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## THE INFLUENCE OF GEN AI ON STUDENTS' CREATIVE CAPACITY: EVIDENCE FROM HANOI, VIETNAM

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### ABSTRACT

The rapid development of GenAI has transformed learning, content creation, and knowledge generation, creating both opportunities and challenges for human creativity. This study investigates the factors influencing creativity enhancement through GenAI among young users by integrating the TAM2 and the Componential Theory of Creativity. A quantitative research approach was employed using a survey of 400 valid respondents aged 18–30 who had prior experience with GenAI tools such as ChatGPT, Gemini, and Midjourney. Data were analyzed using Cronbach's Alpha, EFA, CFA, and SEM. The findings indicate that all proposed hypotheses are supported. Social Influence ( $\beta = 0.694$ ) and Perceived Usefulness ( $\beta = 0.620$ ) significantly affect Habit of Using GenAI, while Technology Trendiness ( $\beta = 0.630$ ) and Innate Creativity ( $\beta = 0.429$ ) positively influence Usage Purpose. Furthermore, Usage Purpose ( $\beta = 0.409$ ), Habit of Using GenAI ( $\beta = 0.334$ ), and Innate Creativity ( $\beta = 0.252$ ) significantly enhance creativity. The SEM model demonstrates excellent fit indices (CFI = 0.981, TLI = 0.978, RMSEA = 0.031), confirming the robustness of the proposed framework. The results suggest that GenAI serves as a co-creative partner that can stimulate idea generation and creative performance when used purposefully and strategically. This study contributes to the literature by providing an integrated framework linking technology acceptance and creativity theories and offers practical implications for educators, policymakers, and technology developers seeking to foster creativity in the era of artificial intelligence.

**KEYWORDS:** GenAI; Creativity Enhancement; TAM2; University Students; SEM.

### 1. INTRODUCTION

The rapid advancement of Generative Artificial Intelligence (GenAI), particularly large language models such as ChatGPT, Gemini, and image-generation systems such as Midjourney, has significantly transformed learning, creativity, and knowledge creation in higher education. These

technologies enable students to generate essays, programming code, visual designs, and other creative outputs efficiently, thereby enhancing idea generation, reducing creative barriers, and improving academic productivity [7, 16]. As a result, GenAI is increasingly recognized as a valuable tool for fostering creativity and innovation among university students [13].

Despite these benefits, concerns have emerged regarding the potential negative consequences of excessive reliance on GenAI. Recent studies suggest that frequent dependence on AI-generated content may reduce cognitive engagement, weaken critical thinking skills, and diminish the originality of creative outputs [17]. A meta-analysis by Doshi and Hauser [6] found that although GenAI enhances individual creative performance, it simultaneously reduces idea diversity, leading to greater convergence of creative outcomes. Similarly, research on AI-assisted design tasks reported the phenomenon of “design fixation,” where exposure to AI-generated suggestions limits users’ exploration of novel and diverse solutions [11]. These findings indicate that GenAI may both support and constrain creativity depending on how it is used.

Conversely, other studies highlight the positive role of GenAI as a collaborative learning partner. AI-assisted tools have been shown to stimulate idea development, strengthen creative confidence, and improve engagement in academic writing and problem-solving activities [13]. In engineering education, GenAI has also been found to enhance learning effectiveness, creative problem-solving skills, and independent thinking [8]. Such contrasting evidence suggests that the impact of GenAI on creativity is complex and influenced by technological, social, and individual factors.

Existing studies have largely relied on the TAM and TAM2 to explain technology adoption through perceived usefulness and social influence [5, 23]. However, limited research has examined how these factors interact with creativity-related mechanisms proposed by the Componential Theory of Creativity [1]. To address this gap, the present study integrates TAM2 and the CTC to investigate how GenAI influences students’ creative outcomes. The proposed framework examines the effects of Perceived Usefulness, Social Influence, Technology Trendiness, Innate Creative Capacity, Habit, and Usage Purpose, while also exploring the mediating and moderating roles of Technology Trendiness and Habit.

Accordingly, this study seeks to answer two research questions: (1) What factors influence students’ creativity when using GenAI? and (2) Do Technology Trendiness and Habit mediate or moderate the relationship between GenAI usage and creative outcomes? This research contributes to a deeper understanding of the mechanisms through which GenAI shapes creativity in higher education.

## 2. LITERATURE REVIEWS AND THE PROPOSED RESEARCH MODEL

### 2.1. Literature Reviews

The rapid development of GenAI has attracted considerable scholarly attention due to its transformative impact on creativity, learning, and innovation. Existing research suggests that the relationship between GenAI and creativity can be explained through two complementary theoretical perspectives: the TAM2 and the CTC. According to TAM2, technology adoption is primarily influenced by perceived usefulness, social influence, and behavioral intention [5, 23]. In educational contexts, students are more likely to adopt GenAI tools when they perceive them as useful for improving learning performance, generating ideas, and enhancing productivity. Social norms and peer influence further shape students' willingness to integrate AI technologies into academic activities. Meanwhile, the CTC argues that creativity emerges from the interaction among domain-relevant skills, creativity-relevant processes, intrinsic motivation, and environmental factors [1, 2]. From this perspective, GenAI can function as a cognitive support mechanism that expands knowledge, stimulates divergent thinking, and strengthens creative engagement.

Recent studies have produced mixed findings regarding the impact of GenAI on creativity. On the positive side, GenAI has been shown to facilitate idea generation, improve creative confidence, and enhance learning outcomes across disciplines, including education, design, engineering, and marketing [13, 8]. Human-AI collaboration often results in higher levels of individual creative performance, particularly among users with limited prior expertise. Furthermore, GenAI can serve as a co-creative partner by providing instant feedback, alternative perspectives, and novel content suggestions, thereby enriching the creative process.

However, growing evidence also highlights several risks associated with excessive reliance on AI-generated content. Studies have reported phenomena such as design fixation, cognitive dependency, and reduced originality, suggesting that users may become overly influenced by AI-generated suggestions and consequently produce less diverse and less novel outcomes [11]. A recent meta-analysis found that while GenAI improves individual creativity, it simultaneously reduces collective idea diversity, leading to greater convergence of creative outputs [6]. These concerns are particularly relevant in higher education, where critical thinking, independent reasoning, and originality remain essential learning objectives.

Overall, prior studies converge on the conclusion that GenAI can simultaneously enhance and constrain creativity depending on how it is used. Nevertheless, significant research gaps remain. Existing studies have largely examined technology acceptance and creativity separately, with limited efforts to integrate TAM2 and the CTC into a unified framework. Moreover, little empirical evidence exists regarding the mediating or moderating roles of factors such as technology trendiness, habit, and usage purpose in shaping students' creative outcomes when using GenAI. Addressing these gaps, the present study develops an integrated model to explain how technological, social, and individual factors collectively influence student creativity in the context of GenAI adoption.

### 2.2. The hypothesis proposal

This study develops an integrated framework that combines the TAM2 and the CTC to explain how GenAI influences students' creativity. The model incorporates six antecedent variables: Perceived Usefulness, Social Influence, Technology Trendiness, Innate Creativity, Habit, and Usage Purpose, and examines their effects on Creativity Enhancement through GenAI. In addition, Habit and Usage Purpose are considered important behavioral mechanisms through which technology adoption translates into creative outcomes.

### **Perceived Usefulness (HI)**

Perceived Usefulness (HI) refers to the degree to which individuals believe that a technology enhances their performance and productivity [5]. In the context of GenAI, students may perceive these tools as valuable because they facilitate idea generation, content development, problem-solving, and creative exploration. Recent studies indicate that GenAI can significantly improve efficiency and support creative tasks when used as a collaborative partner rather than a simple automation tool [12, 19]. Students who perceive GenAI as useful are therefore more likely to integrate it into their daily learning activities and develop regular usage habits.

*H1: Perceived Usefulness positively influences students' Habit of using GenAI.*

### **Social Influence (XH)**

Social Influence (XH) reflects the extent to which individuals perceive that important others believe they should use a particular technology [24]. Drawing on Social Cognitive Theory, social interactions shape behavioral expectations through observation and imitation [3]. In educational settings, students are often influenced by peers, instructors, and online communities that actively adopt GenAI tools. Positive social perceptions can therefore encourage continuous usage and increase technology acceptance.

*H2: Social Influence positively influences students' Habit of using GenAI.*

### **Technology Trendiness (CN)**

Technology Trendiness (CN) refers to the perceived popularity and social visibility of emerging technologies. According to Diffusion of Innovations, individuals are more likely to adopt innovations that are widely accepted within their social environment [20]. Since GenAI has become a prominent digital trend among young people, awareness of its widespread adoption may encourage students to explore broader applications of the technology for academic and creative purposes.

*H3: Technology Trendiness positively influences students' Usage Purpose of GenAI.*

### **Innate Creativity (STBS)**

Innate Creativity represents an individual's natural ability to generate original ideas and solve problems creatively [1]. The CTC suggests that creative performance is influenced by creativity-relevant skills, intrinsic motivation, and personal creative potential [2]. Individuals with higher innate creativity are more likely to use GenAI strategically as a co-creative tool, leveraging its capabilities to expand rather than replace their own thinking processes.

*H4: Innate Creativity positively influences students' Usage Purpose of GenAI.*

**H5:** *Innate Creativity positively influences students' Creativity Enhancement.*

#### **Habit of Using GenAI (MDTQ)**

Habit refers to the extent to which technology use becomes automatic through repeated behavior [18]. Frequent interaction with GenAI enables students to develop greater technological proficiency, optimize prompting strategies, and integrate AI into their creative workflows. Prior studies indicate that habitual use can enhance creative productivity when users actively engage with AI-generated suggestions rather than relying on them passively [24].

**H6:** *Habit of using GenAI positively influences students' Creativity Enhancement.*

#### **Usage Purpose of GenAI (MD)**

Usage Purpose reflects the motivations and objectives underlying GenAI adoption. According to TAM, technology outcomes depend not only on usage frequency but also on the intentions guiding that usage [5]. Students who use GenAI for brainstorming, knowledge expansion, creative exploration, and problem-solving are more likely to benefit from its creative potential. Conversely, using AI merely as a shortcut may reduce originality and critical engagement [21].

**H7:** *Usage Purpose positively influences students' Creativity Enhancement.*

### **2.3. The research proposal**

The proposed research framework integrates the TAM2 and the CTC to examine how GenAI influences students' creativity. The model suggests that Perceived Usefulness and Social Influence positively affect students' Habit of Using GenAI, while Technology Trendiness and Innate Creativity influence their Usage Purpose. Both Habit and Usage Purpose, together with Innate Creativity, contribute to Creativity Enhancement through GenAI, which reflects improvements in originality, idea diversity, and creative performance. In addition, demographic factors such as gender, age, academic discipline, and income are included as control variables. By integrating technology acceptance and creativity theories, the framework provides a comprehensive explanation of how technological, social, and individual factors shape creative outcomes in the GenAI era.

The model was illustrated in Figure 1.

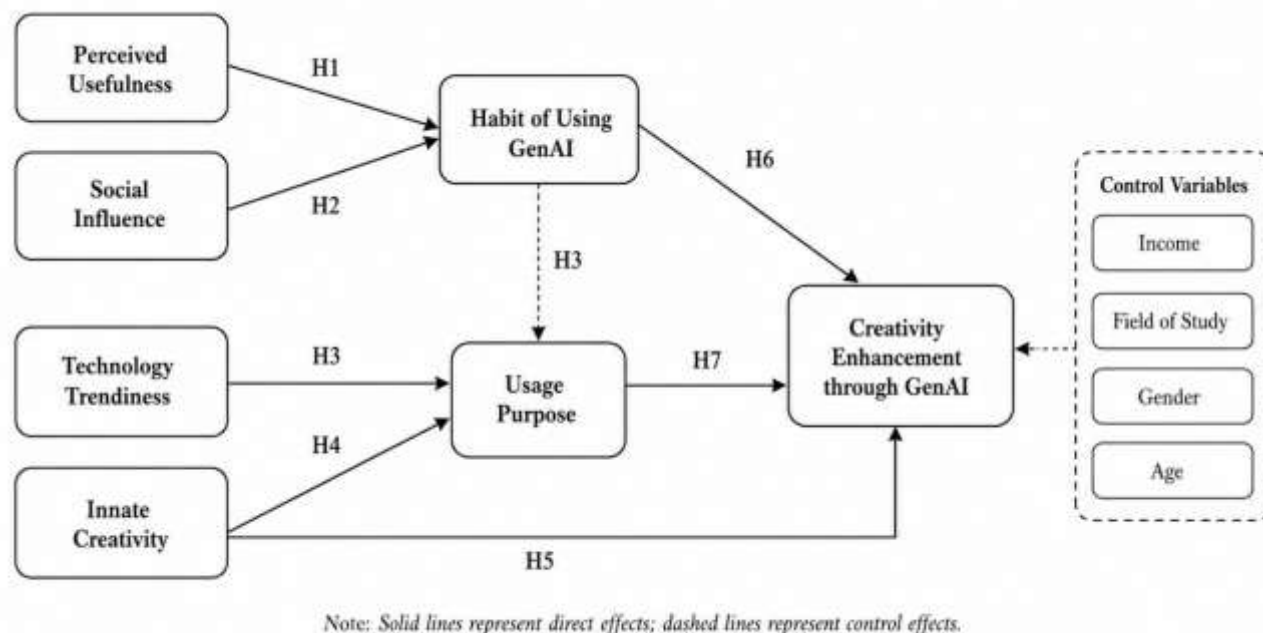


**Figure 1:** The research model proposal

### 3. METHODOLOGY

This study employs a quantitative research design using a cross-sectional survey to examine the factors influencing students' creativity through GenAI. A structured questionnaire was developed based on validated scales from previous studies and measured using a five-point Likert scale ranging from 1 to 5 [10]. The target population consists of university students and young adults aged from 18 to 30 who have used GenAI tools such as ChatGPT, Gemini, or Midjourney for at least three months. A minimum sample size of 300 respondents was targeted to ensure adequate statistical power for structural analysis [14]. Data were collected through online platforms, including Google Forms and Qualtrics. The analysis process included descriptive statistics, reliability assessment using Cronbach's Alpha and CR, and validity testing through EFA and CFA. The proposed hypotheses were examined using SEM, while bootstrapping procedures were employed to assess the significance of direct, mediating, and moderating effects within the research model [9, 10]. This approach provides a robust framework for investigating the relationship between GenAI usage and creativity enhancement.

### 4. FINDINGS

#### 4.1 Descriptive Statistics

A total of 448 questionnaires were collected for this study. After data screening, 48 responses (10.71%) were excluded due to incomplete information or invalid answers, resulting in 400 valid responses for analysis, representing an effective response rate of 89.29%. The demographic characteristics of the respondents are presented in Table 1.

**Table 1:** Descriptive Statistics

| <i>Variable</i>  | <i>Category</i>               | <i>Frequency</i> | <i>Percentage (%)</i> |
|------------------|-------------------------------|------------------|-----------------------|
| GenAI Experience | Used GenAI                    | 371              | 92.80%                |
|                  | Heard of GenAI but never used | 29               | 7.20%                 |
| Gender           | Male                          | 167              | 41.75%                |
|                  | Female                        | 231              | 57.75%                |
|                  | Other                         | 2                | 0.50%                 |
| Age              | 12-17                         | 48               | 12.00%                |
|                  | 18-25                         | 327              | 81.75%                |
|                  | 26-30                         | 25               | 6.25%                 |
| Income           | No income                     | 12               | 3.00%                 |
|                  | 1 - 3 million VND             | 231              | 57.75%                |
|                  | 4 - 7 million VND             | 96               | 24.00%                |
|                  | 8 - 15 million VND            | 38               | 9.50%                 |
|                  | 16 - 30 million VND           | 23               | 5.75%                 |
| Fields           | Science & Engineering         | 74               | 18.50%                |
|                  | Economics & Social Sciences   | 104              | 26.00%                |
|                  | Arts & Entertainment          | 52               | 13.00%                |
|                  | Education & Training          | 57               | 14.20%                |
|                  | Healthcare                    | 61               | 15.30%                |
|                  | Environment & Energy          | 52               | 13.00%                |

(Resource: Data from Survey)

The results indicate that the vast majority of respondents (92.8%) had prior experience using GenAI, while only 7.2% reported being aware of GenAI but had never used it. This finding highlights the widespread adoption of GenAI among young people and confirms its growing presence in educational, professional, and creative activities.

Regarding gender distribution, female respondents accounted for the largest proportion of the sample (57.75%), followed by males (41.75%), while respondents identifying as other genders represented only 0.50%. This relatively balanced distribution provides an appropriate basis for examining potential gender-related differences in GenAI adoption and creative outcomes.

In terms of age, the sample was heavily concentrated in the 18–25 age group, which represented 81.75% of all respondents. Participants aged 12–17 accounted for 12.00%, while those aged 26–30 represented only 6.25%. The dominance of the 18–25 group reflects the strong engagement of

university students and young adults with emerging digital technologies, particularly GenAI applications.

The income profile further confirms the youthful nature of the sample. More than half of the respondents (57.75%) reported a monthly income between 1 and 3 million VND, while 24.00% earned between 4 and 7 million VND. Respondents with incomes ranging from 8 to 15 million VND and 16 to 30 million VND accounted for 9.50% and 5.75%, respectively, whereas only 3.00% reported having no income. These findings suggest that the majority of respondents were students or early-career professionals with relatively modest financial resources.

The distribution across academic disciplines demonstrates the multidisciplinary relevance of GenAI. Respondents from Economics and Social Sciences constituted the largest group (26.00%), followed by Science and Engineering (18.50%), Healthcare (15.30%), Education and Training (14.20%), Arts and Entertainment (13.00%), and Environment and Energy (13.00%). This diversity indicates that GenAI adoption extends beyond technology-related fields and is increasingly utilized across domains requiring creativity, problem-solving, and knowledge generation.

The descriptive statistics reveal that GenAI has become a widely adopted technology among young users, particularly university students and early-career professionals. The high usage rate, combined with the diversity of academic backgrounds represented in the sample, suggests that GenAI is no longer confined to technical disciplines but has evolved into a cross-disciplinary tool supporting learning, creativity, and innovation. These characteristics provide a robust foundation for examining the factors influencing creativity enhancement through GenAI and for testing the proposed research model.

### 5.1 Cronbach's Alpha Analysis

Before conducting EFA and SEM, the reliability of the measurement scales was assessed using Cronbach's Alpha to evaluate internal consistency among observed variables. The analysis was performed on six independent constructs and one dependent construct, comprising a total of 27 observed variables. According to the criteria proposed by [4, 14] and [ a Cronbach's Alpha value above 0.70 indicates satisfactory reliability.

The results demonstrate that all constructs achieved Cronbach's Alpha values ranging from 0.752 to 0.902, exceeding the recommended threshold and confirming strong internal consistency. Furthermore, all Corrected Item Total Correlations were above 0.50, indicating that each observed variable contributed meaningfully to its corresponding construct. No items were removed during the reliability assessment process.

Specifically, the Social Influence (XH) scale exhibited the highest reliability ( $\alpha = 0.902$ ), followed by Technology Trendiness (CN) ( $\alpha = 0.891$ ), Perceived Usefulness (HI) ( $\alpha = 0.883$ ), and Innate Creativity (STBS) ( $\alpha = 0.878$ ). The scales measuring Habit of Using GenAI (MDTQ) and Usage Purpose (MD) both achieved Cronbach's Alpha values of 0.827, indicating good reliability. The dependent construct,

Creativity Enhancement through GenAI (ST), obtained a Cronbach's Alpha value of 0.752, which is considered acceptable for a scale containing only three observed variables [14].

This finding suggests that removing any item would not improve scale reliability, further supporting the retention of all measurement items. Overall, the reliability analysis confirms that all constructs satisfy the recommended standards for internal consistency and are suitable for subsequent EFA, CFA, and SEM analyses.

## 5.2 Exploratory Factor Analysis (EFA)

Following the reliability assessment, the EFA was conducted to evaluate the underlying factor structure, convergent validity, and discriminant validity of the measurement scales. The analysis employed Principal Component Analysis (PCA) with Varimax rotation, a widely accepted technique for identifying latent constructs and maximizing factor interpretability [14]. The EFA procedure was performed separately for the independent variables and mediating variables.

The EFA analysis was first conducted on 16 observed variables representing four independent constructs: Social Influence (XH), Technology Trendiness (CN), Perceived Usefulness (HI), and Innate Creativity (STBS). The results demonstrated excellent sampling adequacy, with a KaiserMeyerOlkin (KMO) value of 0.856, exceeding the recommended threshold of 0.50 [10]. Furthermore, Bartlett's Test of Sphericity was statistically significant ( $\chi^2 = 3784.041$ ,  $df = 120$ ,  $p < 0.001$ ), indicating sufficient correlations among the variables for factor analysis.

**Table 2.** Hệ số KMO và Bartlett's

|                                                        |                    |              |
|--------------------------------------------------------|--------------------|--------------|
| <i>Kaiser-Meyer-Olkin Measure of Sampling Adequacy</i> |                    | <i>0.856</i> |
| Bartlett's Test of Sphericity                          | Approx. Chi-Square | 3784.041     |
|                                                        | df                 | 120          |
|                                                        | Sig.               | 0.000        |

(Resource: Data from Survey)

**Table 3.** Total Variance Explaine

| Comp<br>onent | Total | <i>Initial<br/>Eigenvalues</i> |                  | <i>Extractuion Sums of<br/>Squared Loadings</i> |                      |                  | <i>Rotation Sums of<br/>Squared Loadings</i> |                      |                     |
|---------------|-------|--------------------------------|------------------|-------------------------------------------------|----------------------|------------------|----------------------------------------------|----------------------|---------------------|
|               |       | % of<br>Varian<br>ce           | Cumulat<br>ive % | Total                                           | % of<br>Varian<br>ce | Cumulat<br>ive % | Total                                        | % of<br>Varian<br>ce | Cumul<br>ative<br>% |
| 1             | 4.503 | 28.144                         | 28.144           | 4.503                                           | 28.144               | 28.144           | 3.106                                        | 19.415               | 19.415              |
| 2             | 3.506 | 21.913                         | 50.056           | 3.506                                           | 21.913               | 50.056           | 3.043                                        | 19.018               | 38.433              |
| 3             | 2.644 | 16.522                         | 66.579           | 2.644                                           | 16.522               | 66.579           | 2.972                                        | 18.577               | 57.010              |
| 4             | 1.415 | 8.842                          | 75.420           | 1.415                                           | 8.842                | 75.420           | 2.946                                        | 18.411               | 75.420              |

|    |       |       |         |  |  |  |  |  |  |
|----|-------|-------|---------|--|--|--|--|--|--|
| 5  | 0.507 | 3.169 | 78.589  |  |  |  |  |  |  |
| 6  | 0.421 | 2.630 | 81.219  |  |  |  |  |  |  |
| 7  | 0.389 | 2.430 | 83.648  |  |  |  |  |  |  |
| 8  | 0.366 | 2.285 | 85.934  |  |  |  |  |  |  |
| 9  | 0.335 | 2.093 | 88.026  |  |  |  |  |  |  |
| 10 | 0.322 | 2.011 | 90.038  |  |  |  |  |  |  |
| 11 | 0.311 | 1.943 | 91.981  |  |  |  |  |  |  |
| 12 | 0.281 | 1.754 | 93.735  |  |  |  |  |  |  |
| 13 | 0.279 | 1.746 | 95.481  |  |  |  |  |  |  |
| 14 | 0.254 | 1.585 | 97.066  |  |  |  |  |  |  |
| 15 | 0.246 | 1.537 | 98.603  |  |  |  |  |  |  |
| 16 | 0.224 | 1.397 | 100.000 |  |  |  |  |  |  |

(Resource: Data from Survey)

The PCA results extracted four factors, consistent with the proposed theoretical framework. The cumulative variance explained reached 75.42%, substantially exceeding the minimum recommended level of 50%. All extracted factors exhibited Eigenvalues greater than 1, with the lowest Eigenvalue equal to 1.415, satisfying Kaiser's criterion for factor retention. The rotated component matrix revealed that all factor loadings exceeded 0.80, indicating strong convergent validity. Specifically, factor loadings ranged from 0.811 to 0.873, and no significant cross-loadings were observed. Each observed variable loaded strongly onto its intended construct, confirming clear discriminant validity and supporting the theoretical distinction among the four independent variables.

A second EFA was performed on eight observed variables representing the two mediating constructs: Habit of Using GenAI (MDTQ) and Usage Purpose (MD). The results again confirmed the suitability of the dataset for factor analysis, with a KMO value of 0.838 and a significant Bartlett's Test of Sphericity ( $\chi^2 = 1188.940$ ,  $df = 28$ ,  $p < 0.001$ ).

The PCA extraction identified two distinct factors, explaining 66.05% of the total variance, which exceeds the recommended threshold. Both factors had Eigenvalues greater than 1 (3.543 and 1.741, respectively), supporting their retention. The rotated component matrix demonstrated strong factor loadings ranging from 0.774 to 0.825, with all items loading exclusively on their respective constructs. No problematic cross-loadings were detected, indicating satisfactory convergent and discriminant validity.

Overall, the EFA findings provide strong empirical support for the proposed measurement structure. All 24 observed variables were retained, and the six constructs exhibited clear factor structures and satisfactory psychometric properties. These results confirm the adequacy of the measurement model and provide a solid foundation for subsequent CFA and SEM analyses.

### 5.3 Confirmatory Factor Analysis (CFA)

Following the EFA, CFA was conducted to validate the measurement model and assess the reliability, convergent validity, and discriminant validity of the constructs. CFA enables researchers to verify whether the observed variables adequately represent their corresponding latent constructs and whether the proposed measurement model fits the empirical data [14].

The CFA results indicate that all standardized factor loadings exceeded the recommended threshold of 0.50, with most loadings above 0.70, demonstrating that the observed variables reliably measured their intended latent constructs. No indicators required removal, suggesting strong measurement stability across all constructs.

The overall goodness-of-fit indices demonstrate an excellent fit between the measurement model and the observed data. The model achieved a Chi-square ( $\chi^2$ ) value of 414.451 with 303 degrees of freedom, resulting in a CMIN/df ratio of 1.368, well below the recommended threshold of 2.0. Furthermore, the GFI = 0.930 exceeded the minimum acceptable level of 0.90. The incremental fit indices also indicated excellent model fit, with TLI = 0.978 and CFI = 0.981, both substantially above the recommended threshold of 0.90 [15]. Additionally, the RMSEA = 0.030 was significantly below the recommended cutoff value of 0.06, indicating a very low approximation error and excellent model fit.

The results showed CR values ranging from 0.751 to 0.902, exceeding the recommended threshold of 0.70 and confirming satisfactory internal consistency. Convergent validity was assessed through the AVE, with values ranging from 0.503 to 0.698, all above the minimum acceptable level of 0.50 [9]. These findings indicate that the observed variables adequately explain the variance of their respective latent constructs.

Discriminant validity was examined using both the MSV criterion and the Fornell–Larcker criterion. The results revealed that all AVE values were greater than their corresponding MSV values, satisfying the discriminant validity requirement. Furthermore, the square root of each construct's AVE exceeded its correlations with other constructs, confirming that each construct captures a unique conceptual domain.

The inter-construct correlations showed varying levels of association. A strong positive relationship was observed between Habit of Using GenAI (TQSD) and Usage Purpose (MD) ( $r = 0.65$ ). Moderate correlations were found between Social Influence (XH) and Perceived Usefulness (HI) ( $r = 0.49$ ), as well as between Innate Creativity (STBS) and Social Influence (XH) ( $r = 0.33$ ). In contrast, Technology Trendiness (CN) and Innate Creativity (XH) exhibited a weak correlation ( $r = 0.09$ ). These results indicate that while the constructs are related, they remain conceptually distinct and free from serious multicollinearity issues.

Overall, the CFA results provide strong evidence supporting the adequacy of the measurement model. All constructs demonstrated satisfactory reliability ( $CR > 0.70$ ), convergent validity ( $AVE > 0.50$ ), and discriminant validity ( $MSV < AVE$  and Fornell–Larcker criterion satisfied). The excellent model

fit indices further confirm that the proposed measurement model accurately represents the observed data. Therefore, the model is considered valid and reliable and is suitable for subsequent SEM analysis.

#### 5.4 Structural Equation Modeling (SEM) Results

Following the validation of the measurement model through CFA, SEM was employed to examine the hypothesized causal relationships among the latent constructs. SEM provides a comprehensive framework for simultaneously assessing model fit and testing the proposed hypotheses, thereby offering robust empirical evidence regarding the determinants of creativity enhancement through GenAI.

The SEM results indicate an excellent fit between the proposed structural model and the observed data. As presented in Figure 2, the model achieved a Chi-square ( $\chi^2$ ) value of 427.145 with 311 degrees of freedom, yielding a CMIN/df ratio of 1.373, which is well below the recommended threshold of 3.0 [15]. The GFI reached 0.928, exceeding the recommended value of 0.90 [4]. Furthermore, the incremental fit indices demonstrated outstanding model performance, with TLI = 0.978 and CFI = 0.981, both substantially above the suggested threshold of 0.95. The RMSEA was 0.031, indicating a very low level of approximation error and an excellent model fit [22]. Collectively, these indices confirm that the structural model adequately represents the empirical data and is suitable for hypothesis testing.

The standardized path coefficients reveal several significant relationships among the latent variables. The CN exerted a positive and significant effect on STBS ( $\beta = 0.43$ ), suggesting that individuals who are more responsive to emerging technological trends tend to exhibit higher levels of creative thinking. In turn, STBS positively influenced MD ( $\beta = 0.34$ ), indicating that highly creative individuals are more likely to utilize GenAI strategically for learning, idea generation, and creative exploration. Additionally, Perceived Usefulness HI demonstrated a significant positive effect on TQSD ( $\beta = 0.35$ ), confirming that students who perceive GenAI as beneficial are more likely to integrate it into their daily activities.

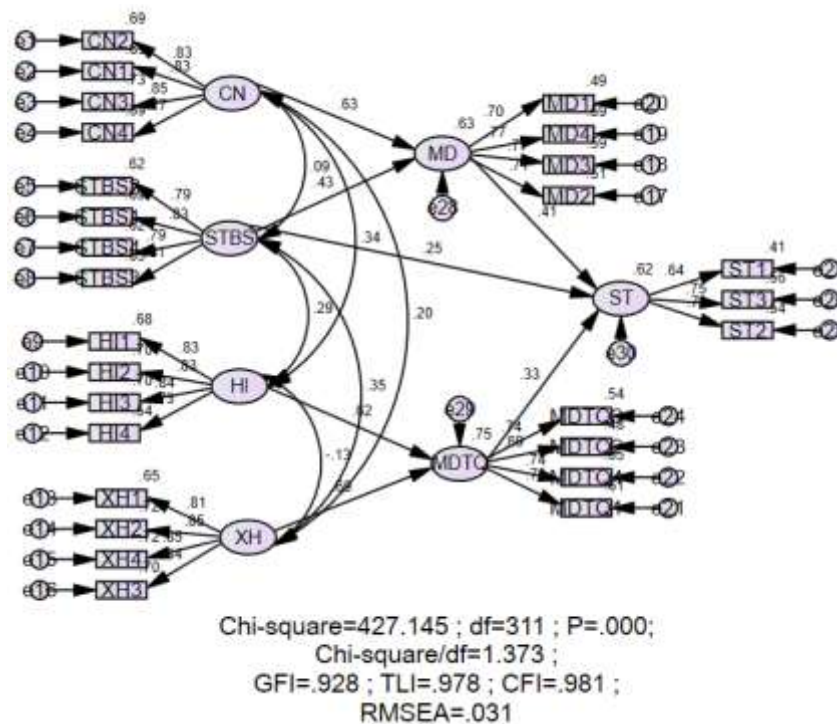


**Figure 3:** The SEM results

These findings support the theoretical assumptions underlying TAM2 and the CTC, highlighting the importance of technological perceptions and personal creative capabilities in shaping GenAI usage behavior and creative outcomes.

The SEM results further confirmed the reliability of the measurement model. All standardized factor loadings exceeded the recommended threshold of 0.50, with most values surpassing 0.70. For example, CN2 → CN (0.83), STBS2 → STBS (0.79), and HI2 → HI (0.84) demonstrated strong relationships between the observed indicators and their corresponding latent constructs. These results indicate that the measurement items reliably capture the theoretical concepts under investigation.

**Table 4:** Structural Model Evaluation Results

| <i>Hypothesis<br/>(Structural Path)</i> | <i>Unstandardized<br/>Coefficient</i> | <i>Standardized<br/>Coefficient<br/>(β)</i> | <i>t-value</i> | <i>p-value</i> | <i>VIF</i> | <i>Result</i> |
|-----------------------------------------|---------------------------------------|---------------------------------------------|----------------|----------------|------------|---------------|
| H1: (MDTQ ← HI)                         | 0.456                                 | 0.620                                       | 12.419         | ***            | 1.015      | Supported     |
| H2: (MDTQ ← XH)                         | 0.532                                 | 0.694                                       | 13.152         | ***            | 1.015      | Supported     |
| H3: (MD ← CN)                           | 0.432                                 | 0.630                                       | 11.148         | ***            | 1.007      | Supported     |
| H4: (MD ← STBS)                         | 0.330                                 | 0.429                                       | 8.463          | ***            | 1.007      | Supported     |
| H5: (ST ← STBS)                         | 0.188                                 | 0.252                                       | 4.236          | ***            | 1.308      | Supported     |

|                            |       |       |       |     |       |           |
|----------------------------|-------|-------|-------|-----|-------|-----------|
| H6: (ST $\leftarrow$ MDTQ) | 0.298 | 0.334 | 5.729 | *** | 1.219 | Supported |
| H7: (ST $\leftarrow$ MD)   | 0.396 | 0.409 | 6.379 | *** | 1.276 | Supported |

Overall, the SEM analysis provides strong empirical support for the proposed research framework. The structural model exhibited excellent goodness of fit indices, the hypothesized relationships were consistent with theoretical expectations, and all constructs demonstrated satisfactory reliability and validity. The findings suggest that perceptions of technology, social and behavioral factors, and innate creative capabilities jointly influence how young individuals utilize GenAI and subsequently enhance their creativity. These results offer valuable insights for educators, policymakers, and technology developers seeking to leverage GenAI as a tool for fostering creativity and innovation among students.

## 5. DISCUSSION AND IMPLICATIONS

The findings of this study provide substantial empirical evidence regarding the role of GenAI in fostering creativity among young users. By integrating the TAM2 [23] and the CTC [1, 2], the study offers a comprehensive explanation of how technological perceptions, social influences, individual creative characteristics, and usage behaviors collectively contribute to creativity enhancement. The results confirm that all proposed hypotheses are supported, highlighting the multifaceted nature of creativity development in AI-assisted environments.

Among the factors influencing the Habit of Using GenAI, Social Influence emerged as the most significant predictor ( $\beta = 0.694$ ), followed by Perceived Usefulness ( $\beta = 0.620$ ). This finding suggests that the adoption and continuous use of GenAI are strongly shaped by interactions with peers, instructors, and online communities, as well as by users' perceptions of the practical benefits offered by AI technologies. Consistent with the TAM2 [23], and Diffusion of Innovations Theory [20], young individuals are more likely to integrate GenAI into their daily activities when they perceive it as socially accepted and functionally valuable. Similar findings have been reported by [7], who argued that social and organizational support significantly influence the adoption of generative AI technologies.

The results further reveal that Technology Trendiness exerts a stronger influence on Usage Purpose ( $\beta = 0.630$ ) than Innate Creativity ( $\beta = 0.429$ ). This indicates that individuals who actively follow technological innovations are more likely to explore GenAI for learning, content creation, and problem-solving. However, innate creative ability remains a critical determinant, suggesting that highly creative individuals tend to use GenAI strategically as a co-creative partner rather than a substitute for independent thinking. This finding aligns with [1, 2] assertion that creativity emerges from the interaction between personal capabilities, motivation, and environmental resources. It also supports recent studies suggesting that AI can amplify human creativity when users possess strong creative self-efficacy and domain knowledge [13, 16].

A particularly important finding is that Usage Purpose exerts the strongest direct influence on Creativity Enhancement ( $\beta = 0.409$ ), followed by Habit of Using GenAI ( $\beta = 0.334$ ) and Innate Creativity ( $\beta = 0.252$ ). These results imply that creativity outcomes are determined not only by the frequency of AI use but also by the intentions underlying its use. Individuals who employ GenAI for idea exploration, knowledge expansion, and creative experimentation derive greater creative benefits than those who use it primarily for automation. This finding is consistent with recent evidence indicating that GenAI can enhance creative performance when applied as a collaborative cognitive tool rather than a replacement for human thinking [6, 8].

From a practical perspective, the findings suggest that educational institutions should promote AI literacy, critical thinking, and responsible AI usage to maximize the creative benefits of GenAI. Simultaneously, AI developers should improve the transparency, reliability, and educational value of AI systems. Although GenAI offers significant opportunities for creativity enhancement, excessive dependence on AI-generated outputs may reduce originality, critical reasoning, and idea diversity [6, 8, 10]. Consequently, GenAI should be viewed as a tool that augments rather than replaces human creativity. By fostering purposeful and balanced AI usage, educators, policymakers, and technology developers can leverage GenAI as a powerful catalyst for creativity, innovation, and lifelong learning in the digital era.

## 6. CONCLUSION

This study provides empirical evidence that GenAI plays a significant role in enhancing creativity among young users by influencing their usage habits, motivations, and creative behaviors. The findings confirm that Social Influence, Perceived Usefulness, Technology Trendiness, and Innate Creativity are important determinants of GenAI adoption and utilization. Moreover, Usage Purpose and Habit of Using GenAI were identified as the strongest predictors of creativity enhancement, highlighting the importance of purposeful and strategic AI usage. The study contributes to the literature by integrating TAM2 and the Componential Theory of Creativity into a unified framework for explaining creativity in AI-assisted environments. Overall, the results suggest that GenAI can serve as a powerful co-creative partner that supports innovation and creative development when used responsibly and effectively.

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