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Gender and Learning via social media: A UTAUT2-Based Study of Management Students in Mumbai

Dr. Deepa Dixit
Director, SIES School of Business Studies, Nerul, Navi Mumbai.

Dr. Swati Kulkarni
Assistant Professor, SIES School of Business Studies ,Nerul, Navi Mumbai.

Dr. Sarika Mahajan
Programme Coordinator, Jamnalal Bajaj Institute of Management Studies Churchgate, Mumbai.

Venkatesh Iyengar
Assistant Professor, Aditya School of Business Management, Borivali, Mumbai.

Abstract
The education sector is undergoing significant transformation driven by technological advancements, affordable telecom services, and the proliferation of smartphones across socioeconomic groups. This study investigates the factors influencing students' use of social media and social networking sites for educational purposes in Mumbai, applying the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. The research examines determinants such as performance expectancy, effort expectancy, social influence, facilitating conditions, habit, hedonic motivation, lecturer support, and student-specific factors. Primary data collection will be conducted via an electronic survey targeting 300 management students in Mumbai & Navi Mumbai Metropolitan region, based on the model developed by Venkatesh et al (UTAUT2). This study challenges the independence assumption between social influence and behavioural intention, exploring the impact of UTAUT2 factors on social media actual usage. Additionally, it assesses the moderating effect of gender on the relationship between hedonic motivation and actual usage.

This study utilizes the variance based structural equation modelling- Partial Least Squares (PLS) methodology to evaluate the proposed research framework. PLS was selected for its advantages in handling non-normally distributed data, its suitability with limited sample sizes. Since the primary goal is to predict outcomes rather than validate an existing theoretical framework, PLS analysis offers an appropriate methodological approach. The research adopts a quantitative, exploratory design, with data analysis conducted through PLS to deliver predictive insights.

Keywords:
Social Media Usage, UTAUT2 Model, Hedonic Motivation, Facilitating Conditions, Partial Least Squares (PLS), Gender Moderation.

Introduction:
In today's rapidly evolving technological landscape, understanding the adoption of emerging technologies has become increasingly vital in higher education. As digital tools reshape teaching, learning, and administrative functions, it is essential to examine how students, faculty, and institutions embrace and integrate these innovations to enhance educational outcomes.

One such innovation—**social media**—has gained prominence in educational settings, particularly among management students in metropolitan cities like Mumbai. Its integration into academic environments raises important questions about user acceptance, making it a relevant area of inquiry.

The **Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)**, proposed by Venkatesh et al. (2012), offers a comprehensive framework for analysing technology adoption. By extending the original UTAUT model to include **hedonic motivation, price value**, and **habit**, UTAUT2 enhances its relevance to consumer and individual users, beyond organizational contexts.

Previous studies (Balakrishnan, 2017; Gharrah & Aljaafreh, 2021; Tamilmani et al., 2020) have successfully applied the UTAUT2 model to explore social media usage in education. Key constructs—**performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation**, and **habit**—consistently emerge as significant predictors of users' behavioural intentions and actual technology use. However, these influences can differ across cultures and educational settings, necessitating localized investigations.

In the context of **management students in Mumbai**, there remains a gap in empirical research examining how these UTAUT2 factors interact to influence the adoption of social media for academic purposes. Gaining a deeper understanding of these dynamics can help educators and policymakers develop more effective strategies to integrate social media into the learning experience.

Review of Literature:
The application of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) in education has gained considerable traction. Gharrah and Aljaafreh (2021) examined the factors affecting students' use of social network sites for educational purposes in Jordanian universities, applying UTAUT2. Their study found that performance expectancy, effort expectancy, social influence, habit, lecturer support, and student-related factors all positively impacted the use of social networks for educational purposes. However, facilitating conditions and hedonic motivation were not found to have a significant effect on usage.

Similarly, Balakrishnan (2017) focused on the adoption of social media among university students, using the UTAUT2 framework. The results indicated that performance expectancy, effort expectancy, social influence, and facilitating conditions were significant predictors of students' behavioural intentions to use social media for academic purposes. Additionally, hedonic motivation and habit were substantial predictors of actual usage behaviour. This study reinforced the idea that ease of use and the perceived benefits of technology are crucial factors in its adoption for educational purposes.

Further, Tamilmani et al. (2020) provided a comprehensive review of UTAUT2, focusing on its constructs and applications in various settings. The authors analysed multiple studies where UTAUT2 was applied and highlighted the model's robustness in explaining technology acceptance, especially in consumer contexts. In their review, Tamilmani et al. (2020) emphasized the importance of constructs such as hedonic motivation and habit in influencing user behaviour. They also pointed out that while performance expectancy and effort expectancy are critical drivers in technology adoption, habit and hedonic motivation are often more influential in determining actual usage.

Another notable paper by Al-Emran et al. (2018), titled The Unified Theory of Acceptance and Use of Technology (UTAUT) in Higher Education: A Systematic Review, provides a thorough analysis of how UTAUT has been applied within higher education contexts. This systematic review identified key factors influencing technology acceptance and usage among students and educators. It underscores the importance of understanding not only the technological aspects but also the social and institutional factors that influence adoption in educational environments. The authors also noted that faculty members' perceptions and support play a critical role in technology integration in educational settings.

The literature consistently supports the UTAUT2 model as an effective tool for understanding technology adoption in educational settings. The following key factors have emerged across various studies:

Performance Expectancy: The belief that using a technology will enhance academic performance is one of the most significant predictors of its acceptance. Studies have shown that when students perceive that a particular technology will improve their learning outcomes, they are more inclined to adopt it (Balakrishnan, 2017; Gharrah & Aljaafreh, 2021). This is particularly important for tools like social media, where students seek benefits like increased access to information, collaboration opportunities, and engagement with educational content.
Effort Expectancy: The perceived ease of use is another critical factor. Technologies that are easy to use and do not require substantial effort to operate are more likely to be adopted by both students and educators (Tamilmani et al., 2020). The simplicity of social media platforms, for instance, contributes to their widespread use among students, as they are familiar and accessible.

Social Influence: The role of peers, instructors, and institutional culture in shaping students' technology adoption decisions has been well-documented. When influential individuals or groups endorse a particular technology, others are more likely to follow suit (Venkatesh et al., 2012). In educational settings, faculty recommendations, peer use, and institutional support are crucial in driving the adoption of tools like social media for educational purposes.

Facilitating Conditions: Adequate support structures, including technical resources, training, and infrastructure, play a significant role in technology adoption. A lack of proper resources or insufficient support can hinder the acceptance and usage of new technologies (Al-Emran et al., 2018). In the case of social media for education, facilitating conditions such as access to reliable internet, digital literacy, and technical training are necessary for effective integration into the educational process.

Hedonic Motivation: While traditionally not a focus in organizational technology adoption models, hedonic motivation, which refers to the enjoyment or pleasure derived from using a technology, plays an important role in educational contexts. Social media platforms, for example, are often used for their entertainment value, and this enjoyment can enhance students' willingness to engage with them for educational purposes. Tamilmani et al. (2020) found that hedonic motivation was a significant predictor of actual technology usage, emphasizing that

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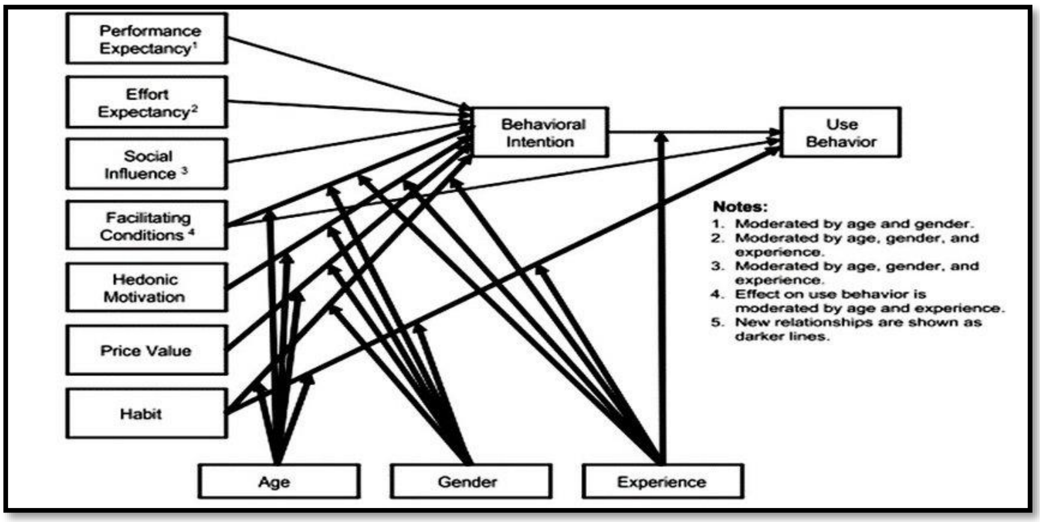
students are more likely to adopt and continue using technologies that provide enjoyment alongside utility.

Habit: Habit, or the automatic use of a technology, is another important factor influencing adoption. Once students become accustomed to using social media for educational purposes, it becomes an integral part of their learning routine. Habitual usage often leads to increased engagement and sustained technology adoption over time (Gharrah & Aljaafreh, 2021).

In summary, these studies underline the importance of both functional and experiential factors in technology adoption, highlighting the comprehensive nature of the UTAUT2 model. Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit all contribute to students' decisions to use social media for educational purposes. However, the relative importance of these factors may vary depending on cultural and contextual influences. For example, while performance expectancy and effort expectancy are consistently important, the influence of hedonic motivation may be more pronounced in certain cultural or demographic groups, where social media use for entertainment is a significant part of everyday life.

The applicability of UTAUT2 in diverse educational settings, especially among management students in Mumbai, warrants further empirical investigation. By exploring how these constructs interact and affect social media adoption for educational purposes in this specific context, this research aims to contribute valuable insights that can inform the integration of social media into management education. Educators, policymakers, and institutions can benefit from understanding how these factors shape technology adoption and can develop strategies to enhance students' educational experiences using social media.

Table: A1- Theoretical Framework- UTAUT2



Objectives of the Research Study:

1. To identify the key UTAUT2 factors (Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions) that influence Hedonic Motivation to use social media for learning among Management students in Mumbai and Navi Mumbai.

2. To assess the impact of Hedonic Motivation on the actual usage behavior of social media for learning.

3. To examine the moderating effect of gender on the relationship between Hedonic Motivation and Actual Usage Behavior.

Hypothesis: Keeping in view the above objectives, this study proceeds to evaluate the following hypotheses.

1. H1: Performance Expectancy (PE) has a significant positive influence on Hedonic Motivation (HM) to use social media for learning.

2. H2: Effort Expectancy (EE) has a significant positive influence on Hedonic Motivation (HM) to use social media for learning.

3. H3: Social Influence (SI) has a significant positive influence on Hedonic Motivation (HM) to use social media for learning.

4. H4: Facilitating Conditions (FC) have a significant positive influence on Hedonic Motivation (HM) to use social media for learning.

5. H5: Hedonic Motivation (HM) has a significant positive influence on Actual Usage Behavior (UB) of social media for learning.

6. H6: Gender moderates the relationship between Hedonic Motivation (HM) and Actual Usage Behavior (UB), such that the relationship differs between males and females.

Research Methodology:

Research methodology refers to the systematic strategy employed to answer research questions. According to Sekaran and Bougie (2010), research methodology is a structured framework consisting of principles and activities that help in producing valid and trustworthy research findings. Rajasekar, Philominathan, and Chinnathambi (2006) describe research methodology as a planned approach to solving research problems and a guide to how the research will be conducted. Irny and Rose (2005) further define it as a systematic, constructive way of analysis to gain insights into the solution of a study. The methodology of a research project encompasses the methods and techniques of theoretical analysis, ultimately selecting the best fit for the study.

In this study, information was collected using a survey questionnaire, divided into two main sections. The first section gathers background information about the respondents, including demographic data such as age, gender, educational qualification, nature of organization, years of experience, and the companies they work for. The second section consists of specific questions, which are measured on a 5-point Likert scale. The use of a 5-point Likert scale is considered appropriate and reliable for measuring attitudes and perceptions (Jenkins & Lloyd, 1985; Lissitz & Green, 1975).

To enhance the reach and minimize delays, electronic surveys were distributed across various social media platforms such as Meta (Facebook, Instagram, WhatsApp), Google (Emails, Google Groups), ensuring a broad outreach and increasing awareness. This approach was particularly effective in the context of developing countries.

To test the proposed model and evaluate the relationships among the hypotheses, this study employs Structural Equation Modelling (SEM), a second-generation multivariate data analysis technique. Specifically, Partial Least Squares (PLS) path modelling is used, which is a well-regarded method for handling complex models (Ringle, Wende, & Becker, 2015). SEM is widely recognized for hypothesis testing using real-world data (Oliver, Kerstin, & Manfred, 2010).

Research Design

This study follows a quantitative research design, employing structured questionnaires to collect data. By using quantitative data, the study ensures a systematic and standardized collection of information that can be subjected to statistical analysis to identify patterns and trends in technology adoption. The research design is grounded in the existing literature, with a survey tool developed to capture relevant information (see Table B for the survey tool).

Sampling Technique

The study uses a purposive random sampling technique to select a representative and diverse sample of management students from Mumbai and the Navi Mumbai Metropolitan Region. This sampling approach ensures that the sample adequately represents the target population in terms of relevant characteristics.

Geographical Focus

The geographical focus of the research is within India, specifically targeting management students in the Mumbai and Navi Mumbai regions. This localized focus allows for an in-depth exploration of the adoption of Data Science in this particular demographic.

Data Collection

Primary data is collected through purposive sampling, ensuring that the selected participants are representative of the target group, which is management students in Mumbai. The data collection process primarily relies on electronic surveys distributed across various social media platforms to maximize participation.

Data Analysis

The data analysis process integrates both quantitative and latent variable dimensions. Quantitative data are analysed using statistical tools to identify patterns, trends, and statistical significance. Basic descriptive statistics such as frequency distributions and percentages provide a foundational understanding of the data.

For in-depth analyses, correlation and cross-tabulation techniques are used to explore relationships and associations, particularly in comparing responses from different groups, such as between government and private institutions. Advanced statistical methods, including Structural Equation Modelling (SEM), Linear Regression, Confirmatory Factor Analysis (CFA), Generalized Linear Models (GLM), and Multilayer Models, are applied to derive nuanced insights into the adoption patterns of technology.

Ethical Considerations

Ethical principles are central to this research, ensuring that the rights and well-being of all participants are upheld throughout the study. Participants are fully informed about the objectives, procedures, and potential impacts of the research prior to their involvement. Explicit and voluntary consent is obtained from all participants, emphasizing respect for their autonomy and privacy.

Scope and Limitations

This study is limited to management students between the ages of 18 and 30 in the Mumbai metropolitan area. Future research could expand the sample to include older demographics and students from Tier 2 cities to examine broader patterns in gender and social media adoption.

Data Analysis & Results

Respondent Profile: Table -1

The respondents for this study are postgraduate students enrolled in various specializations of a management program. The total sample size comprises 273 students, categorized based on their area of specialization and gender distribution as follows:

Program	Male	Female	Total
Finance	58	54	112
HR	4	24	28
Marketing	70	44	114
Operations	10	3	13
Systems	5	1	6
Grand Total	**147**	**126**	**273**

This gender distribution reflects a near balance between male and female students, with males constituting a slight majority. The Finance and Marketing specializations have the highest number of respondents, collectively accounting for 226 students (82.8%) of the total sample. Other specializations, such as HR, Operations, and Systems, have smaller representations.
This diverse composition ensures a comprehensive representation of perspectives across various management domains.

Data Analysis using Structural Equation Modelling

For a considerable time, covariance-based structural equation modelling (CB-SEM) was the dominant technique for analysing complex relationships between observed and latent variables in social sciences. Until around 2010, the majority of published research in this domain relied on CB-SEM. However, over the past decade, the use of partial least squares structural equation modelling (PLS-SEM) has grown significantly, surpassing CB-SEM in many disciplines (Hair et al., 2017b).

PLS-SEM is now widely adopted across various fields including organizational management (Sosik et al., 2009), international management (Richter et al., 2015), human resources (Ringle et al., 2019), marketing (Hair et al., 2012b), information systems (Ringle et al., 2012), operations (Peng & Lai, 2012), hospitality (Ali et al., 2018b), supply chain (Kaufmann & Gaeckler, 2015), and management accounting (Nitz, 2016). This expansion is further supported by dedicated textbooks (e.g., Garson, 2016; Ramayah et al., 2016), edited volumes (e.g., Avkiran & Ringle, 2018), and special journal issues (e.g., Rasoolimanesh & Ali, 2018; Shiau et al., 2019) focusing on methodological developments in PLS-SEM.

The appeal of PLS-SEM lies in its flexibility and predictive focus. Unlike CB-SEM, which relies on strict assumptions and prioritizes theory confirmation, PLS-SEM is a causal-predictive technique that emphasizes prediction and is better suited for complex models with multiple constructs, indicators, and paths (Wold, 1982; Sarstedt et al., 2017a). It does not impose distributional assumptions, making it especially valuable when data is non-normally distributed.

Importantly, user-friendly software like SmartPLS (Ringle et al., 2015) and PLS-Graph (Chin, 2003) has made the technique accessible to researchers with limited technical expertise. More advanced tools, such as the semPLS package in R (Monecke & Leisch, 2012), provide additional flexibility for statistical computing environments.

Originally developed by Herman Wold (1975, 1982, 1985), PLS-SEM—also known as PLS path modelling—combines principal component analysis with ordinary least squares (OLS) regressions to estimate model parameters (Mateos-Aparicio, 2011). Unlike CB-SEM, which estimates parameters using only common variance through covariance matrices (e.g., in AMOS or LISREL), PLS-SEM uses total variance, thus enabling it to handle formatively measured constructs and small sample sizes more effectively (Hair et al., 2011; 2017b).

When to Use PLS-SEM: Key Considerations

Researchers are increasingly choosing PLS-SEM when the study design or data characteristics align with the following conditions (Hair et al., 2018):

1. The objective is to test theoretical models from a predictive perspective.
2. The model is complex, involving numerous constructs and relationships.
3. The study is exploratory in nature, aiming to develop or extend theory.
4. The model includes formatively measured constructs.
5. The data includes financial ratios or archival variables that are not well supported by measurement theory.
6. The research is based on secondary or archival data.
7. The sample size is small, which is common in niche or B2B studies.
8. The data exhibits non-normality, making distribution-free methods preferable.
9. The research requires latent variable scores for further analysis.

PLS-SEM is well-suited for studies with complex models and small to moderate sample sizes due to its ability to separately estimate the measurement and structural models using OLS. This characteristic, along with its minimal distributional assumptions, makes it especially effective when working with real-world, non-normal datasets.

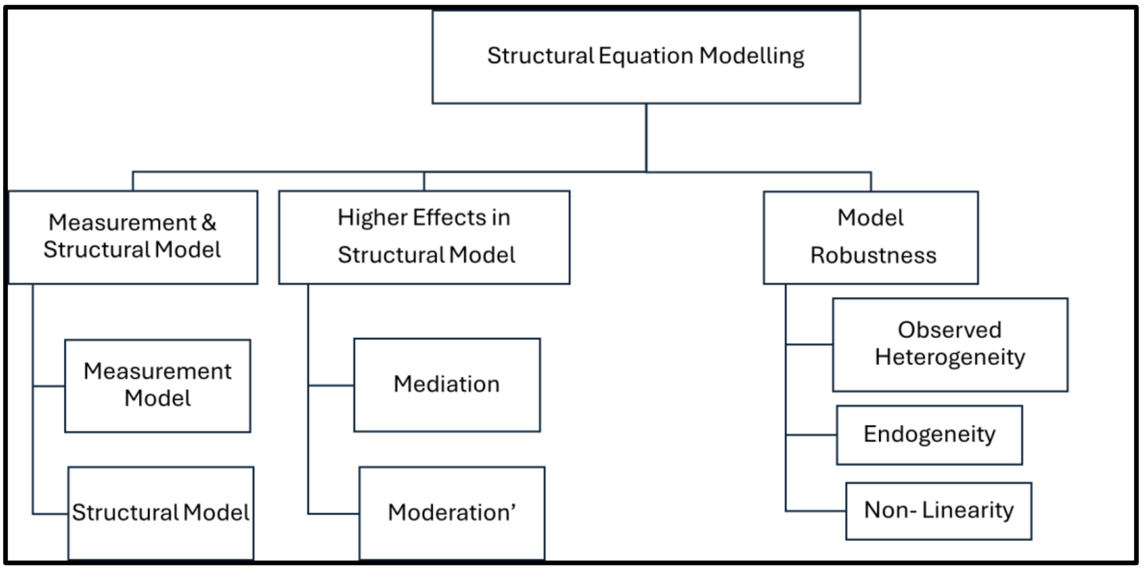
Empirical Justification in the Current Study

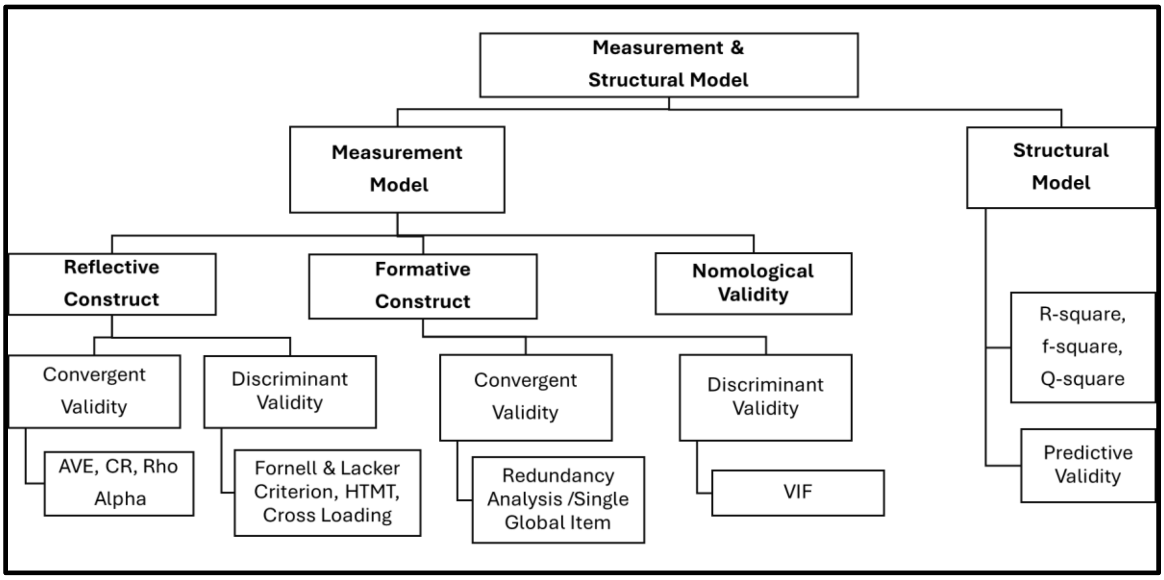
In this study, the KG test (Cramér–von Mises P test) was employed to assess data normality. Results indicated that p-values for all construct items were < 0.05, confirming non-normality in the dataset. This statistical evidence further justifies the use of PLS-SEM over CB-SEM for this research.

Overview of Analysis Steps

Charts 1 and 2 (referenced below) present a sequential overview of the steps involved in conducting variance-based structural equation modelling using PLS-SEM. These charts illustrate the full process from data preparation and model specification to assessment and interpretation of results.

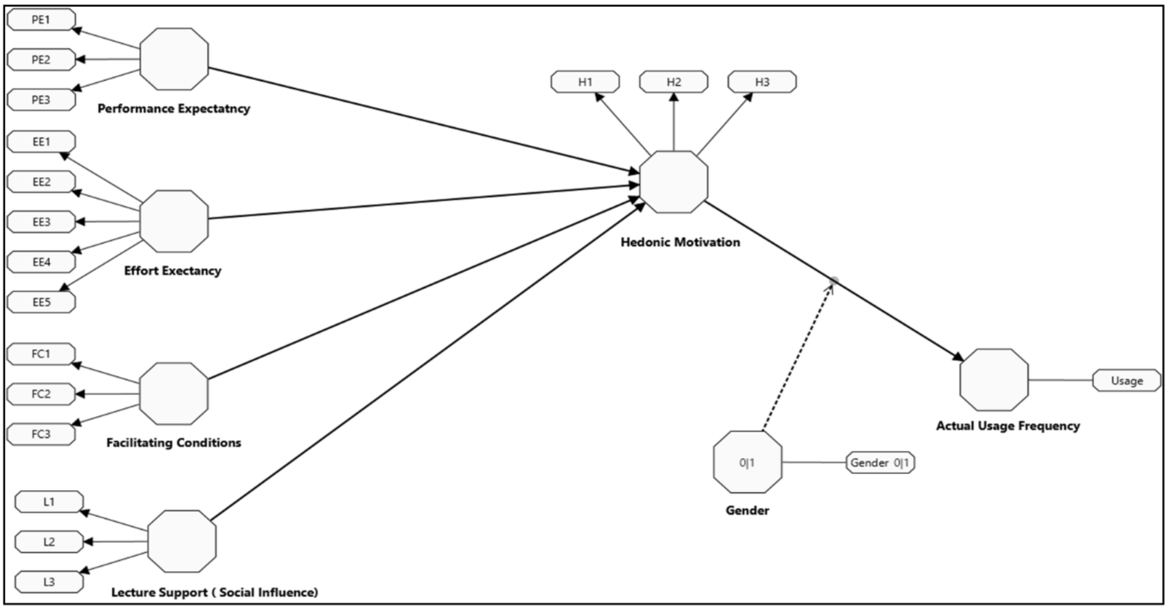
Chart 1





Results & Discussion

Table: A2- Conceptual Framework- UTAUT2



The Measurement Model
Construct Types: Reflective and Formative
In structural equation modelling (SEM), constructs are generally classified as reflective or formative, and the type of construct determines the approach to data analysis.

- Reflective constructs assume that the latent construct causes the observed indicators, and measurement error results from the construct's inability to fully explain the indicators (Hair et al., 2011). Arrows in the model flow from the construct to its indicators. For example, indicators like blood pressure, perspiration, nervousness, and frustration can be seen as reflections of the latent construct "stress."
- Formative constructs, in contrast, assume that the indicators cause the construct, and errors arise from the inability of the indicators to fully define the latent variable. Here, arrows flow from indicators to the construct. Unlike reflective constructs, formative constructs are not latent in nature.

In the present study, the UTAUT2 framework is employed, where the constructs are modelled as reflective—indicating that the latent variables drive the indicators. Accordingly, the subsequent measurement model evaluation follows the guidelines for reflective constructs.

Convergent Validity
Convergent validity assesses whether a construct correlates positively with alternative measures of the same concept. For reflective constructs, this is determined by evaluating the extent to which the indicators share a high proportion of variance with the underlying construct.

- A commonly accepted metric is Average Variance Extracted (AVE), which should be ≥ 0.50. This implies that the construct explains more than half the variance of its indicators. An AVE below 0.50 indicates that measurement error dominates (Hair et al., 2022).
- Outer loadings (indicator reliability) represent the correlation between the construct and its indicators. These should ideally be ≥ 0.708, indicating that at least 50% of the variance in an item is captured by the construct (Hulland, 1999; Hair et al., 2022, p. 117). The square of the factor loading is referred to as communality.

- Indicators with loadings between 0.40 and 0.70 may be considered for removal if doing so increases AVE and improves model reliability. However, researchers should also assess content validity before removing indicators in this range.
- Indicators with loadings below 0.40 should be removed from the model (Bagozzi, Yi & Phillips, 1991; Hair, Ringle & Sarstedt, 2011).

Convergent validity for this study was evaluated following the guidelines and standards outlined in A Primer on Partial Least Squares Structural Equation Modelling (Hair et al., 2022). Refer to Chart 3 for the outer loading assessments. Indicator selection was based on their statistical significance and relevance to the theoretical constructs.

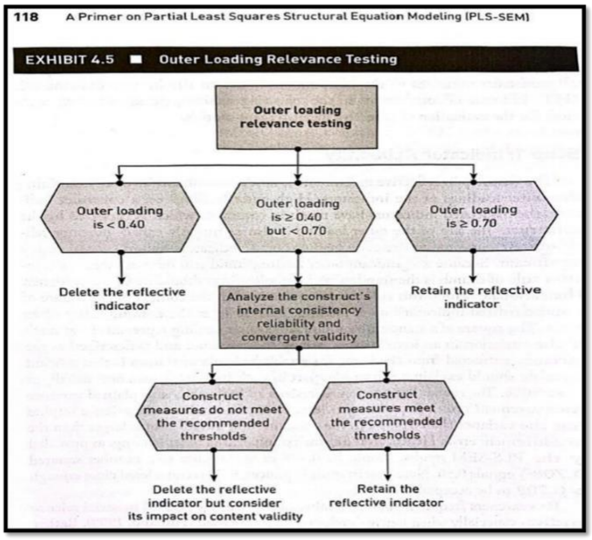
Construct Operationalization and Indicators

The reflective constructs and their respective measurement items used in this study are summarized below. Detailed construct definitions are provided in Annexure I.

1. Performance Expectancy (PE)
   - Items: PE1, PE2, PE3
2. Effort Expectancy (EE)
   - Items: EE1, EE2, EE3, EE4, EE5
3. Social Influence – Lecture Support (L)
   - Items: L1, L2, L3
4. Facilitating Conditions (FC)
   - Items: FC1, FC2, FC3
5. Hedonic Motivation (HM)
   - Items: H1, H2, H3
6. Use Behaviour (UB) – Actual Frequency of Usage
   - Item: UB1

Each construct was measured using validated scales adapted to the context of this research. The indicator relevance and outer loading assessments were cross-verified with the guidelines from Hair et al. (2022) to ensure robustness.

Chart 3



Internal Consistency and Reliability: The internal consistency and reliability of the constructs in the study were assessed using three statistical techniques:

1. **Cronbach's Alpha**: This criterion provides an estimate of reliability based on the inter-correlations of the observed indicator variables.
2. **Composite Reliability (CR or Rho)**: Unlike Cronbach's Alpha, composite reliability considers the different outer loadings of the indicator variables, making it a more precise measure.
3. **Dijkstra–Henseler's Rho_A**: Recognized as a compromise between the conservative Cronbach's Alpha and the more liberal Composite Reliability. Based on the works of Dijkstra (2010), Dijkstra and Henseler (2015), and endorsed by Hair et al. (2019), this measure lies between the two extremes and offers a more accurate assessment of internal consistency.

Before hypothesis testing, the reliability and validity of the data were established. Following Bagozzi, Yi, and Phillips (1991), Cronbach's alpha and composite reliability were computed. Values above 0.70 were deemed acceptable (Hair Jr. et al., 2016), with values below 0.60 indicating poor internal consistency. All constructs had Cronbach's alpha and composite reliability scores above 0.702, indicating satisfactory reliability.
Convergent validity was assessed through Average Variance Extracted (AVE), with a threshold of 0.50 (Hair Jr. et al., 1995). All AVE values ranged from 0.651 to 0.842, surpassing this benchmark.

Findings:
Cronbach's Alpha values ranged from 0.70 to 0.90, confirming internal reliability. ii. Composite reliability values ranged between 0.70 and 0.95, suggesting high internal consistency. iii. Rho_A values were within expected limits, lying between Cronbach's Alpha and Composite Reliability, further affirming internal consistency. iv. AVE values exceeded 0.50 for all constructs, supporting convergent validity. v. All factor loadings were above 0.70, validating strong correlations between items and their constructs.

Before conducting hypothesis testing, the reliability and validity of the data were assessed, as recommended by Bagozzi, Yi, and Phillips (1991). To evaluate the trustworthiness of the constructs, both Cronbach's alpha (α) and Composite Reliability (CR) were calculated. According to Hair Jr., Hult, Ringle, and Sarstedt (2016), reliability is considered acceptable when these values exceed 0.70, while values below 0.60 indicate inadequate internal consistency. In this study, all constructs demonstrated Cronbach's alpha and CR values above 0.702, indicating strong internal reliability.
Next, the validity of the measurement model was examined, focusing on convergent and discriminant validity. Convergent validity is confirmed when the Average Variance Extracted (AVE) for each construct is at least 0.50 (Hair Jr., Anderson, Tatham, & William, 1995). The AVE values in this study ranged from 0.651 to 0.842, all exceeding the recommended threshold. These results confirm that the constructs capture a substantial portion of variance from their respective indicators, thereby supporting convergent validity.

Table:1

Details	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Effort Exectancy	0.797	0.817	0.859	0.552
Facilitating Conditions	0.745	0.857	0.845	0.653
Hedonic Motivation	0.876	0.880	0.923	0.801
Lecture Support	0.867	0.904	0.917	0.787
Performance Expectatncy	0.852	0.858	0.910	0.771

Findings:

I. **Cronbach's Alpha** values ranged from 0.70 to 0.90, indicating acceptable to high reliability across constructs.
ii. **Composite Reliability (Rho)** values ranged between 0.70 and 0.95, demonstrating strong internal consistency without redundancy.
iii. **Roha values** (Dijkstra-Henseler's rho_A) fell between Cronbach's Alpha and Composite Reliability, offering a balanced estimate of internal consistency.
iv. **Average Variance Extracted (AVE)** values exceeded 0.50 for all constructs, confirming that the constructs account for a significant proportion of variance in their indicators—thus supporting convergent validity.
v. **Factor Loadings** for all items were above 0.70, reflecting strong correlations with their respective constructs and further reinforcing convergent validity.

Discriminant Validity: Discriminant validity refers to the degree to which constructs are distinct from each other and measure unique concepts. It was assessed using three methods:

i. Fornell and Larcker Criterion (1981):

This approach compares the square root of each construct's AVE with its correlations with other constructs. Discriminant validity is established when the square root of a construct's AVE is greater than its highest correlation with any other construct.

ii. Cross Loadings:

Each item should load more strongly on its associated construct than on any other construct. However, Henseler, Ringle, and Sarstedt (2015) cautioned that cross-loading analysis is insufficient for detecting discriminant validity issues, especially in applied research (Hair et al., 2022, p.122).

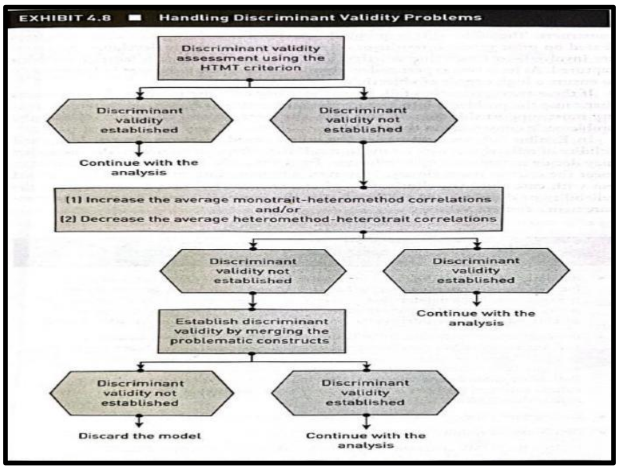
iii. HTMT (Heterotrait-Monotrait) Ratio of Correlations:

HTMT is calculated as the ratio of average correlations across constructs (heterotrait-heteromethod) to those within the same construct (monotrait-heteromethod). Values close to 1 suggest a lack of discriminant validity. Acceptable thresholds are:

- HTMT < 0.85 for conceptually distinct constructs
- HTMT < 0.90 for conceptually similar constructs (Henseler et al., 2015; Ringle et al., 2018)

This metric offers a more accurate assessment and is especially recommended for structural equation modelling.

Chart 4



The HTMT results as per the table below affirm the support of divergent validity. The scores are in line with the threshold as prescribed. For conceptually similar constructs: HTMT < 0.90

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For conceptually different constructs: HTMT < 0.85 (Ringle et all.,2018). The results are detailed below in Table 4. The results from the measurement model elucidate and confirm the construct validity of the defined model.

Table 2

Constructs	Actual Usage	Effort Expectancy	Facilitating Conditions	Hedonic Motivation	Lecture Support	Performance Expectancy	Actual Usage Frequency	Effort Expectancy
Actual Usage Frequency	0.892							
Effort Expectancy	0.715	0.807						
Facilitating Conditions	0.496	0.508	0.830					
Hedonic Motivation	0.810	0.619	0.628	0.899				
Lecture Support	0.643	0.598	0.576	0.649	0.918			
Performance Expectancy	0.400	0.469	0.446	0.315	0.470	0.878		
Actual Usage Frequency	0.641	0.689	0.525	0.623	0.605	0.510	0.859	
Effort Expectancy	0.730	0.692	0.545	0.624	0.643	0.600	0.735	0.852

Table 3

Constructs	Actual Usage	Effort Expectancy	Facilitating Conditions	Hedonic Motivation	Lecture Support	Performance Expectancy	Actual Usage Frequency	Effort Expectancy
Actual Usage Frequency	0.892							
Effort Expectancy	0.715	0.807						
Facilitating Conditions	0.496	0.508	0.830					
Hedonic Motivation	0.810	0.619	0.628	0.899				
Lecture Support	0.643	0.598	0.576	0.649	0.918			
Performance Expectancy	0.400	0.469	0.446	0.315	0.470	0.878		
Actual Usage Frequency	0.641	0.689	0.525	0.623	0.605	0.510	0.859	
Effort Expectancy	0.730	0.692	0.545	0.624	0.643	0.600	0.735	0.852

Table 4

HTMT Construct wise	Actual Usage Frequency	Effort Exectancy	Facilitating Conditions	Hedonic Motivation	Lecture Support	Performance Expectatncy
Actual Usage Frequency						
Effort Exectancy	**0.247**					
Facilitating Conditions	**0.142**	**0.531**				
Hedonic Motivation	**0.164**	**0.702**	**0.468**			
Lecture Support	**0.125**	**0.483**	**0.444**	**0.344**		
Performance Expectatncy	**0.244**	**0.791**	**0.487**	**0.748**	**0.441**	

Good Discriminant Validity: All constructs exhibit good discriminant validity, with HTMT values below the threshold of 0.85, indicating distinct and reliable measurements. The model is deemed to be tested for the relationships between the variables and their path. This is measured using the structural model approach.

1. The Structural Model: The structural model assessment entails the following steps.

- Asses the structural model for collinearity issues
- Assess the significance and relevance of the structural models and relationships.
- Assess the level of R Square
- Assess the effect sizes f Square.
- Assess the predictive relevance Q Square

To assess the collinearity, the VIF values are considered – VIF - The variance inflation factor (VIF) quantifies the extent of correlation between one predictor and the other predictors in a model. It is used for diagnosing collinearity/multicollinearity. Higher values signify that it is difficult to impossible to assess accurately the contribution of predictors to a model. There is a Probable (i.e., critical) collinearity issues when VIF greater than 5, Possible collinearity issues when VIF between 3-5 & ideally no collinearity when VIF < 3. (Ringle et all.,2018)/ The Model affirms and confirms that the constructs do not exhibit collinearity as per Table :5-A & 5B given.

Table 4

Details	Actual Usage	Hedonic Motivation
Actual Usage Frequency		**1.058**
Effort Expectancy		**1.924**
Facilitating Conditions	**1.268**	**1.326**
Hedonic Motivation	**1.268**	
Lecture Support		**1.260**
Performance Expectancy		**1.863**

Level of Significance: - R Square is the measure of model's predictive accuracy. It represents the amounts of variance in the endogenous construct explained by all the exogenous constructs linked to it. R Square ranges from 0 to 1, higher values indicating higher levels of accuracy. R2 values of 0.75, 0.50 and 0.25 are considered substantial, moderate and weak. R2 values of 0.90 and higher are typical indicative of overfit. The table below indicates that moderate levels of accuracy have been estimated for the model.

Table 5

Constructs	R-square	R-square adjusted
AA	0.040	0.033
Hedonic Motivation	**0.509**	0.500

Table 6

	Actual Usage Frequency	Hedonic Motivation
Actual Usage Frequency		
Effort Exectancy		0.071
Facilitating Conditions		0.024
Hedonic Motivation	0.024	0.033
Lecture Support		0.000
Performance Expectancy		0.188

Level of effect size - Referring to Table 6- F² (f-square) is a measure of the effect size of a predictor variable on an endogenous variable. It represents the proportion of variance in the endogenous variable explained by the predictor variable. $f^2 = 0.02$ (small effect)- $f^2 = 0.15$ (medium effect)- $f^2 = 0.35$ (large effect). F^2 is useful for evaluating the relative importance of predictor variables. Comparing the effect sizes of different predictor variables. Assessing the practical significance of the relationships between variables. The F Square results elucidate the practical behaviors on technology adoption, showing Performance Expectancy, Effort Expectancy, facilitating conditions & Hedonic Motivation important and has a large effect size, However, the Lecture Support (Social Influence does not have any effect on the Actual Use.

Hypothesis Test Summary

The constructed structural model was built to identify the path relations between the components. This hypothesis was tested using the bootstrap method. This study examined the association between endogenous and exogenous variables using path coefficients (β) and t-statistics. This research revealed the substantial effects of many factors on Social Media usage. In all hypotheses, the t-test results were above the critical threshold of 1.96, barring Social Influence (Lecture Support) Thus, Hypotheses H1, H2, and H4 were supported All findings are supported by a statistically significant t-value and beta coefficient hence providing support for hypothesis, as presented in Table 7

Table 7

Hypotheses	Details	Beta	T statistics (|O/STDEV|)	P values	Comment
H1	Performance Expectancy -> Hedonic Motivation	0.424	5.739	0.000	Accepted
H2	Effort Expectancy -> Hedonic Motivation	0.265	3.671	0.000	Accepted
H3	Social Influence(Lecture Support)-> Hedonic Motivation	0.001	0.020	0.984	Rejected
H4	Facilitating Conditions -> Hedonic Motivation	0.126	2.018	0.044	Accepted
H5	Hedonic Motivation -> Actual Usage Frequency	0.155	2.481	0.013	Accepted
H-6(a)	Gender x PE -> H	-0.099	0.710	0.477	Rejected
H-6(b)	Gender x FC -> H	0.194	1.466	0.143	Rejected
H-6(c)	Gender x L -> H	-0.040	0.325	0.745	Rejected
H-6(d)	Gender x EE -> H	0.028	0.180	0.857	Rejected
H-6(e)	Gender -> AA	0.128	0.527	0.598	Rejected
H-6(f))	Gender x HM Motivation -> AA	0.129	0.384	0.701	Rejected

Significant Factors Influencing Social Media Adoption

The study examined the relationship between various factors and the actual usage of social media in higher education using path coefficients (β) and t-statistics, with significance considered at $p < 0.05$.

- **Performance Expectancy (PE)** had the strongest influence on adoption (β = 0.424, *t* = 5.739), suggesting students are more inclined to use social media if they perceive it enhances their learning.
- **Effort Expectancy (EE)** also had a significant impact (β = 0.265, *t* = 3.671), indicating that ease of use plays a crucial role.
- **Facilitating Conditions (FC)** (β = 0.126, *t* = 2.018) and **Hedonic Motivation (HM)** (β = 0.155, *t* = 2.481) were found to be statistically significant, highlighting the importance of access to resources and enjoyment in influencing adoption.

Since all these t-values exceeded the critical threshold of 1.96, **Hypotheses H3, H4, H5, and H6** were supported.

Insignificant Factors

- **Social Influence (SI)** (β = 0.001, *t* = 0.020) had no significant impact on adoption, implying that peer or societal influence does not affect students' decisions to use social media for educational purposes.
- **Gender (H6)** (β = 0.129, *t* = 0.1384) also did not moderate adoption behavior, indicating similar patterns of usage among male and female students of Generation Z. It is hypothesized that including individuals above 30 years might yield different results, as older generations may exhibit varying behavior patterns.

Key Insights and Implications

Drivers of Social Media Adoption

- **Performance Expectancy:** Students adopt social media when they see clear educational benefits.
- **Effort Expectancy:** Platforms that are easy to use are more likely to be adopted.
- **Facilitating Conditions:** Access to devices and internet positively affects usage.
- **Hedonic Motivation:** Enjoyment encourages students to integrate social media into their learning.

Factors with Limited Influence

- **Social Influence:** Contrary to expectations, societal or peer pressure does not significantly drive adoption.
- **Gender:** Minimal gender-based variation was found among Generation Z users.

Scope for Further Research

The finding that gender does not significantly impact social media usage highlights the equitable behavior typical of Generation Z in learning contexts. Future studies could expand to include older age groups (30+), particularly in **Tier 2 city management institutes**, to explore whether generational differences influence social media adoption.

Social Relevance of the Study

This research offers critical insights into how technology, particularly social media, is reshaping learning environments in higher education:

1. **Enhancing Digital Learning:** By identifying key adoption drivers, the study supports the design of engaging, learner-centered digital education models—especially relevant in the post-pandemic era.

2. **Bridging the Digital Divide:** Highlighting the role of facilitating conditions stresses the need to improve access to technology for students from varied socioeconomic backgrounds.
3. **Promoting Gender-Neutral Learning:** The absence of gender bias reflects growing inclusivity and can guide the development of equitable learning strategies.
4. **Supporting Lifelong Learning:** Understanding user-friendly and effective learning tools aids in building flexible educational frameworks that support continuous learning.
5. **Improving Institutional Practices:** Insights into constructs like hedonic motivation and facilitating conditions can help institutions design tech-supported, student-friendly curricula.
6. **Fostering Engagement and Motivation:** Recognizing the role of enjoyment in learning emphasizes the need for engaging content to sustain learner interest.
7. **Preparing the Future Workforce:** Encouraging social media use in education aligns with real-world digital collaboration and communication practices.
8. **Encouraging Evidence-Based Decisions:** The study offers a data-driven framework for policymakers and educators to implement digital tools strategically.

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