2991/978-2-38476-198-2_158
- Ascent. (2020). How Rural India is Consuming Youtube Channel. *Ascent Group India*. <https://ascentgroupindia.com/blog/how-rural-india-is-consuming-youtube-channel/>
- Asrani, C. (2020). Bridging the Digital Divide in India: Barriers to Adoption and Usage. *Indian Council for Research on International Economic Relations*. https://icrier.org/pdf/Bridging_the_Digital_Divide_in_India.pdf
- Bachmann, R., & Hertweck, F. (2025). The gender gap in digital literacy: A cohort analysis for Germany. *Applied Economics Letters*, 32(5), 608–613. <https://doi.org/10.1080/13504851.2023.2277685>
- Bahji, A., Acion, L., Laslett, A.-M., & Adinoff, B. (2023). Exclusion of the non-English-speaking world from the scientific literature: Recommendations for change for addiction journals and publishers. *Nordisk Alkohol- & Narkotikatidskrift : NAT*, 40(1), 6–13. <https://doi.org/10.1177/14550725221102227>
- Bailey, E. R., Matz, S. C., Youyou, W., & Iyengar, S. S. (2020). Authentic self-expression on social media is associated with greater subjective well-being. *Nature Communications*, 11(1), 4889. <https://doi.org/10.1038/s41467-020-18539-w>
- Bailey, J., Steeves, V., Burkell, J., & Regan, P. (2013). Negotiating With Gender Stereotypes on Social Networking Sites: From “Bicycle Face” to Facebook. *Journal of Communication Inquiry*, 37(2), 91–112. <https://doi.org/10.1177/0196859912473777>
- Bansal, D. C. (2021). Digital Literacy of School Students in India: A Study. *Learning Community: An International Journal on Educational and Social Development*,. <https://doi.org/10.30954/2231-458X.02.2021.3>
- Barot, A. U. (2020). The Digital Divide in Higher Education: Challenges and Opportunities. *RISHING - A Journal of Researchers*, 4(2), 1–13. https://www.raioniversity.edu/wp-content/uploads/july_2020_2_1_THE_DIGITAL_DIVIDE_IN_HIGHER_EDUCATION_CHALLENGES_AND_OPPORTUNITIES.pdf
- Barr, M. S. (2012). *No Slack: The Financial Lives of Low-Income Americans* (1st ed., Vol. 1). Brookings Institution Press. https://www.brookings.edu/wp-content/uploads/2016/07/noslack_chapter.pdf <http://www.jstor.org/stable/10.7864/j.ctt1280xc>
- Bentaouet Kattan, R., Khan, M. M., & Merchant, M. (2023). *Achieving Gender Equality in Education: Examining Progress and Constraints*. Washington, DC: World Bank. <https://doi.org/10.1596/40595>
- Bhogle, S. (2021). Learning and Study Strategies: Academic Achievement and Gender Differences. *Artha - Journal of Social Sciences*. <https://doi.org/10.12724/AJSS.27.4>
- Bigio, J., Hannay, E., Pai, M., Alisjahbana, B., Das, R., Huynh, H. B., Khan, U., Mortera, L., Nguyen, T. A., Safdar, M. A., Shrestha, S., Raman, A. V., Verma, S. C., Yellappa, V., & Srivastava, D. (2023). The inclusion of diagnostics in national health insurance schemes in Cambodia, India, Indonesia, Nepal, Pakistan, Philippines and Viet Nam. *BMJ Global Health*, 8(7). <https://doi.org/10.1136/bmjgh-2023-012512>
- Boruzie, P. K., Kolog, E. A., Afful-Dazie, E., & Egala, S. B. (2022). Social network for collaborative learning: What are the determining factors? *Universal Access in the Information Society*, 1–15. <https://doi.org/10.1007/s10209-022-00942-3>
- Borzekowski, D. L. G. (2022). Media Content for and Research on Children in Low- and Middle-Income Countries. In *The Routledge International Handbook of Children, Adolescents, and Media* (2nd ed., p. 8). Routledge, Taylor & Francis. <https://www.taylorfrancis.com/chapters/edit/10.4324/9781003118824-49/media-content-research-children-low-middle-income-countries-dina-borzekowski>
- Boulianne, S., & Shehata, A. (2022). Age Differences in Online News Consumption and Online Political Expression in the United States, United Kingdom, and France. *The International Journal of Press/Politics*, 27(3), 763–783. <https://doi.org/10.1177/19401612211060271>

- Buckingham, D. (2003). *Media Education: Literacy, Learning and Contemporary Culture* | Wiley (1st ed., Vol. 1). <https://www.wiley.com/en-us/Media+Education%3A+Literacy%2C+Learning+and+Contemporary+Culture-p-9780745659411>
- Buckingham, D. (2015). Defining digital literacy—What do young people need to know about digital media? *Scandinavian University Press*, 10(Jubileumsnummer), 21–34. <https://doi.org/10.18261/ISSN1891-943X-2015-Jubileumsnummer-03>
- Burton, J. W., Herzog, S. M., & Lorenz-Spreen, P. (2024). Simple changes to content curation algorithms affect the beliefs people form in a collaborative filtering experiment. *PsyArXiv*. <https://doi.org/10.31234/osf.io/5yfbt>
- Campos, D. G., & Scherer, R. (2024). Digital gender gaps in Students' knowledge, attitudes and skills: An integrative data analysis across 32 Countries. *Education and Information Technologies*, 29(1), 655–693. <https://doi.org/10.1007/s10639-023-12272-9>
- Cardoso-Leite, P., Buchard, A., Tissieres, I., Mussack, D., & Bavelier, D. (2021). Media use, attention, mental health and academic performance among 8 to 12 year old children. *PLoS ONE*, 16(11), e0259163. <https://doi.org/10.1371/journal.pone.0259163>
- Carretero, G. S., Vuorikari, R., & Punie, Y. (2017). *DigComp 2.1: The Digital Competence Framework for Citizens with eight proficiency levels and examples of use*. JRC Publications Repository. <https://doi.org/10.2760/38842>
- Casula, P., & Wong, R. Y. (2025). "I see it, I scroll past it": Exploring Perceptions of Social Media Political Discourse Among Gen Z Young Adult Women In The U.S. *Proc. ACM Hum.-Comput. Interact.*, 9(2), CSCW109:1–CSCW109:29. <https://doi.org/10.1145/3711007>
- Chadda, R. K., & Deb, K. S. (2013). Indian family systems, collectivistic society and psychotherapy. *Indian Journal of Psychiatry*, 55(Suppl 2), S299–S309. <https://doi.org/10.4103/0019-5545.105555>
- Chalukian, M. (2015). Pedagogy of Curiosity: Initial Explorations of Instructional Practice in a Critical Thinking and Curious Classroom Practice in a Critical Thinking and Curious Classroom. *ScholarWorks at UMass Boston* ScholarWorks at UMass Boston, 1, 1–77. <https://doi.org/Chalukian>
- Chaturvedi, U., & Osama, M. (2018). *WhatsApp consumption and trend patterns in rural India*. Digital Empowerment Foundation. https://www.defindia.org/wp-content/uploads/2018/10/WhatsApp-Rural-Study_V3.pdf
- Chaudhry, M. K., & Shabbir, F. (2019a). Exploring Gender Differences in Academic Motivation among Adolescents. *Integrative Journal of Conference Proceedings*, 2(1), 1–10. <http://dx.doi.org/10.31031/IJCP.2019.02.000527>
- Chaudhry, M. K., & Shabbir, F. (2019b). Exploring Gender Differences in Academic Motivation among Adolescents. *Integrative Journal of Conference Proceedings*, 2(1), 1–19. <http://dx.doi.org/10.31031/IJCP.2019.02.000527>
- Chaudhuri, A. (2024). Analysing the Digital Divide Factors: Evidence of a Rural-urban Comparison from an Indian District. *Journal of Scientific Research and Reports*, 30(5), 243–250. <https://doi.org/10.9734/jsrr/2024/v30i51939>
- Chen, F. (2025). [Review of *The relationship between digital literacy and college students' academic achievement: The chain mediating role of learning adaptation and online self-regulated learning*, by R. Cruz]. *Frontiers in Psychology*, 16(1590649), 1–9. <https://doi.org/10.3389/fpsyg.2025.1590649>
- Chen, L., Zheng, Z., Liang, J., Lin, Y., & Miao, Q. (2025). Understanding gender differences in reasoning and specific paradigm using meta-analysis of neuroimaging. *Frontiers in Behavioral Neuroscience*, 18, 1457663. <https://doi.org/10.3389/fnbeh.2024.1457663>
- Cheng, H., Lyu, K., Li, J., & Shiu, H. (2021). Bridging the Digital Divide for Rural Older Adults by Family Intergenerational Learning: A Classroom Case in a Rural Primary School in China. *International Journal of Environmental Research and Public Health*, 19(1), 371. <https://doi.org/10.3390/ijerph19010371>
- Cho, H., Cannon, J., Lopez, R., & Li, W. (2024). Social media literacy: A conceptual framework. *New Media & Society*, 26(2), 941–960. <https://doi.org/10.1177/14614448211068530>
- Chowdhury, B., Bhattacharyya, D., Majumdar, D., & Majumdar, D. (2015). Effect of Dravidian vernacular, English and Hindi during onscreen reading text: A physiological, subjective and objective evaluation study. *Journal of Eye Movement Research*, 8(2), Article 2. <https://doi.org/10.16910/jemr.8.2.4>
- Cole, E. (2024). Media Literacy: Empowering Critical Engagement in the Digital Age. *Global Media Journal*, 22(70), 1–3.

- Coyne, S. M., Rogers, A., Holmgren, H. G., Booth, M. A., Van Alfen, M., Harris, H., Barr, R., Padilla-Walker, L. M., Sheppard, J. A., Shawcroft, J., & Ober, M. (2023). Masters of Media: A longitudinal study of parental media efficacy, media monitoring, and child problematic media use across early childhood in the United States. *Journal of Children and Media*, 17(3), 318–335.
<https://doi.org/10.1080/17482798.2023.2200958>
- d'Haenens, L., Vissenberg, J., Puusepp, M., Edisherashvili, N., Martinez-Castro, D., Helsper, E. J., Tomczyk, Ł., Azadi, T., Opozda-Suder, S., Maksniemi, E., Spurava, G., Salmela-Aro, K., Sormanen, N., Tiisonen, S., Wilska, T.-A., Hietajärvi, L., Martínez, G., Larrañaga, N., Garmendia, M., ... Sepielak, D. (2025). Fostering Media Literacy: A Systematic Evidence Review of Intervention Effectiveness for Diverse Target Groups. *Media and Communication*, 13(0).
<https://doi.org/10.17645/mac.8901>
- Daliya, B. R., & Bhogle, S. (2013). Learning and Study Strategies: Academic Achievement and Gender Differences. *Artha Journal of Social Sciences*, 12(4), 49–59. <https://doi.org/10.12724/ajss.27.4>
- Dara, P., Mopuri, R., & A, S. (2025). Evaluation of online active learning strategies in first year medical students. *The National Medical Journal of India*, 37(5), 267–269.
https://doi.org/10.25259/NMJI_618_2022
- Department of Education, Babcock University, Ilisan, Ogun State, Nigeria, & Bankole Adeyemi, F. (2019). Peer group influence on academic performance of undergraduate students in Babcock University, Ogun State. *African Educational Research Journal*, 7(2), 81–87.
<https://doi.org/10.30918/AERJ.72.19.010>
- Dwyer, C. P. (2023). An Evaluative Review of Barriers to Critical Thinking in Educational and Real-World Settings. *Journal of Intelligence*, 11(6), 105.
<https://doi.org/10.3390/jintelligence11060105>
- Enrique Torralbas Oslé, J., & Corcho Rosales, E. (2023). Personal Exposure to Social Media and Variations by Gender among Cuban Youth. *Psychology in Russia*, 16(4), 72–89.
<https://doi.org/10.11621/pir.2023.0405>
- Eppard, J., Kaviani, A., Bowles, M., & Johnson, J. (2021). EdTech Culturation: Integrating A Culturally Relevant Pedagogy into Educational Technology. *Electronic Journal of E-Learning*, 19(6), pp516-530.
<https://doi.org/10.34190/ejel.19.6.2065>
- Eshet-Alkalai, Y. (2004). Digital Literacy: A Conceptual Framework for Survival Skills in the Digital era. *Journal of Educational Multimedia and Hypermedia*, 13(1), 93–106.
<https://www.learntechlib.org/primary/p/4793/>
- Feng, Q., Luo, H., Li, W., Chen, T., & Song, N. (2023). Effects of gender diversity on college students' collaborative learning: From individual gender to gender pairing. *Heliyon*, 9(6), e16237.
<https://doi.org/10.1016/j.heliyon.2023.e16237>
- Flanagin, A. J., & Metzger, M. J. (2007). The role of site features, user attributes, and information verification behaviors on the perceived credibility of web-based information. *New Media & Society*, 9(2), 319–342.
<https://doi.org/10.1177/1461444807075015>
- Fletcher, R., Andi, S., Badrinathan, S., Eddy, K. A., Kalogeropoulos, A., Mont'Alverne, C., Robertson, C. T., Ross Arguedas, A., Schulz, A., Toff, B., & Nielsen, R. K. (2025). The link between changing news use and trust: Longitudinal analysis of 46 countries. *Journal of Communication*, 75(1), 1–15.
<https://doi.org/10.1093/joc/jqae044>
- Fletcher, R., & Nielsen, R. K. (2024). *What Does the Public in Six Countries Think of Generative AI in News?* 1–42. <https://doi.org/doi.org/10.60625/risi-4zb8-cg87>
- Forsgren, E., & Byström, K. (2018). Multiple social media in the workplace: Contradictions and congruencies. *Information Systems Journal*, 28(3), 442–464. <https://doi.org/10.1111/isj.12156>
- Frielingsdorf, H., Fomichov, V., Rystedt, I., Lindstrand, S., Korhonen, L., & Henriksson, H. (2025). Associations of time spent on different types of digital media with self-rated general and mental health in Swedish adolescents. *Scientific Reports*, 15(1), 993. <https://doi.org/10.1038/s41598-024-83951-x>
- Garg, C. (2021). Is Mobile Phone Use Invading Multiple Boundaries? A Study of Rural Illiterate Women in India—Chhavi Garg, 2021. *Indian Journal of Gender Studies*, 28(1), 29–45.
<https://doi.org/10.1177/0971521520974845>
- Gee, J. P. (2005). *What video games have to teach us about learning and literacy* (1. paperback ed, Vol. 1). Palgrave Macmillan.
<https://blog.ufes.br/kyriafinardi/files/2017/10/What-Video-Games-Have-to-Teach-us-About-Learning-and-Literacy-2003.-ilovepdf-compressed.pdf>
- Genova, B. K. L., & Greenberg, B. S. (1979). Interests in News and the Knowledge Gap. *Public Opinion*

- Quarterly, 43(1), 79–91.
<https://doi.org/10.1086/268493>
- Gogoi, A., & Mansar, O. (2021). *Policy Brief: Bridging the Digital Divide for Girls in India* (Policy Report No. 1; Bridge the Gap, pp. 1–32). Digital Empowerment Foundation.
[https://www.c3india.org/uploads/news/Bridging_the_Digital_Divide-Policy_Brief_2021_\(website\)1.pdf](https://www.c3india.org/uploads/news/Bridging_the_Digital_Divide-Policy_Brief_2021_(website)1.pdf)
- Gopika, J. S., & Rekha, R. V. (2023). Awareness and Use of Digital Learning Before and During COVID-19. *International Journal of Educational Reform*, 10567879231173389.
<https://doi.org/10.1177/10567879231173389>
- Greene, J. O., & Bursleson, B. R. (2003). *Handbook of Communication and Social Interaction Skills*. Routledge.
- Guess, A. M., Lerner, M., Lyons, B., Montgomery, J. M., Nyhan, B., Reifler, J., & Sircar, N. (2020). A digital media literacy intervention increases discernment between mainstream and false news in the United States and India. *Proceedings of the National Academy of Sciences*, 117(27), 15536–15545. <https://doi.org/10.1073/pnas.1920498117>
- Guha, A., & Mukerji, M. (2021). Determinants of Digital Divide using Demand-Supply Framework: Evidence from India. *Australasian Journal of Information Systems*, 25.
<https://doi.org/10.3127/ajis.v25i0.3029>
- Gurumurthy, A., & Chami, N. (2014). Digital Technologies and Gender Justice in India -An analysis of key policy and programming concerns Input to the High Level Committee on the Status of Women in India. *Research Gate*, 1(1), 1–51.
https://www.researchgate.net/publication/344158173_Digital_Technologies_and_Gender_Justice_in_India_-_An_analysis_of_key_policy_and_programming_concerns_Input_to_the_High_Level_Committee_on_the_Status_of_Women_in_India
- Habibi, A., Sofyan, S., & Mukminin, A. (2023). Factors affecting digital technology access in vocational education. *Scientific Reports*, 13, 5682.
<https://doi.org/10.1038/s41598-023-32755-6>
- Haddock, A., Ward, N., Yu, R., & O'Dea, N. (2022). Positive Effects of Digital Technology Use by Adolescents: A Scoping Review of the Literature. *International Journal of Environmental Research and Public Health*, 19(21), 14009.
<https://doi.org/10.3390/ijerph192114009>
- Hameleers, M., Brosius, A., & de Vreese, C. H. (2022). Whom to trust? Media exposure patterns of citizens with perceptions of misinformation and disinformation related to the news media. *European Journal of Communication*, 37(3), 237–268.
<https://doi.org/10.1177/02673231211072667>
- Hamid, H., Ruahim, R. bt A., & Abdullah, S. H. bt. (2024). *Challenges of Digital Literacy among Urban and Rural Pre-University Students*. 423–438. https://doi.org/10.2991/978-2-38476-321-4_31
- Hatlevik, O. E., & Christophersen, K.-A. (2013). Digital competence at the beginning of upper secondary school: Identifying factors explaining digital inclusion. *Computers & Education*, 63(1), 240–247.
<https://doi.org/10.1016/j.compedu.2012.11.015>
- Heeks, R. (2022). Digital inequality beyond the digital divide: Conceptualizing adverse digital incorporation in the global South. *Information Technology for Development*, 28(4), 688–704.
<https://doi.org/10.1080/02681102.2022.2068492>
- Hertweck, F., & Lehner, J. (2025). The gender gap in STEM: (Female) teenagers' ICT skills and subsequent career paths. *PLOS ONE*, 20(1), e0308074.
<https://doi.org/10.1371/journal.pone.0308074>
- Hobbs, R. (2010). News Literacy: What Works and What Doesn't. *Association for Education in Journalism and Mass Communication*, 1–9.
<https://mediaeducationlab.com/sites/mediaeducationlab.com/files/Hobbs,%20NEWS%20LITERACY%20AEJMC%202010.pdf>
- Hu, Y., & Talib, M. B. A. (2023). Student Engagement and its Association with Peer Relation and Student-Teacher Relation: A Systematic Review. *Educational Administration: Theory and Practice*, 29(4), 1–15.
<https://doi.org/10.52152/kuety.v29i4.763>
- Islam, A., & Manchanda, P. (2023). Gender Inequalities in Digital India A survey on digital literacy, access, and use. *Digital Futures at Work Research Centre*.
<https://doi.org/10.20919/MCUU2363>
- Ji, H., Dong, J., Pan, W., & Yu, Y. (2024). Associations between digital literacy, health literacy, and digital health behaviors among rural residents: Evidence from Zhejiang, China. *International Journal for Equity in Health*, 23, 68.
<https://doi.org/10.1186/s12939-024-02150-2>
- Joselin, J., Vaishya, A., Upadhyay, D., & Poornima, V. (2025). A Study on the Influence of Social Media Algorithms on Public and Political Opinion. *International Journal of Advanced Research in Science, Communication and Technology*, 5(1), 112–119. <https://doi.org/10.48175/568>

- Joshi, A., Malhotra, B., Amadi, C., Loomba, M., Misra, A., Sharma, S., Arora, A., & Amatya, J. (2020). Gender and the Digital Divide Across Urban Slums of New Delhi, India: Cross-Sectional Study. *Journal of Medical Internet Research*, 22(6), e14714. <https://doi.org/10.2196/14714>
- Joshi, D. N. (2024). The Digital Divide and Educational Inequalities: A Survey-Based Examination among Students of Rajasthan. *International Research Journal of Humanities and Interdisciplinary Studies*, 5(7), 133–150. <https://doi.org/doi:10.2024-88731633/IRJHIS2407012>
- Karakainen, M.-T., Kivinen, O., & Vainio, T. (2018). Performance-based testing for ICT skills assessing: A case study of students and teachers' ICT skills in Finnish schools. *Universal Access in the Information Society*, 17(2), 349–360. <https://doi.org/10.1007/s10209-017-0553-9>
- Kantar. (2024). *Internet in India in 2024* (Research Report No. 1; pp. 1–27). Internet and Mobile Association of India. <https://www.iamai.in/sites/default/files/research/Kantar%20IAMAI%20report%2024.pdf>
- Kapilashrami, A., Hill, S., & Meer, N. (2015). What can health inequalities researchers learn from an intersectionality perspective? Understanding social dynamics with an inter-categorical approach? *Social Theory & Health*, 13(3), 288–307. <https://doi.org/10.1057/sth.2015.16>
- Katz, E., & Blumer, J. G. (1974). Uses and Gratifications Research. *Public Opinion Quarterly*, 37(4), 509–523. <https://doi.org/10.1086/268109>
- Kibria, G. M. A., & Nayeem, J. (2023). Association of rural-urban place of residence with adequate antenatal care visit in Bangladesh. *PLOS Global Public Health*, 3(10), e0002528. <https://doi.org/10.1371/journal.pgph.0002528>
- Knight Survey. (2018). *American views: Trust, media and democracy*. Knight Foundation. <https://knightfoundation.org/reports/american-views-trust-media-and-democracy/>
- Korlat, S., Kollmayer, M., Holzer, J., Lüftenegger, M., Pelikan, E. R., Schober, B., & Spiel, C. (2021). Gender Differences in Digital Learning During COVID-19: Competence Beliefs, Intrinsic Value, Learning Engagement, and Perceived Teacher Support. *Frontiers in Psychology*, 12. <https://doi.org/10.3389/fpsyg.2021.637776>
- Kormelink, T. G., & Meijer, I. C. (2020). A User Perspective on Time Spent: Temporal Experiences of Everyday News Use. *Journalism Studies*, 21(2), 271–286. <https://doi.org/10.1080/1461670X.2019.1639538>
- Kraaykamp, G., & Notten, N. (2016). Parental cultural socialization and educational attainment. Trend effects of traditional cultural capital and media involvement. *Research in Social Stratification and Mobility*, 45(1), 63–71. <https://doi.org/10.1016/j.rssm.2016.08.003>
- Kte'pi, Bill, & MA. (2021). Media Consumption theory. *EBSCO Research Starters*, 1(1). <https://www.ebsco.com/research-starters/social-sciences-and-humanities/media-consumption-theory>
- Kumar, B. T. S., & Kumara, S. U. S. (2018). The digital divide in India: Use and non-use of ICT by rural and urban students. *World Journal of Science, Technology and Sustainable Development*, 15(2), 156–168. <https://doi.org/10.1108/WJSTSD-07-2017-0021>
- Kumar, S., & Sarma, V. V. S. (2015). *Performance and Challenges of Newspapers in India: A Case Study on English versus Vernacular Dailies in India*. 901–912. <http://www.aims-international.org/conferences.asp>
- Kumawat, S., & Garg, C. (2025). Mobile phones, mothers, and patriarchy: Understanding digital interactions of adolescent Indian rural girls under watchful eyes. *Media, Culture & Society*, 47(5), 972–988. <https://doi.org/10.1177/01634437251320845>
- Lafifa, F., & Rosana, D. (2023). *Exploring the Digital Literacy Profile: A Closer Look Based on Gender*. 1924–1934. https://doi.org/10.2991/978-2-38476-152-4_194
- Lalrinsangi, R., & Kharbiryumbai, B. B. (2024). Empowering Women through ICT: A study. *Indian Journal of Educational Technology*, 6(1), 273–282.
- Landrum, A. R. (2021). Are Women a Missing Audience for Science on YouTube? An Exploratory Study. *Frontiers in Communication*, 6. <https://doi.org/10.3389/fcomm.2021.610920>
- Laskar, M. H. (2023). Examining the emergence of digital society and the digital divide in India: A comparative evaluation between urban and rural areas. *Frontiers in Sociology*, 8. <https://doi.org/10.3389/fsoc.2023.1145221>
- Laursen, B., & Veenstra, R. (2021). Toward understanding the functions of peer influence: A summary and synthesis of recent empirical research. *Journal of Research on Adolescence*, 31(4), 889–907. <https://doi.org/10.1111/jora.12606>

- Lee, H. E., Kim, J. Y., & Kim, C. (2022). The Influence of Parent Media Use, Parent Attitude on Media, and Parenting Style on Children's Media Use. *Children*, 9(1), 37. <https://doi.org/10.3390/children9010037>
- Lee, S. H. (2011). Does Trust Really Matter? A Quantitative Study of College Students' Trust and Use of News Media. *College of Journalism and Mass Communications: Theses*, 1. <https://digitalcommons.unl.edu/journalismdiss/15>
- Lee, S., Kim, D., & Shin, Y. (2024). Screen time among preschoolers: Exploring individual, familial, and environmental factors. *Clinical and Experimental Pediatrics*, 67(12), 641–650. <https://doi.org/10.3345/cep.2023.01746>
- Lemish, D., & Elias, N. (2009). Spinning the web of identity: The roles of the internet in the lives of immigrant adolescents—Nelly Elias, Dafna Lemish, 2009. *Sage Publications: New Media & Society*, 11(4), 533–551. <https://doi.org/10.1177/1461444809102959>
- Lessard, L. M., & Juvonen, J. (2020). Engagement Norms Buffer Academic Risks Associated with Peer Rejection in Middle School. *International Journal of Behavioral Development*, 29(3), 235–241. <https://doi.org/10.1177/0165025420915779>
- Li, H., Yang, Z., & Li, J. (2025). The impact of digital literacy on individual health: A perspective based on fitness exercise. *Frontiers in Public Health*, 13, 1625235. <https://doi.org/10.3389/fpubh.2025.1625235>
- Li, P.-P., & Zhong, F. (2022). A Study on the Correlation Between Media Usage Frequency and Audiences' Risk Perception, Emotion and Behavior. *Frontiers in Psychology*, 12(1). <https://doi.org/10.3389/fpsyg.2021.822300>
- Linos, K., Carlson, M., Jakli, L., Dalma, N., Cohen, I., Veloudaki, A., & Spyrellis, S. N. (2022). How Do Disadvantaged Groups Seek Information About Public Services? A Randomized Controlled Trial of Communication Technologies. *Public Administration Review*, 82(4), 708–720. <https://doi.org/10.1111/puar.13437>
- Liu, X., & Lu, J. (2020). Comparative Media Studies in the Digital Age: Does the Internet Erode Trust in Media? A Comparative Study of 46 Countries. *International Journal of Communication*, 14(0), Article 0.
- Liu, Y., & Pásztor, A. (2023). Moderated mediating effects of gender among the components of critical thinking disposition in undergraduate students. *Heliyon*, 9(4), e14664. <https://doi.org/10.1016/j.heliyon.2023.e14664>
- Livingstone, S. (2004). Media Literacy and the Challenge of New Information and Communication Technologies. *The Communication Review*, 7(1), 3–14. <https://doi.org/10.1080/10714420490280152>
- Lu, G., Chen, T., & Ding, J. (2023). Research on the Construction of Digital Literacy Framework for Citizens—Comparative Analysis Based on Five International Digital Literacy Frameworks. *Frontiers in Educational Research*, 6(30), 1–10. <https://doi.org/10.25236/FER.2023.063001>
- Luitel, P. (2024). Gender Differences in Academic Motivation and Classroom Engagement among University Students in Kathmandu. *Scientific Researches in Academia*, 2(2), 43–56. <https://doi.org/10.3126/sra.v2i2.74283>
- Lukáč, J., Kudlová, Z., Kopčáková, J., & Gallo, P. (2025). Impact of Socio-Economic Factors on Digital Literacy and Security. *TEM Journal*, 14(1), 925–932. <https://doi.org/10.18421/TEM141-81>
- Lundberg, S. (2020). Educational Gender Gaps. *Southern Economic Journal*, 87(2), 416–439. <https://doi.org/10.1002/soej.12460>
- Lyons, A., McCreanor, T., Goodwin, I., & Barnes, H. M. (Eds.). (2017). *Youth Drinking Cultures in a Digital World: Alcohol, Social Media and Cultures of Intoxication* (1st ed., Vol. 1). Routledge. <https://doi.org/10.4324/9781315660844>
- Maksl, A., Ashley, S., & Craft, S. (2015). Measuring News Media Literacy. *Journal of Media Literacy Education*, 6(3), 29–45. <https://doi.org/10.23860/jmle-6-3-3>
- Makwana, V., & Bhatia, K. (2024). *Navigating the Infodemic: Fostering Critical Media Literacy in the Digital Age to Combat Misinformation* (SSRN Scholarly Paper No. 4991514). Social Science Research Network. <https://doi.org/10.2139/ssrn.4991514>
- McClure, I. (2003). The Essential Difference: Men, Women and the Extreme Male Brain. *BMJ: British Medical Journal*, 327(7405), 57.
- McDougall, J., & Rega, I. (2022). Beyond Solutionism: Differently Motivating Media Literacy. *Media and Communication*, 10(4), 267–276. <https://doi.org/10.17645/mac.v10i4.5715>
- McGrew, S., & Breakstone, J. (2023). Civic Online Reasoning Across the Curriculum: Developing and Testing the Efficacy of Digital Literacy Lessons. *Sage Journal, AERA Open*, 9. <https://doi.org/10.1177/23328584231176451>
- McMillan, C., Felmlee, D., & Osgood, D. W. (2018). Peer Influence, Friend Selection, and Gender: How

- Network Processes Shape Adolescent Smoking, Drinking, And Delinquency. *Social Networks*, 55, 86–96. <https://doi.org/10.1016/j.socnet.2018.05.008>
- Meelissen, M. R. M., & Drent, M. (2008). Gender differences in computer attitudes: Does the school matter? *Computers in Human Behavior*, 24(3), 969–985. <https://doi.org/10.1016/j.chb.2007.03.001>
- Metzger, M. J., & Flanagin, A. J. (2015a). Psychological Approaches to Credibility Assessment Online. In *The Handbook of the Psychology of Communication Technology* (1st ed., Vol. 1, pp. 445–466). John Wiley & Sons, Ltd. <https://doi.org/10.1002/9781118426456.ch20>
- Metzger, M. J., & Flanagin, A. J. (2015b). Psychological approaches to credibility assessment online. *The Handbook of the Psychology of Communication Technology*, 1(1), 445–466. <https://psycnet.apa.org/doi/10.1002/9781118426456.ch20>
- Meyers-Levy, J., & Loken, B. (2015). Revisiting gender differences: What we know and what lies ahead. *Journal of Consumer Psychology*, 25(1), 129–149. <https://psycnet.apa.org/doi/10.1016/j.jcps.2014.06.003>
- Mihailidis, P., & Viotty, S. (2017). Spreadable Spectacle in Digital Culture: Civic Expression, Fake News, and the Role of Media Literacies in “Post-Fact” Society. *Sage Publications: American Behavioral Scientist*, 61(4), 441–454. <https://doi.org/10.1177/0002764217701217>
- Mishra, D., Kedia, M., Ramnath, K., Manish, M., & Reddy, Aarti. (2024). *The State of India's Digital Economy Report* (Nos. 978-81-954132-8-7; p. 92). IPCIDE, ICRIER Indian Council for Research on International Economic Relations (ICRIER). https://icrier.org/pdf/State_of_India_Digital_Economy_Report_2024.pdf
- Mishra, D., Kedia, M., Reddy, A., Fernandez, C., Shukla, S., Ramnath, K., & Vanguri, S. (2025). *Estimation and Measurement of India's Digital Economy* (pp. 1–96). Ministry of Electronics and Information Technology, Government of India. <https://www.meity.gov.in/static/uploads/2025/01/5ff397f9e8152d5562ed4cecf1a6b767b.pdf>
- Mitchell, A., Oliphant, J. B., & Klein, H. (2020). *Americans Who Mainly Get Their News on Social Media Are Less Engaged, Less Knowledgeable Those who rely on social media for news are less likely to get the facts right about the coronavirus and politics and more likely to hear some unproven claims* (Pew Research Center No. 1; Original Research, pp. 1–37). Pew Research Center., https://www.pewresearch.org/wp-content/uploads/sites/20/2020/07/PJ_2020.07.30_social-media-news_REPORT.pdf
- Nassar, H., & Oumais, N. (2016). The Impact of Socio-economic Status on the Utilization of Smartphones in Lebanon. *International Journal of Management and Applied Science*, 2(12), 38–41. https://www.ijaj.in/journal/journal_file/journal_pdf/14-328-148525954138-41.pdf
- Nechushta, S. (2024). Audience Fragmentation: Navigating the Shifting Landscape of Media Consumption. *Global Media Journal*, 22(70), 1–3.
- Nelson, J. L., Sanderson, Z., & Lewis, S. C. (2024). There is a growing disconnect between how journalists see themselves and how people see journalists. *Columbia Journalism Review*. https://www.cjr.org/tow_center/people-trust-themselves-more-than-they-trust-the-news-they-shouldnt.php
- Nesi, J., Choukas-Bradley, S., & Prinstein, M. J. (2018a). Transformation of Adolescent Peer Relations in the Social Media Context: Part 1-A Theoretical Framework and Application to Dyadic Peer Relationships. *Clinical Child and Family Psychology Review*, 21(3), 267–294. <https://doi.org/10.1007/s10567-018-0261-x>
- Nesi, J., Choukas-Bradley, S., & Prinstein, M. J. (2018b). Transformation of Adolescent Peer Relations in the Social Media Context: Part 2—Application to Peer Group Processes and Future Directions for Research. *Clinical Child and Family Psychology Review*, 21(3), 295–319. <https://doi.org/10.1007/s10567-018-0262-9>
- Nhedzi, A. (2018). The relationship between traditional and digital media as an influence on generational consumer preference. *Communitas*, 23, 18–38. <https://doi.org/10.38140/com.v23i0.3718>
- Noverli, M., & Cahya, E. (2021, August 19). *Analysis of Student's Critical Thinking Ability Based on Gender*. Proceedings of The 6th Asia-Pacific Education And Science Conference, AECon 2020, 19-20 December 2020, Purwokerto, Indonesia. <https://eudl.eu/doi/10.4108/eai.19-12-2020.2309168>
- Nygaard, L. P., Aksnes, D. W., & Piro, F. N. (2022). Identifying gender disparities in research performance: The importance of comparing apples with apples. *Higher Education*, 84(5), 1127–1142. <https://doi.org/10.1007/s10734-022-00820-0>
- Ognyanova, K., Lazer, D., Robertson, R. E., & Wilson, C. (2020). Misinformation in action: Fake news exposure is linked to lower trust in media, higher

- trust in government when your side is in power. *Harvard Kennedy School Misinformation Review*. <https://doi.org/10.37016/mr-2020-024>
- Ophir, E., Nass, C., & Wagner, A. D. (2009). Cognitive control in media multitaskers. *Proceedings of the National Academy of Sciences*, 106(37), 15583–15587. <https://doi.org/10.1073/pnas.0903620106>
- Otero, I., Martínez, A., Cuadrado, D., Lado, M., Moscoso, S., & Salgado, J. F. (2024). Sex Differences in Cognitive Reflection: A Meta-Analysis. *Journal of Intelligence*, 12(4), 39. <https://doi.org/10.3390/jintelligence12040039>
- Panda, A., & Gope, L. (2024). Breaking barriers: The digital revolution in girls education across India. *Journal of Interdisciplinary Studies in Education*, 13(S1), 147–171. <https://doi.org/10.32674/ffkmbm80>
- Pandey, A. (2020). *Youth and Inequality: A Sociological Study of Digital Inequality among Youth in India*. Indian Revenue Service, Government of India. International Centre for Social Development Working Paper Series. <https://ic-sd.org/wp-content/uploads/2020/11/Avinash-Pandey.pdf>
- Papagari, B., & Rayudu, C. S. (2012). Digital Education in the era of COVID-19 pandemic. *IJFANS International Journal of Food and Nutritional Sciences*, 11(13), 716–721.
- Pappas, I. O., Mikalef, P., Dwivedi, Y. K., Jaccheri, L., & Krogstie, J. (2023). Responsible Digital Transformation for a Sustainable Society. *Information Systems Frontiers*, 25(3), 945–953. <https://doi.org/10.1007/s10796-023-10406-5>
- Park, K., Ging, D., Murphy, S., & Mcgrath, C. (2023). *The impact of the use of social media on women and girls*. [https://www.europarl.europa.eu/RegData/etudes/STUD/2023/743341/IPOL_STU\(2023\)743341_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/STUD/2023/743341/IPOL_STU(2023)743341_EN.pdf)
- Park, S., Fisher, C., Tandoc Jr, E., Dulleck, U., Yao, S. P., & Lukamto, W. (2024). The relationship between news trust, mistrust and audience disengagement. *Journalism*, 0(0), 14648849241299775. <https://doi.org/10.1177/14648849241299775>
- Pawluczuk, A. (2020). Digital youth inclusion and the big data divide: Examining the Scottish perspective. *Internet Policy Review*, 9(2). <https://doi.org/10.14763/2020.2.1480>
- Pazer, S. (2024). The Impact of Social Media Use on Identity Formation among Adolescents. *International Journal of Advance Research, Ideas and Innovations in Technology*, 10(5), 299–304. https://www.researchgate.net/profile/Sora-Pazer/publication/384893227_The_Impact_of_Social_Media_Use_on_Identity_Formation_among_Adolescents/links/670cdfeaab0241709970572b/The-Impact-of-Social-Media-Use-on-Identity-Formation-among-Adolescents.pdf?tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIn19
- Peláez-Sánchez, I. C., George Reyes, C. E., & Glasserman-Morales, L. D. (2023). Gender digital divide in education 4.0: A systematic literature review of factors and strategies for inclusion. *Future in Educational Research*, 1(2), 129–146. <https://doi.org/doi.org/10.1002/fer3.16>
- Pérez-Torres, V. (2024). Problematic use of social media in adolescents or excessive social gratification? The mediating role of nomophobia. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, 18(4). <https://doi.org/10.5817/CP2024-4-2>
- Polanco-Levicán, K., & Salvo-Garrido, S. (2022). Understanding Social Media Literacy: A Systematic Review of the Concept and Its Competences. *International Journal of Environmental Research and Public Health*, 19(14), 8807. <https://doi.org/10.3390/ijerph19148807>
- Pop, M.-I., & Ene, I. (2019). Influence of the educational level on the spreading of Fake News regarding the energy field in the online environment. *Proceedings of the International Conference on Business Excellence*, 13(1), 1108–1117. <https://doi.org/10.2478/picbe-2019-0097>
- Posey, P. D. (2023). Information Inequality: How Race and Financial Access Reflect the Information Needs of Lower-Income Individuals. *The ANNALS of the American Academy of Political and Social Science*, 707(1), 125–141. <https://doi.org/10.1177/00027162231219551>
- Prakash, S., Puri, H., & Fernandez, C. (2024). *Digital Technology as an Instrument to Bridge the Gender Gaps in Access to Labour Markets* (Policy Report No. UNDP Policy Brief #31). https://www.undp.org/sites/g/files/zskgke326/files/2025-02/undp-icrier_policy_brief_31.pdf
- Prensky, M. (2001). Digital Natives, Digital Immigrants. *Digital Natives Digital Immigrants*, 9(5), 1–6. <https://www.marcprensky.com/writing/Prensky%20-%20Digital%20Natives,%20Digital%20Immigrants%20-%20Part1.pdf>

- Psaki, S., Haberland, N., Mensch, B., Woyczynski, L., & Chuang, E. (2022). Policies and interventions to remove gender-related barriers to girls' school participation and learning in low- and middle-income countries: A systematic review of the evidence. *Campbell Systematic Reviews*, 18(1), e1207. <https://doi.org/10.1002/cl2.1207>
- Qazi, A., Hasan, N., Abayomi-Alli, O., Hardaker, G., Scherer, R., Sarker, Y., Kumar Paul, S., & Maitama, J. Z. (2022). Gender differences in information and communication technology use & skills: A systematic review and meta-analysis. *Education and Information Technologies*, 27(3), 4225–4258. <https://doi.org/10.1007/s10639-021-10775-x>
- Rahman, P., & Mehnaz, S. (2024). Evaluating the Impact of the ICT @ Schools Program on Learning Experiences: A Study of Secondary Government Schools in Chikkaballapur Taluk, Karnataka. *International Journal for Multidisciplinary Research (IJFMR)*, 7(2), 1–8. <https://doi.org/10.2139/ssrn.5054029>
- Rai, G. A., & Shahila, Z. (2013). Rural India: The Next Frontier for Social Media Networks. *International Journal of Engineering Research & Technology*, 2(1). <https://doi.org/10.17577/IJERTV2IS1352>
- Rakesh, D., Lee, P. A., Gaikwad, A., & McLaughlin, K. A. (2025). Annual Research Review: Associations of socioeconomic status with cognitive function, language ability, and academic achievement in youth: a systematic review of mechanisms and protective factors. *Journal of Child Psychology and Psychiatry, and Allied Disciplines*, 66(4), 417–439. <https://doi.org/10.1111/jcpp.14082>
- Rana, U., & Singh, R. (2025). The Hidden Trauma of Digital Disenfranchisement in an AI-Driven World. *Journal of Emergency Practice and Trauma*, 10(1), 1–3. <https://doi.org/10.34172/jept.2025.07>
- Rani, Dr. P., Acharya, B., & Trehan, K. (2024). *Digital Inequalities in Media Education in South Asia: Context and Consequences of the Covid-19 Pandemic* (1st ed., Vol. 1). <https://doi.org/10.4324/9781003432074>
- Rayland, A., & Andrews, J. (2023). From Social Network to Peer Support Network: Opportunities to Explore Mechanisms of Online Peer Support for Mental Health. *JMIR Mental Health*, 10, e41855. <https://doi.org/10.2196/41855>
- Reindl, M. (2021). Peer Group Embeddedness and Academic Motivation: A Developmental Perspective. *Frontiers in Psychology*, 12. <https://doi.org/10.3389/fpsyg.2021.701600>
- Reis, J., & Melão, N. (2023). Digital transformation: A meta-review and guidelines for future research. *Heliyon*, 9(1), e12834. <https://doi.org/10.1016/j.heliyon.2023.e12834>
- Rek, M., & Eva, M. (2025). The Interdependence of Socio-economic Factors and Media Literacy: Focus on Critical Media Content Analysis and Evaluation. *Central European Journal of International and Security Studies*, 20(4), 605–619. <https://doi.org/10.2478/pce-2024-0027>
- Richardson, A., Allen, J. A., Xiao, H., & Vallone, D. (2012). Effects of race/ethnicity and socioeconomic status on health information-seeking, confidence, and trust. *Journal of Health Care for the Poor and Underserved*, 23(4), 1477–1493. <https://doi.org/10.1353/hpu.2012.0181>
- Saha, P., Prusty, A. K., & Nanda, C. (2024). Extension strategies for bridging gender digital divide. *Journal of Applied Biology & Biotechnology*, 12(4), 76–80. <https://doi.org/10.7324/JABB.2024.159452>
- Sahoo, N., Kulkarni, P., Ahmad, A., Goyal, T., Asad, N., Garimella, A., & Bhattacharyya, P. (2024). IndiBias: A Benchmark Dataset to Measure Social Biases in Language Models for Indian Context. *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, 8786–8806. <https://doi.org/10.18653/v1/2024.naacl-long.487>
- Samardzic, T., Gutierrez, X., Bentz, C., Moran, S., & Pelloni, O. (2024). A Measure for Transparent Comparison of Linguistic Diversity in Multilingual NLP Data Sets. In K. Duh, H. Gomez, & S. Bethard (Eds.), *Findings of the Association for Computational Linguistics: NAACL 2024* (pp. 3367–3382). Association for Computational Linguistics. <https://doi.org/10.18653/v1/2024.findings-naacl.213>
- Samudra, A. (2022). *Gendering the Digital Divide in India* (SSRN Scholarly Paper No. 4112879). Social Science Research Network. <https://doi.org/10.2139/ssrn.4112879>
- Sawyer, N., & Temkin, K. (2004). *Analysis of Alternative Financial Service Providers* (1st ed., Vol. 1). The Urban Institute. <https://www.urban.org/sites/default/files/publication/57871/410935-analysis-of-alternative-financial-service-providers.pdf>
- Saxena, S., Wright, W. S., & Khalil, M. K. (2024). Gender differences in learning and study strategies

- impact medical students' preclinical and USMLE step 1 examination performance. *BMC Medical Education*, 24, 504. <https://doi.org/10.1186/s12909-024-05494-z>
- Scheerder, A., van Deursen, A., & van Dijk, J. (2017). Determinants of Internet skills, uses and outcomes. A systematic review of the second- and third-level digital divide. *Telematics and Informatics*, 34(8), 1607–1624. <https://doi.org/10.1016/j.tele.2017.07.007>
- Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, 128, 13–35. <https://doi.org/10.1016/j.compedu.2018.09.009>
- Schneider, S., Beege, M., Nebel, S., Schnaubert, L., & Rey, G. D. (2022). The Cognitive-Affective-Social Theory of Learning in digital Environments (CASTLE). *Educational Psychology Review*, 34(1), 1–38. <https://doi.org/10.1007/s10648-021-09626-5>
- Scott, K., Shinde, A., Ummer, O., Yadav, S., Sharma, M., Purty, N., Jairath, A., Chamberlain, S., & LeFevre, A. E. (2021). Freedom within a cage: How patriarchal gender norms limit women's use of mobile phones in rural central India. *BMJ Global Health*, 6(Suppl 5), e005596. <https://doi.org/10.1136/bmjgh-2021-005596>
- Seerangan, C., & Ravi, V. (2025). Digital Technologies Enable Knowledge Sharing Among the Tribe. *International Research Journal of Education and Technology*, 08(04), 311–315. <https://www.irjweb.com/Digital%20Technologies%20Enable%20Knowledge%20Sharing%20Among%20the%20Tribe.pdf>
- Sharma, A. (2024). The Indian Telecom Services Yearly Performance Indicators 2023-2024. *Telecom Regulatory Authority of India*, 1(11), 1–161. https://www.trai.gov.in/sites/default/files/2024-09/Report_14082024.pdf
- Sharma, A., & Banerjee. (2022). Socio-Economic Determinants of Digital Divide in India. *Demography India*, 51(1), 78–92. <https://iasp.ac.in/uploads/journal/5.%20Socio-Economic%20Determinants%20of%20Digital%20Divide%20in%20India-1669206597.pdf>
- Sindakis, S., & Showkat, G. (2024). The digital revolution in India: Bridging the gap in rural technology adoption. *Journal of Innovation and Entrepreneurship*, 13(1), 1–28. <https://doi.org/10.1186/s13731-024-00380-w>
- Singh, S. (2010). Digital Divide in India: Measurement, Determinants and Policy for Addressing the Challenges in Bridging the Digital Divide. *International Journal of Innovation in the Digital Economy (IJIDE)*, 1(2), 1–24. <https://doi.org/10.4018/ijide.2010040101>
- Singh, S. (2023). Demographic Variation in Media Consumption: A Comparative Analysis. *Journal of Visual and Performing Arts*, 4(1), 2109–2117. <http://dx.doi.org/10.29121/shodhkosh.v4.i2.2023.3351>
- Singh, S., & Singh, G. A. (2022). Assessing the Impact of the Digital Divide on Indian Society: A Study of Social Exclusion. *Research in Social Change*, 13(1), 181–190. <https://doi.org/10.2478/rsc-2021-0018>
- Singh, U., & Singh, M. (2023). Gender Differences in Self-esteem, Parental Pressure and Peer Pressure among Adolescents. *Indian Journal of Health and Well-Being*, 14(4), 499–502.
- Sirlin, N., Epstein, Z., Arechar, A. A., & Rand, D. G. (2021). Digital literacy is associated with more discerning accuracy judgments but not sharing intentions. *Harvard Kennedy School Misinformation Review*. <https://doi.org/10.37016/mr-2020-83>
- Skogen, J. C., Bøe, T., Finserås, T. R., Sivertsen, B., Hella, R. T., & Hjetland, G. J. (2022). Lower Subjective Socioeconomic Status Is Associated With Increased Risk of Reporting Negative Experiences on Social Media. Findings From the “LifeOnSoMe”-Study. *Frontiers in Public Health*, 10, 873463. <https://doi.org/10.3389/fpubh.2022.873463>
- Smith, A. R., Steinberg, L., Strang, N., & Chein, J. (2015). Age differences in the impact of peers on adolescents' and adults' neural response to reward. *Developmental Cognitive Neuroscience*, 11(1), 75–82. <https://doi.org/10.1016/j.dcn.2014.08.010>
- Steinberg, L. (2008). A Social Neuroscience Perspective on Adolescent Risk-Taking. *Developmental Review* : DR, 28(1), 78–106. <https://doi.org/10.1016/j.dr.2007.08.002>
- Sternberg, R. J. (2020). Critical Thinking in STEM Disciplines. In D. F. Halpern & R. J. Sternberg (Eds.), *Critical Thinking in Psychology* (2nd ed., pp. 309–327). Cambridge University Press. <https://doi.org/10.1017/9781108684354.014>
- Stockdale, L. A., & Coyne, S. M. (2020). Bored and online: Reasons for using social media, problematic social networking site use, and behavioral outcomes across the transition from adolescence to

- emerging adulthood. *Journal of Adolescence*, 79, 173–183.
<https://doi.org/10.1016/j.adolescence.2020.01.010>
- Strömbäck, J., Tsifti, Y., Boomgaarden, H., Damstra, A., Lindgren, E., Vliegenthart, R., & Lindholm, T. (2020). News Media Trust and its Impact on Media Use: Toward a Framework for Future Research. *Annals of the International Communication Association*, 44(2), 139–156.
<https://doi.org/10.1080/23808985.2020.1755338>
- Sultanbayeva, G., Akynbekova, A., Belgarayeva, A., Buyenbayeva, Z., & Ashimova, A. (2024). Digital Literacy as a Tool for Identifying Fake News: A Comparative Analysis Using the Example of European and Kazakh Media. *Journal of Information Policy*, 1(1), 1–30.
<https://doi.org/10.5325/jinfopoli.15.2025.0001>
- Světlík, J., & Bačíková, Z. (2022). Digital Natives, Immigrants and Literacy: Age and Gender Differences. *Procedia Computer Science*, 192(1), 450–458.
<https://journals.indexcopernicus.com/api/file/viewByFileId/66933>
- Tambe, S. N., & Hussein, N. A.-H. K. (2023). Exploring the Impact of Digital Literacy on Media Consumer Empowerment in the Age of Misinformation. *MEDAAD*, 2023(1), 1–9.
<https://doi.org/10.70470/MEDAAD/2023/001>
- Tandoc, E. (2018). Tell Me Who Your Sources Are: Perceptions of news credibility on social media | Request PDF. *Journalism Practice*, ResearchGate, 13(4), 1–13.
<http://dx.doi.org/10.1080/17512786.2017.1423237>
- Tandoc Jr., E. C., Lim, Z. W., & Ling, R. (2018). Defining “Fake News”: A typology of scholarly definitions. *Digital Journalism*, 6(2), 137–153.
<https://doi.org/10.1080/21670811.2017.1360143>
- Tandoc Jr., E. C., Lim, D., & Ling, R. (2020). Diffusion of disinformation: How social media users respond to fake news and why. *Journalism*, 21(3), 381–398.
<https://doi.org/10.1177/1464884919868325>
- Temitope, B., & Christy, O. F. (2015). Influence of Peer Group on Academic Performance of Secondary School Students in Ekiti State. *International Journal of Innovative Research and Development*, 4(1).
<https://www.semanticscholar.org/paper/Influence-of-Peer-Group-on-Academic-Performance-of-Temitope-Christy/e29cfeed8c84bc891f344eec9f043f960b25d79>
- Terrell, S. R. (2004). Wrong Turn on the Information Superhighway: Education and the Commercialization of the Internet. *Sage Publications: Teachers College Record*, 106(12), 2388–2391.
<https://doi.org/10.1177/016146812004106122388>
- Tewathia, N., Kamath, A., & Ilavarasan, P. V. (2020). Social inequalities, fundamental inequities, and recurring of the digital divide: Insights from India. *Technology in Society*, 61, 101251.
<https://doi.org/10.1016/j.techsoc.2020.101251>
- Tichenor, P. J., Donohue, G. A., & Olien, C. N. (1970). Mass Media Flow and Differential Growth in Knowledge. *Public Opinion Quarterly*, 34(2), 159–170. <https://doi.org/10.1086/267786>
- Timotheou, S., Miliou, O., Dimitriadis, Y., Sobrino, S. V., Giannoutsou, N., Cachia, R., Monés, A. M., & Ioannou, A. (2023). Impacts of digital technologies on education and factors influencing schools’ digital capacity and transformation: A literature review. *Education and Information Technologies*, 28(6), 6695–6726. <https://doi.org/10.1007/s10639-022-11431-8>
- Tinmaz, H., Lee, Y.-T., Fanea-Ivanovici, M., & Baber, H. (2022). A systematic review on digital literacy. *Smart Learning Environments*, 9(1), 1–18.
<https://doi.org/10.1186/s40561-022-00204-y>
- Tolochko, P., Bernhard-Harrer, J., Kakavand, A. E., Kulichkina, A., Song, H., & Boomgaarden, H. G. (2025). *Digital Skills Formation in Gendered Peer Networks: Exploring advice giving and taking in classrooms* (No. arXiv:2508.19102). arXiv.
<https://doi.org/10.48550/arXiv.2508.19102>
- Toma, C. L., & Hancock, J. T. (2013). Self-Affirmation Underlies Facebook Use. *Personality and Social Psychology Bulletin*, 39(3), 321–331.
<https://doi.org/10.1177/0146167212474694>
- Totland, T. H., Bjelland, M., Lien, N., Bergh, I. H., Gebremariam, M. K., Grydeland, M., Ommundsen, Y., & Andersen, L. F. (2013). Adolescents’ prospective screen time by gender and parental education, the mediation of parental influences. *International Journal of Behavioral Nutrition and Physical Activity*, 10(1), 89.
<https://doi.org/10.1186/1479-5868-10-89>
- Tran, M. C., Labrique, A. B., Mehra, S., Ali, H., Shaikh, S., Mitra, M., Christian, P., & Jr, K. W. (2015). Analyzing the Mobile “Digital Divide”: Changing Determinants of Household Phone Ownership Over Time in Rural Bangladesh. *JMIR mHealth and uHealth*, 3(1), e3663.
<https://doi.org/10.2196/mhealth.3663>

- Tripathi, P. (2025). A Study of the Digital Media Consumption among Indian Youths with Special Reference to Uttar Pradesh. *International Journal of Advanced Research*, 13(02), 1314–1320. <https://doi.org/10.21474/IJAR01/20494>
- Tsfati, Y., & Barnoy, A. (2025). Media Cynicism, Media Skepticism and Automatic Media Trust: Explicating Their Connection with News Processing and Exposure. *Communication Research*, 00936502251327717. <https://doi.org/10.1177/00936502251327717>
- Tsfati, Y., Strömbäck, J., Lindgren, E., Damstra, A., Boomgaarden, H. G., & Vliegenthart, R. (2022). Going Beyond General Media Trust: An Analysis of Topical Media Trust, its Antecedents and Effects on Issue (Mis)perceptions. *International Journal of Public Opinion Research*, 34(2), edac010. <https://doi.org/10.1093/ijpor/edac010>
- Tucker-Drob, E. M., & Briley, D. A. (2012). Socioeconomic Status Modifies Interest-Knowledge Associations among Adolescents. *Personality and Individual Differences*, 53(1), 9–15. <https://doi.org/10.1016/j.paid.2012.02.004>
- Ucar, I., Gramaglia, M., Fiore, M., Smoreda, Z., & Moro, E. (2021). News or social media? Socio-economic divide of mobile service consumption. *Journal of The Royal Society Interface*, 18(185), 20210350. <https://doi.org/10.1098/rsif.2021.0350>
- Uncapher, M. R., Lin, L., Rosen, L. D., Kirkorian, H. L., Baron, N. S., Bailey, K., Cantor, J., Strayer, D. L., Parsons, T. D., & Wagner, A. D. (2017). Media Multitasking and Cognitive, Psychological, Neural, and Learning Differences. *Pediatrics*, 140(Suppl 2), S62–S66. <https://doi.org/10.1542/peds.2016-1758D>
- Urbancikova, N., Manakova, N., & Ganna, B. (2017). Socio-Economic and Regional Factors of Digital Literacy Related to Prosperity. *Quality Innovation Prosperity*, 21(2), 124–141. <https://doi.org/10.12776/qip.v21i2.942>
- Vaidehi, R., Reddy, A. B., & Banerjee, S. (2021). *Explaining Caste-based Digital Divide in India* (No. arXiv:2106.15917). arXiv. <https://doi.org/10.48550/arXiv.2106.15917>
- Vaishnav, S. A., Prasada, S. J., & Krishnan, S. S. (2024). *Annual Report 2024-2025* (Annual Government Report Nos. 2024–2025; Ministry of Electronics and Information Technology Annual Report, p. 288). Ministry of Electronics and Information Technology, Government of India. <https://www.meity.gov.in/static/uploads/2024/12/10fcadec462c330211502fed3d24ea83.pdf>
- van de Werfhorst, H. G., Kessenich, E., & Geven, S. (2022). The digital divide in online education: Inequality in digital readiness of students and schools. *Computers and Education Open*, 3, 100100. <https://doi.org/10.1016/j.caeo.2022.100100>
- van Deursen, A. J., & van Dijk, J. A. (2019). The first-level digital divide shifts from inequalities in physical access to inequalities in material access. *New Media & Society*, 21(2), 354–375. <https://doi.org/10.1177/1461444818797082>
- van Dijk, J. A. G. M. (2006). Digital divide research, achievements and shortcomings. *Poetics*, 34(4), 221–235. <https://doi.org/10.1016/j.poetic.2006.05.004>
- Vashistha, D. D., Chandel, P. K., & Gaur, S. (2024a). Investigating Socioeconomic Disparities in Digital Education Experiences. *The International Journal of Indian Psychology*, 12(3), 1001–1010. <https://doi.org/10.25215/1203.096>
- Vashistha, D. D., Chandel, P. K., & Gaur, S. (2024b). Investigating Socioeconomic Disparities in Digital Education Experiences. *The International Journal of Indian Psychology*, 12(3), 1–9. <https://doi.org/10.25215/1203.096>
- Viswanath, K., McCloud, R., Minsky, S., Puleo, E., Kontos, E., Bigman-Galimore, C., Rudd, R., & Emmons, K. M. (2013). Internet Use, Browsing, and the Urban Poor: Implications for Cancer Control. *Journal of the National Cancer Institute. Monographs*, 2013(47), 199–205. <https://doi.org/10.1093/jncimonographs/igt029>
- Vivion, M., Reid, V., Dubé, E., Coutant, A., Benoit, A., & Tourigny, A. (2024). How older adults manage misinformation and information overload—A qualitative study. *BMC Public Health*, 24, 871. <https://doi.org/10.1186/s12889-024-18335-x>
- Wang, J., Liu, C., & Cai, Z. (2022). Digital literacy and subjective happiness of low-income groups: Evidence from rural China. *Frontiers in Psychology*, 13, 1045187. <https://doi.org/10.3389/fpsyg.2022.1045187>
- Warschauer, M. (2003). *Technology and Social Inclusion: Rethinking the Digital Divide* (Vol. 1). The MIT Press. <https://doi.org/10.7551/mitpress/6699.001.0001>
- Watts, L. L. F., Hamza, E. A., Bedewy, D. A., & Moustafa, A. A. (2024). A meta-analysis study on peer influence and adolescent substance use. https://dro.deakin.edu.au/articles/journal_contribution/A_meta-analysis_study_on_peer_influence_and_adolescent_substance_use/25143200/3

- Wentzel, K. R., & Muenks, K. (2016). Peer Influence on Students' Motivation, Academic Achievement, and Social Behavior. In *Handbook of Social Influences in School Contexts*. Routledge.
- Wiley, J., Goldman, S. R., Graesser, A. C., Sanchez, C. A., Ash, I. K., & Hemmerich, J. A. (2009). Source Evaluation, Comprehension, and Learning in Internet Science Inquiry Tasks. *American Educational Research Journal*, 46(4), 1060–1106. <https://doi.org/10.3102/0002831209333183>
- Williams, E. J., Beardmore, A., & Joinson, A. N. (2017). Individual differences in susceptibility to online influence: A theoretical review. *Computers in Human Behavior*, 72, 412–421. <https://doi.org/10.1016/j.chb.2017.03.002>
- Wineburg, S., McGrew, S., Breakstone, J., & Ortega, T. (2020). Evaluating Information: The Cornerstone of Civic Online Reasoning. *Stanford Digital Repository*, 1(1), 1–29.
- Xiao, X., & Li, D. K. L. (2021). Who Consumes New Media Content More Wisely? Examining Personality Factors, SNS Use, and New Media Literacy in the Era of Misinformation. *Sage Publications: Social Media + Society*, 7(1), 1. <https://doi.org/10.1177/2056305121990635>
- Yadav, S. (2023). Promoting Gender Equality and Addressing Gender Discrimination through Education: The Beti Bachao Beti Padhao Initiative (BBBP) in India. *Educational Quest- An International Journal of Education and Applied Social Sciences*, 14(2). <https://doi.org/10.30954/2230-7311.2.2023.3>
- Yu, Z., & Deng, X. (2022). A Meta-Analysis of Gender Differences in e-Learners' Self-Efficacy, Satisfaction, Motivation, Attitude, and Performance Across the World. *Frontiers in Psychology*, 13, 897327. <https://doi.org/10.3389/fpsyg.2022.897327>
- Zakir, S., Hoque, M. E., Susanto, P., Nisaa, V., Alam, M. K., Khatimah, H., & Mulyani, E. (2025). Digital literacy and academic performance: The mediating roles of digital informal learning, self-efficacy, and students' digital competence. *Frontiers in Education*, 10. <https://doi.org/10.3389/feduc.2025.1590274>
- Zhang, Y., Zhong, Y.-L., Luo, J., He, J.-L., Lin, C., Zauszniewski, J. A., Zhou, J.-H., Chen, Y., Wu, C.-Y., Wang, S.-R., Li, Z.-H., Tang, J., Li, W.-N., Wu, J., & Luo, J.-M. (2023). Effects of resourcefulness on internet game addiction among college students: The mediating role of anxiety and the moderating role of gender. *Frontiers in Public Health*, 11, 986550. <https://doi.org/10.3389/fpubh.2023.986550>
- Zhou, Y., He, T., & Lin, F. (2022). The Digital Divide Is Aging: An Intergenerational Investigation of Social Media Engagement in China. *International Journal of Environmental Research and Public Health*, 19(19), 12965. <https://doi.org/10.3390/ijerph191912965>
- Zimmer, F., Scheibe, K., Stock, M., & Stock, W. G. (2019). Journal of Information Science Theory and Practice / Journal of Information Science Theory and Practice. *Journal of Information Science Theory and Practice / Journal of Information Science Theory and Practice*, 7(2), 40–53. <https://doi.org/10.1633/JISTaP.2019.7.2.4>
- Zou, Y., Kuek, F., Feng, W., & Cheng, X. (2025). Digital learning in the 21st century: Trends, challenges, and innovations in technology integration. *Frontiers in Education*, 10, 1562391. <https://doi.org/10.3389/feduc.2025.1562391>