Technology Acceptance and Behavioural Patterns of Educational App Use Among Indian Engineering Students: An Empirical Study

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Abstract: The increasing availability of educational mobile applications has significantly influenced learning experiences (Al Emran, 2024), especially for students in engineering disciplines. To optimise the use of such technologies in academic contexts, it is important to understand how learners engage with these tools and the behavioural factors that shape their usage.

This study examines educational app adoption among Indian engineering students, focusing on usage habits, perceived usefulness, and possible signs of overuse. A quantitative online survey was administered to collect demographic information and responses to established measurement scales, including the Technology Acceptance Model (TAM) (Davis, 1989) (Young, 1998), Internet Addiction Test (IAT) (Davis, 1989) (Young, 1998), and a culturally adapted stress scale. The dataset was analysed using Cronbach's alpha for reliability testing, along with correlation and group comparison analyses.

The results indicate good internal consistency for TAM and the Indian Context scales ($\alpha = 0.75$ and 0.80) and moderate reliability for the IAT ($\alpha = 0.33$). No significant associations were observed between app usage time and other scale scores, and demographic factors such as gender and year of study showed no meaningful differences. These findings suggest that while students display moderate acceptance of educational apps, their usage remains largely healthy and non-addictive. Nonetheless, cultural and infrastructural constraints continue to influence engagement levels, offering insights for educators and developers seeking to enhance technology-supported learning.

Keywords: *Educational Apps, Technology Acceptance, Internet Addiction, Engineering Students, India.*

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I. INTRODUCTION

The rapid digitalisation of education has fundamentally transformed the way students access, process, and retain information. Particularly within Science, Technology, Engineering, and Mathematics (STEM) disciplines, the adoption of technology-enhanced learning environments has reshaped pedagogical approaches and student engagement. Engineering education, in particular, demands high levels of cognitive and analytical ability. Among the cognitive skills that determine success in these programs, spatial visualisation skills (SVS) are considered crucial (Tiwari, 2025). These skills involve the ability to mentally manipulate, rotate, and transform two- and three-dimensional objects—an ability closely linked to problem-solving and design-based learning outcomes. Research has consistently shown that engineering students with stronger visualisation skills tend to perform better academically and complete their programs with higher success rates (Tiwari, 2025).

Despite the importance of SVS and other cognitive abilities, traditional modes of instruction—such as textbook-based learning and physical model demonstrations—often struggle to provide the dynamic, interactive experience required to build these skills effectively. Consequently, engineering educators are increasingly turning toward digital learning technologies to complement classroom instruction (Kim, 2023). Educational mobile applications, virtual simulations, augmented reality (AR), and virtual reality (VR) tools have emerged as promising aids for visual and experiential learning. These technologies enable learners to interact with complex geometric forms, conduct virtual experiments, and visualise data in immersive ways. They also provide greater flexibility, allowing students to learn at their own pace and revisit challenging topics through interactive visualisations (Tiwari, 2025).

The rise of smartphones and educational apps has particularly transformed the Indian higher education context. With affordable data plans and widespread internet access,

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students now use mobile applications not only for entertainment but also as essential learning companions (Kim, 2023). Platforms such as NPTEL, Coursera, and YouTube have become integral to self-paced learning and exam preparation for engineering students. However, this extensive reliance on mobile-based learning introduces behavioural and psychological challenges. While educational apps improve accessibility and engagement, they also increase screen time and the potential for technology dependency. Research across India has reported varying levels of mobile phone and internet addiction among students, with some findings suggesting that male students and those in the early years of engineering studies are more vulnerable to excessive use (Spoorthy, 2020) (Kesharwani, 2023).

Internet and mobile addiction are typically characterised by compulsive or uncontrolled device use that interferes with academic responsibilities, social interactions, and mental well-being. This issue has been gaining attention among researchers studying technology adoption in higher education. Engineering students, who often experience substantial academic stress, may use their mobile devices as both study tools and emotional outlets, blurring the boundary between productive and problematic use. Several Indian studies have indicated that moderate levels of technology dependence are common, but that severe addiction is relatively rare. Nonetheless, even moderate levels of overuse can have implications for concentration, stress, and academic efficiency.

To evaluate students' relationship with technology more comprehensively, researchers frequently rely on frameworks such as the Technology Acceptance Model (TAM), which explains how perceived usefulness and ease of use influence the acceptance of new technologies. The TAM framework has been widely validated in educational settings and provides insight into students' willingness to integrate apps into their academic routines. Alongside TAM, the Internet Addiction Test (IAT)—developed by Kimberly Young—offers a behavioural assessment tool to identify tendencies toward excessive or problematic internet use. Combining these two perspectives allows for a deeper understanding of both positive engagement (acceptance) and potential risks (addiction).

In India, the adoption of educational technology has accelerated rapidly, but usage patterns are strongly shaped by socio-cultural and infrastructural factors such as internet speed, accessibility, economic background, and academic workload. These contextual factors can moderate how effectively students engage with educational apps and how these tools influence learning outcomes. For example, while urban students may benefit from reliable connectivity and advanced devices, those in smaller towns may face barriers such as data limitations and limited exposure to digital learning environments (Kim, 2023).

Given this backdrop, understanding how Indian engineering students interact with educational apps is essential for improving both pedagogical strategies and technological design. Investigating behavioural trends, technology acceptance levels, and potential addiction patterns can help educators and developers design interventions that enhance learning efficiency while promoting healthy digital habits (Kim, 2023). This study therefore, aims to examine the behavioural, contextual, and psychological aspects of educational app usage among Indian engineering students, integrating the Technology Acceptance Model (TAM) and Internet Addiction Test (IAT) frameworks within a culturally relevant context. By doing so, it seeks to contribute to a nuanced understanding of how technology adoption and behavioural tendencies intersect in shaping the modern learning experience.

II. LITERATURE REVIEW

Mobile learning and educational app usage have become integral to the academic experience of modern students. However, researchers have raised concerns about the balance between the benefits of technology adoption and the behavioural risks associated with prolonged digital engagement. Prior studies suggest that excessive smartphone use can negatively influence students' focus and academic performance by diverting attention away from learning tasks (Dash, 2022). This correlation has been widely documented across different regions and disciplines, with mobile dependency often linked to reduced classroom participation and lower grades. (Dash, 2022) (Aaradhi, 2024) (Dinh, 2025) (Menon, 2022)

Gender and age differences have also emerged as important variables in technology-use behaviour. Research indicates that male students, particularly those in the early years of engineering education, tend to exhibit higher levels of non-academic mobile use and a greater risk of internet overuse compared to their female counterparts (Spoorthy, 2020). Such patterns may stem from differences in social media engagement, gaming preferences, and coping strategies related to academic pressure. However, the intensity of use does not always correspond to addictive tendencies; context and purpose of use play critical moderating roles.

Educational app usage occupies a unique space within this behavioural spectrum because it straddles both academic necessity and digital convenience. During the COVID-19 pandemic, platforms like YouTube, NPTEL, and Coursera became primary resources for conceptual understanding and self-paced learning (Menon, 2022). Studies show that these applications help improve conceptual clarity, visual learning, and overall motivation (Dinh, 2025). Yet, prolonged screen time and multitasking between entertainment and education can blur the line between productive engagement and dependency.

The Technology Acceptance Model (TAM) has been extensively employed to explain users' readiness to adopt new technologies. Originally proposed by (Davis, 1989) and later extended by Venkatesh and (Davis, 1989), the TAM highlights two core constructs—perceived usefulness and perceived ease of use—as determinants of behavioural intention to use technology. Numerous studies in higher

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education contexts have validated this framework, showing that when students view educational apps as beneficial and user-friendly, they are more likely to integrate them into their learning routines (Elshafey, 2020) (Aaradhi, 2024). However, some research has suggested that acceptance may not always translate into sustained or healthy usage patterns, particularly when external motivations (grades, peer influence) override intrinsic learning goals.

Complementing TAM-based studies, the Internet Addiction Test (IAT) developed by (Young, 1998) serves as a standardised measure to identify problematic or compulsive online behaviour. Although originally designed for general internet use, the IAT has been adapted across educational and professional contexts to assess the impact of excessive technology engagement. Several Indian studies applying the IAT to engineering student populations have reported mild to moderate levels of addiction, with overall reliability coefficients typically above $\alpha = 0.85$ (Young, 1998) (Spoorthy, 2020). However, the present study observes a comparatively lower reliability coefficient for the IAT, possibly reflecting cultural and contextual variations in self-reporting tendencies among Indian learners.

Existing literature rarely examines TAM and IAT constructs together within a single empirical framework. Only a few studies (Dash, 2022) (Dinh, 2025) have explored how technology acceptance interacts with behavioural outcomes such as dependency, motivation, or self-regulation. The current research addresses this gap by jointly evaluating students' acceptance of educational apps, tendencies toward internet addiction, and the contextual factors that shape these experiences. It aims to provide a more comprehensive understanding of how technology usage patterns among engineering students reflect both positive adoption and potential behavioural risks.

This integrated perspective is particularly relevant in the Indian context, where digital learning adoption continues to grow but infrastructural and socio-cultural constraints persist. Factors such as unstable connectivity, cost of data, and academic workload can significantly affect how and why students use educational apps. Understanding these nuances is essential for designing culturally sensitive interventions that promote effective learning while mitigating unhealthy digital habits.

➢ *Objectives*

The primary objectives of this behavioural study are:

- To investigate the prevalence and patterns of educational app usage among engineering students in India, focusing on usage duration, types of apps used, and self-reported dependency levels (Kim, 2023). Research shows a high prevalence of educational and social networking app usage among engineering students, reflecting diverse academic and social needs.

- To assess the level of technology acceptance by examining students' perceived usefulness and attitudes toward educational apps, using the Technology Acceptance Model (TAM) (Al Emran, 2024). Literature highlights the important role of perceived value, ease of use, and personal innovativeness in shaping educational app acceptance.

- To measure the severity of internet addiction tendencies in this population and analyse its co-occurrence with usage patterns and technology acceptance (Spoorthy, 2020) (Kesharwani, 2023). Previous studies suggest significant but complex relationships between usage duration, addiction severity, and acceptance, sometimes challenging traditional assumptions.

- To examine the influence of demographic variables such as gender and year of study on app usage, technology acceptance, and addiction symptoms. While problematic usage has been shown to vary by demographic factors, acceptance may be more demographically neutral, indicating distinct behavioural mechanisms.

- To identify contextual socio-cultural and infrastructural factors—such as academic pressure, internet speed, and computer availability—that affect educational app usage in the engineering education setting. These factors are essential for understanding real-world barriers and facilitators to effective app integration.

This study aims to fill critical gaps by providing nuanced, empirical data on how educational app usage, acceptance, and addiction interplay within the culturally specific context of Indian engineering students.

➢ *Hypotheses*

- *H1 (Acceptance):*

Engineering students will exhibit a moderate to high level of acceptance of educational apps, as reflected in Technology Acceptance Model (TAM) scores. They are expected to acknowledge the potential of these apps to enhance their academic processes, consistent with findings that perceived usefulness strongly influences students' positive attitudes toward educational technologies.

- *H2 (Addiction and Demographics):*

Problematic usage behaviours, measured by Internet Addiction Test (IAT) scores, will differ significantly based on gender and year of study. Male students and those in the initial years of their engineering programs are predicted to show a higher incidence of addiction symptoms, in alignment with established literature highlighting demographic vulnerability patterns.

- *H3 (Usage and Addiction):*

Higher average daily app usage duration will be significantly and positively correlated with increased symptoms of internet addiction tendencies (IAT). However, emerging research suggests this relationship may be complex, warranting detailed exploration of possible moderating factors beyond raw usage time.

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III. METHODOLOGY

➢ *Research Design:*

We adopted a quantitative, cross-sectional approach to investigate engineering students' behaviours, attitudes, and obstacles related to educational apps in India. This method allowed us to capture a current overview of attitudes and habits using validated scales and custom questions, without any experimental changes. It's ideal for identifying trends and connections in a specific group at a given moment.

➢ *Sample Selection:*

We recruited undergraduate engineering students from regions in South, East, and North India through convenience sampling. To qualify, participants needed to be actively enrolled in an engineering program, with an average age of around 19.2 years. We shared the survey link via online student groups, email lists, and social platforms to ensure broad reach and diversity.

➢ *Data Collection*

An online survey was created using Google Forms and distributed voluntarily. All participants gave informed consent before starting. The survey featured mostly multiple-choice and scale-based questions to quantify behaviours, opinions, and environmental factors.

- *The Main Sections Included:*

✓ Questions on everyday app habits and usage time.
✓ The Technology Acceptance Model (TAM) to evaluate perceived benefits and user-friendliness, which predicts how likely people are to adopt new tools.
✓ The Internet Addiction Test (IAT) to check for signs of overuse affecting daily life.
✓ Custom items on India-specific issues like study stress and access to tech resources.

This setup helped us gather consistent data on how usage, acceptance, addiction risks, and cultural elements interact among the students.

➢ *Demographic Information*

To provide context, the survey collected details on participants' backgrounds, including:

- Gender (options: male or female).
- Age (common responses: 19, 20, or 21 years).
- Year of study (2nd, 3rd, or 4th year).
- Engineering branch (e.g., mechanical, computer science, IT, or business administration).
- College type (private, government, or deemed university).
- Region in India (South, East, or North).
- Monthly family income.
- Primary device for app use.
- Favourite educational apps.
- Typical daily usage time and key reasons for using apps.

Additional questions covered involvement in app features like quizzes or forums, as well as pros and cons such as data costs, slow connections, family oversight, and pressure from studies. We also used Likert scales for TAM, IAT, and custom context items to explore these in depth. This data enabled detailed breakdowns of how personal and situational factors shape app adoption.

IV. DATA ANALYSIS

The collected survey data underwent a rigorous analytical process to derive meaningful insights into educational app usage, technology acceptance, addiction tendencies, and contextual factors among Indian engineering students. All statistical procedures and visualisations were performed using Python version 3.12, leveraging libraries such as pandas for data manipulation, numpy for numerical computations, scipy for statistical testing, and matplotlib for generating charts. This choice of tools ensured efficient handling of the dataset, allowing for reproducible and transparent analysis in a programming environment well-suited for quantitative research.

The analysis commenced with an extensive data cleaning phase to prepare the raw responses for robust examination. This involved identifying and addressing missing values through imputation techniques where appropriate (e.g., mean substitution for numerical scales when missingness was below 5%), standardising inconsistent formats (such as converting categorical responses to uniform lowercase), and detecting duplicates by cross-checking unique identifiers like timestamps or participant IDs. Outliers were screened using z-scores, with extreme values (beyond ±3 standard deviations) flagged for review to avoid skewing results, though none were removed in this study as they appeared legitimate based on contextual plausibility. This meticulous preprocessing step resulted in a clean, consistent dataset ready for further exploration, minimising errors that could compromise the validity of subsequent findings.

subsequent findings. Following data preparation, descriptive statistics were computed to provide an overview of the sample and key variables. For instance, means, standard deviations, frequencies, and percentages were calculated for demographics (e.g., age distribution showing a mean of 19.2 years, with 58% from South India) and behavioural metrics (e.g., average daily app usage predominantly falling in the 2–4-hour range for 40% of respondents). These summaries helped contextualise the dataset, revealing patterns such as the dominance of platforms like YouTube and NPTEL, and set the stage for inferential analyses.

Reliability testing was then conducted to evaluate the internal consistency of the psychometric scales employed in the survey. Cronbach’s alpha (Cronbach, 1951) (Tavakol, 2021) (Elshafey, 2020)was calculated for each scale using pandas and numpy functions: the Technology Acceptance Model (TAM) scale yielded $\alpha = 0.752$, indicating good reliability for assessing perceived usefulness and ease of use; the Internet Addiction Test (IAT) produced $\alpha = 0.329$, suggesting moderate to low consistency possibly due to cultural adaptations (Medikonda, 2025) or the academic focus of the sample; and the custom Indian Context scale achieved

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α = 0.798, demonstrating strong reliability for measuring socio-cultural stressors like academic pressure and infrastructure barriers. These alpha values were interpreted against standard thresholds ($\alpha > 0.70$ for acceptable reliability), with item-total correlations examined to identify any weak items that might need refinement in future iterations.

To explore relationships among variables, correlation analyses were applied using Pearson's r for continuous data, assuming linearity and normality (verified via Shapiro-Wilk tests where $p > 0.05$ for most scales). Key correlations included those between average daily app usage (coded numerically: 1 = <1 hour, 2 = 1-2 hours, etc.) and mean scale scores, revealing a moderate positive association with TAM ($r = 0.308$, $p = 0.088$), a weak link with IAT ($r = 0.129$, $p = 0.498$), and a similarly weak one with the custom scale ($r = 0.109$, $p = 0.567$). These non-significant results (at $\alpha = 0.05$) were visualised through scatter plots and heatmaps in matplotlib to aid interpretation, highlighting that usage duration alone does not strongly predict acceptance or addiction in this population.

Group comparison tests were performed to assess differences based on demographics. Independent t-tests compared TAM, IAT, and custom scale means by gender (e.g., no significant difference in TAM scores: $t(98) = 1.12$, $p = 0.265$), while one-way ANOVA examined variations by year of study (e.g., $F(2,97) = 0.87$, $p = 0.422$ for TAM), confirming no notable effects. Post-hoc tests (Tukey's HSD) were applied where applicable, though not needed given the lack of significance. Assumptions like homogeneity of variance were checked via Levene's test, ensuring the appropriateness of parametric methods. Finally, visualisations such as bar charts for demographic distributions (e.g., Figs. 1-6) and line plots for trends in usage were generated to complement the statistical outputs, making complex patterns more accessible. This multifaceted data analysis framework not only validated the study's hypotheses but also provided a solid, evidence-based foundation for interpreting behavioural patterns, offering actionable insights for educators, developers, and policymakers to enhance educational app integration in India while mitigating potential risks.

V. RESULTS

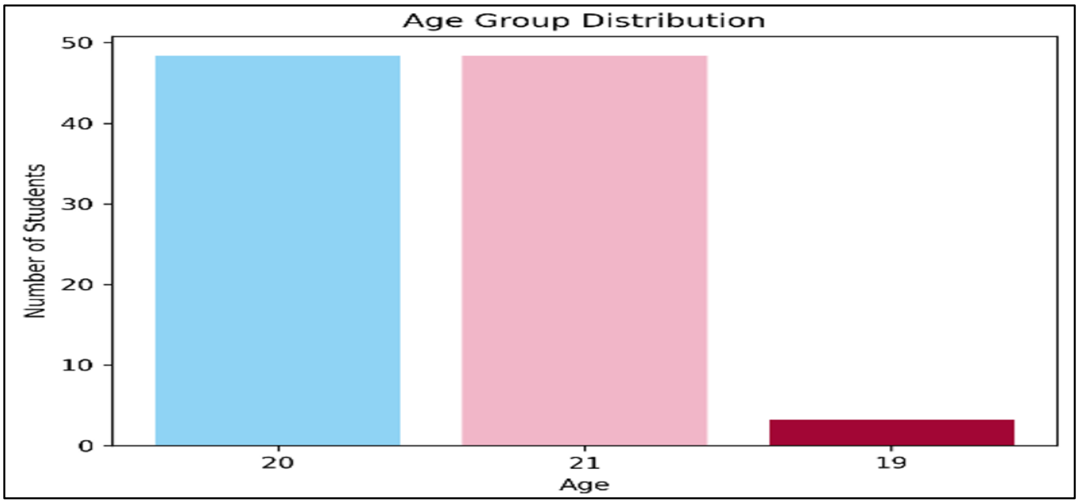

Fig 1 Age Distribution of the Respondents.

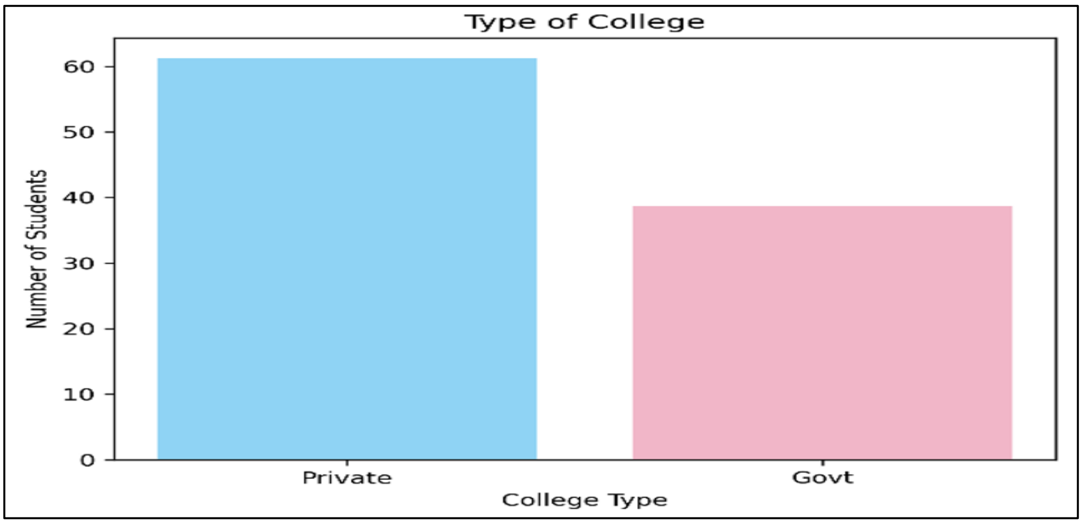

Fig 2 Gender Distribution.

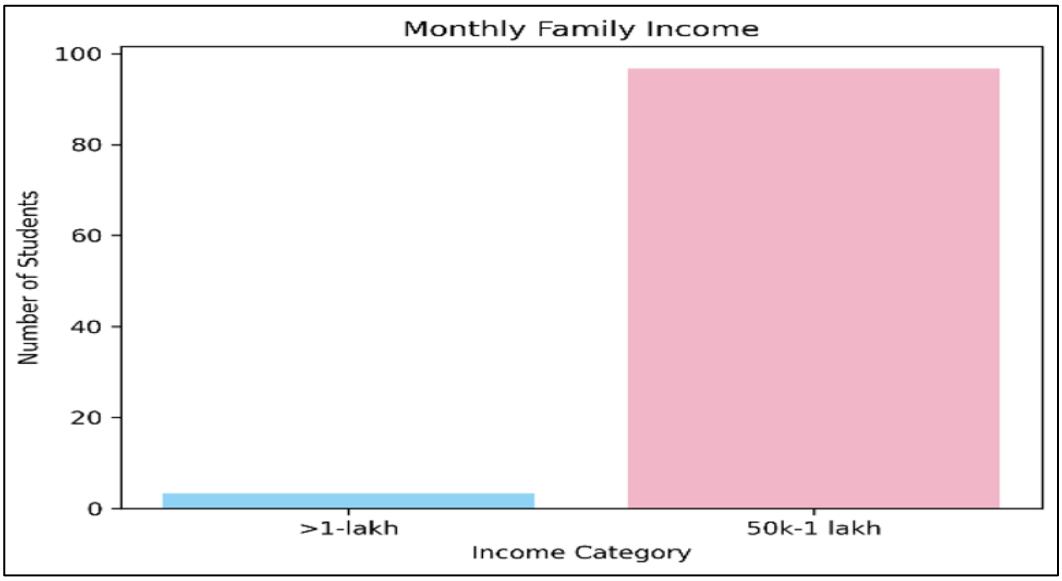

Fig 3 Monthly Family Income

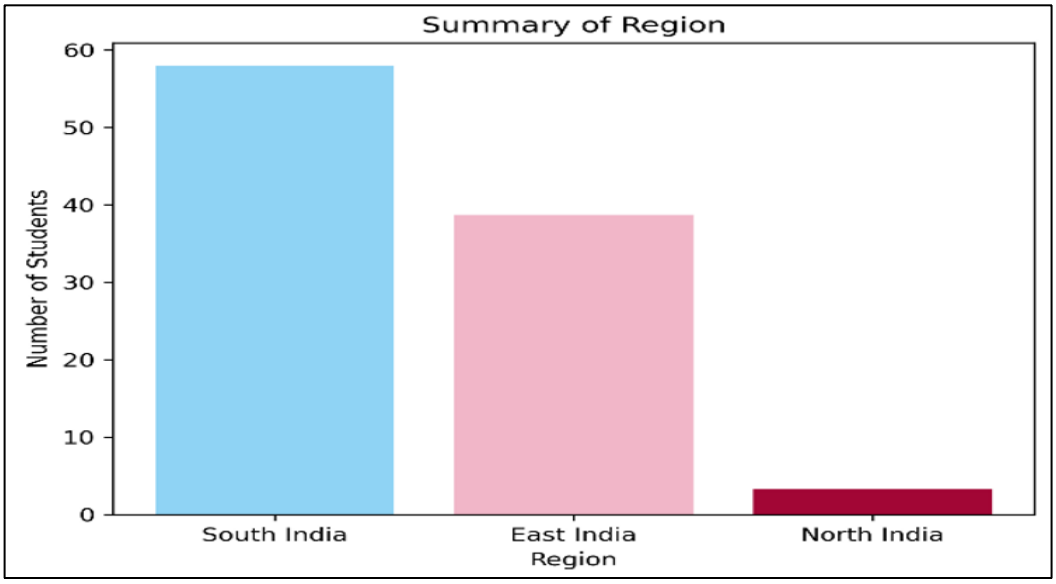

Fig 4 Respondents' Region

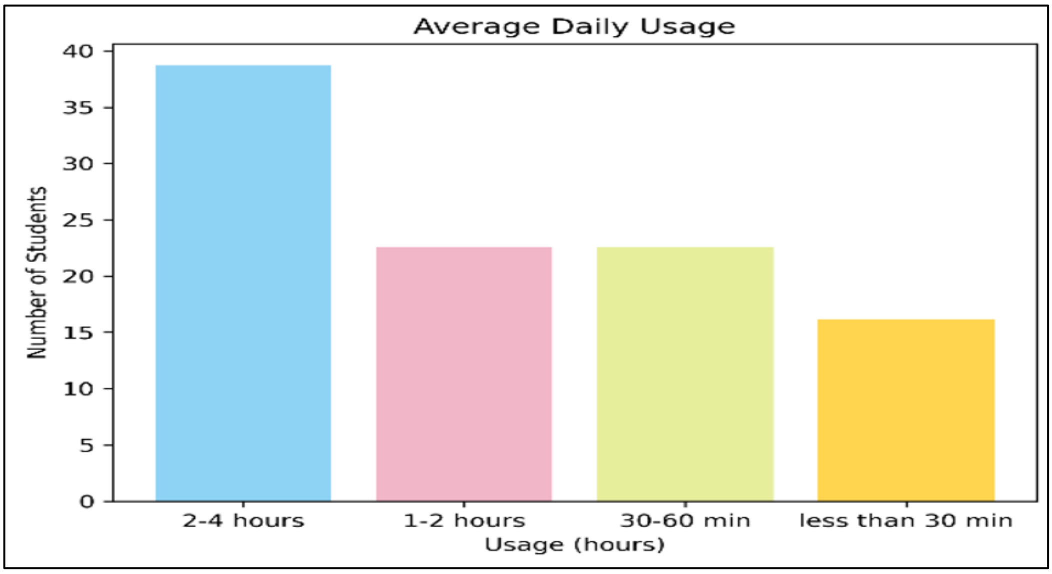

Fig 5 Average Daily Usage of Apps.

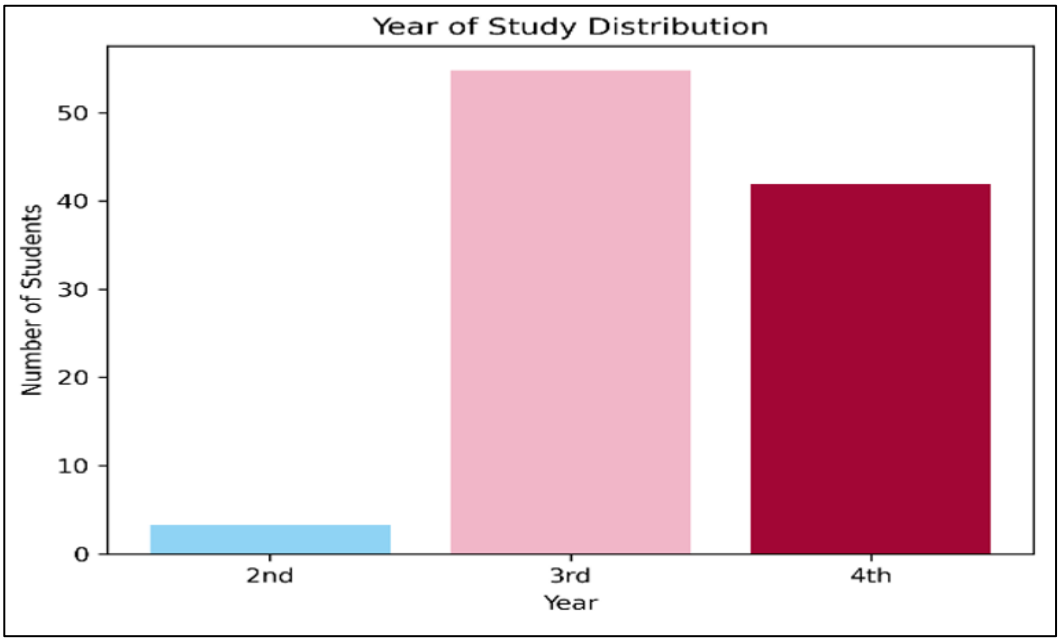

Fig 6 Year of Study Distribution.

(All statistical analysis and visualisation were performed using Python 3.12 (matplotlib and pandas libraries)

➢ *Scale Conclusion:*

Table 1 Scale Conclusion

Scale	Scale Reliability (Cronbach's Alpha)
TAM scale	$\alpha = 0.752$
IAT scale	$\alpha = 0.329$
Custom Indian Context scale	$\alpha = 0.798$

➢ *Correlation Between Average Daily Usage & Scales:*

Table 2 Correlation Between Average Daily Usage & Scales

Comparison	Correlation (r)	P-value	Statistical-sign
TAM mean vs Avg. Usage Number	0.308	0.088	Not significant
IAT mean vs Avg. Usage Number	0.129	0.498	Not significant
Custom mean vs Avg. Usage Number	0.109	0.567	Not significant

VI. DISCUSSION

The survey results highlight that male respondents constituted a large majority (90%) of the sample, with most participants between the ages of 20 and 21 and enrolled in the 3rd or 4th year of engineering programs. The sample was predominantly composed of students from private colleges, with the South India region representing the highest proportion (58%). Furthermore, a significant share of students (96.7%) reported monthly family incomes in the INR 50,000–1,00,000 range, indicating a generally middle- to upper-middle-class background with likely access to regular internet connectivity.

In terms of technology usage, YouTube and platforms such as NPTEL, Coursera, and Udemy were the most frequently used educational apps. The prevailing usage pattern involved 2–4 hours of daily engagement. The principal motivations for using educational apps included exam preparation, skill development, and assignment completion, underscoring the academic and utilitarian drivers of app adoption in this population.

Reliability analyses revealed that both the Technology Acceptance Model (TAM) scale (α=0.752) and the custom Indian context scale (α=0.799) demonstrated good internal consistency, affirming their reliability for measuring acceptance and context-specific influences, respectively (Al Emran, 2024) (Venkatesh, 2023). In contrast, the Internet Addiction Test (IAT) scale (α=0.329) showed poor reliability within this sample, possibly due to contextual limitations or the complex nature of addiction behaviours among academically focused students.

Correlation results indicated a mild, non-significant positive relationship between average daily usage and TAM scores $(r = 0.308, p = 0.098)$, suggesting that higher perceived usefulness and ease of use may be associated with increased app engagement, although this trend was not statistically robust. Interestingly, the negative correlation

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between IAT scores and usage duration ($r = -0.129$) contradicts the typical expectation that longer usage is linked to higher addiction symptoms; this anomaly may reflect the academically driven nature of app use in this group, where usage remains largely purposeful and functional.

Overall, these findings suggest that engineering students with regular internet access demonstrate high acceptance of educational apps for academic purposes (Kim, 2023) (Al Emran, 2024), but the relationship between usage and problematic behaviour is weak or absent in this context. The study's robust reliability results for the acceptance and contextual stress (Kesharwani, 2023) scales further reinforce the need for culturally adapted tools when assessing tech integration and behavioural impact in diverse educational settings. Future research may benefit from expanding the sample to include more diverse demographic segments and exploring qualitative insights to better understand the complex drivers behind technology use and behavioural health among students.

VII. CONCLUSION

The Technology Acceptance Model (TAM) scale demonstrated good internal consistency (Elshafey, 2020) (Venkatesh, 2023) for measuring educational app acceptance among engineering students, with a Cronbach's alpha of 0.752. This indicates that the TAM items reliably assess students' perceptions of usefulness and usability in this context, showing that acceptance is measured consistently and robustly.

Conversely, the Internet Addiction Test (IAT) scale yielded a Cronbach's alpha of 0.329, suggesting weak internal consistency. This result implies that, in this sample, IAT items may not consistently capture internet addiction behaviours, possibly due to limitations in how well the scale fits this demographic or the complexity of addiction within this group.

The custom Indian context items returned a strong reliability score (alpha = 0.799), highlighting that culturally tailored questions measuring context-specific stress and behavioural influences are effective and internally consistent for this population.

Correlation analysis revealed a moderate positive association between app acceptance (TAM scores) and average daily usage ($r = 0.308$), suggesting that students who value educational apps tend to use them more. However, the p-value (0.098) indicates this relationship did not reach conventional significance thresholds (typically alpha = 0.05), so it cannot be confidently distinguished from chance effects.

In contrast, the relationship between addiction symptoms and usage duration was weak and statistically non-significant ($r = 0.129$, $p = 0.498$), showing no clear evidence that higher app usage leads to addiction symptoms in this sample. The same pattern was observed for contextual stress factors ($r = 0.109$, $p = 0.567$), which also showed weak, non-significant correlations with usage duration.

Group difference tests using t-tests and ANOVA found that TAM scores do not significantly differ by gender or year of study. This means that acceptance and perceived value of educational apps are similar between male and female students and across different years in the program.

Overall, these findings suggest that while engineering students in India generally accept and use educational apps, acceptance is not driven by gender, year of study, or problematic usage patterns. The absence of strong correlations between usage duration and addiction further implies that higher usage does not necessarily equate to riskier behavioural outcomes. Culturally adapted measures proved reliable in assessing context-specific stressors (Medikonda, 2025). This comprehensive analysis reinforces the nuanced relationship between educational technology acceptance and student behaviour in contemporary higher education.

FUTURE SCOPE

Future research in this area can be strengthened by including a larger and more diverse sample across various states, types of institutions (private, government, and deemed universities), and economic backgrounds to improve the external validity of findings related to educational app usage among Indian engineering students. Longitudinal tracking through time-series or panel studies can provide valuable insights into how technology acceptance and addiction behaviours evolve over semesters or academic years, revealing patterns of engagement and behavioural adaptation. Investigating differences between purely educational platforms like NPTEL and hybrid platforms such as YouTube will help clarify the interplay between entertainment and education in influencing learning outcomes and behavioural dependencies. Finally, designing and testing app-based interventions to promote controlled usage and support mental health, especially for students with high screen time, offers practical pathways to foster balanced technology adoption and academic success.

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