

# A Study on the Factors Influencing Young People's Choice to Use AI Tools for Creative Activities

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**Abstract:** Based on the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB) and the Theory of Social Norms, this study constructs a three-dimensional integrated 'technology–society–individual' model to investigate the key psychological and social factors driving young people's use of AI image and video generation tools. A total of 107 valid questionnaires were collected, and SPSS 27.0 was utilised to conduct descriptive statistics and multiple linear regression analyses. The findings revealed that respondents' perceived usefulness of AI tools had the highest mean score (5.51), whilst their behavioural intention had a mean of 5.26; however, perceived risk (5.22) and technology anxiety (4.87) were also at medium-to-high levels. The regression model indicated that professional background had a significant effect on usage frequency ( $\beta = 0.312$ ,  $p = 0.020$ ), whilst the direct effects of the various psychological variables on usage frequency were not statistically significant. The findings suggest that, in the context of AI creative tools, adoption behaviour is not only a product of psychological cognition but also the result of 'practical embedding'.

**Keywords:** AI Creative Tools; Technology Acceptance Model; Theory of Planned Behaviour; Usage Behaviour; Influencing Factors

## 1. Introduction

### 1.1 Research Background

1.1.1 Technological background: the explosive growth of generative AI and the democratisation of creative tools

In late 2022, OpenAI released ChatGPT, sparking a global cognitive revolution in artificial intelligence. Shortly thereafter, the successive emergence of AI image-generation tools-such as Midjourney, Stable Diffusion and DALL·E-alongside AI video-generation tools

including Runway, Pika and Sora, is rewriting the rules of visual content production at an unprecedented pace.

The far-reaching significance of this technological transformation lies in the fact that it liberates 'creative ability' from the monopoly of professional training. In the past, anyone wishing to produce professional-standard paintings, designs or video works often had to undergo years, or even decades, of systematic training. Today, a single natural-language description-known as a 'prompt'-is all that is needed to generate stunning visual works in a matter of seconds. As Manovich observes, AI-generated technology is liberating 'creative expression' from the constraints of 'skill scarcity', enabling more people to participate in the production of visual culture [1].

This trend towards the democratisation of technology means that AI creative tools are no longer merely the playthings of tech enthusiasts, but are rapidly permeating the everyday creative practices of ordinary people. From generating personal profile pictures on social media, to producing visual materials for commercial advertisements, to concept design previews in the film and television industry, the boundaries of AI-generated content (AIGC) applications are constantly expanding. According to relevant statistics, by the end of 2025, over 200 million users worldwide will have used AI image-generation tools, a significant proportion of whom will be young people [2].

1.1.2 User background: young people as 'natives' of the AI era

In this technological transformation, young people-particularly university students and young professionals aged between 18 and 35-have consistently played the dual roles of 'pioneers' and 'driving force'. Having grown up in an era of highly developed internet and mobile communication technologies, this demographic demonstrates a far greater acceptance of and adaptability to emerging digital tools than other age groups. They are not

only the earliest adopters of AI tools but also their most active users and promoters.

Relevant surveys indicate that the usage rate of AI tools among the surveyed university student population has reached 99.18 per cent (China Youth Daily, 2026a) [3]. This implies that, on contemporary university campuses, almost every student has, to a greater or lesser extent, encountered or utilised AI tools. AI is no longer an 'optional extra', but rather a 'default setting' embedded in the fabric of their studies and daily lives—from assisting with coursework, to visual design for student society promotions, to the creative production of personal portfolios, AI tools are ubiquitous.

However, behind this high usage rate lies a more complex question: what factors are driving young people to choose these AI tools? Is it a practical consideration to improve efficiency, or a psychological need for social recognition? Is it an intrinsic motivation driven by curiosity, or invisible pressure from the external environment? What, then, are the concerns of those young people who have not yet adopted these tools or remain hesitant? These questions pertain not only to an understanding of user behaviour, but also to the product design logic of AI tools, the direction of literacy education in higher education institutions, and even society's level of acceptance of the new paradigm of 'human-machine co-creation'.

**1.1.3 Theoretical background: controversy over the applicability of technology acceptance models**

In the field of information systems research, the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB) are the most classic theoretical frameworks for explaining users' technology adoption behaviour [4–5]. However, the core constructs of these two theories—perceived usefulness, perceived ease of use and subjective norm—were primarily developed in the late 1980s and early 1990s. The technological contexts upon which their theoretical frameworks were based centred mainly on productivity tools focused on office automation (such as word processors and spreadsheets).

The emergence of AI creative tools has posed new challenges to this theoretical framework. Such tools possess a unique 'dual nature': on the one hand, they are 'tools' that enhance creative efficiency—capable of generating visual content more rapidly and reducing the costs of repetitive

labour; on the other hand, they are 'partners' in the creative process—their outputs often exhibit unpredictable 'creativity' and can even spark new inspiration in users. This intertwining of the roles of 'tool' and 'partner' means that the adoption process for AI creative tools may be far more complex than that for traditional office software. At the same time, existing research exhibits a tendency to 'emphasise promotion whilst downplaying inhibition'. A vast body of literature is dedicated to verifying the positive impact of factors such as perceived usefulness and perceived ease of use on usage intention, whilst the examination of inhibitory factors—such as perceived risk and technological anxiety—remains relatively limited. For potential users who are hesitant about adopting AI tools, the explanatory power of inhibitory factors may be more critical than that of facilitating factors. Therefore, incorporating both facilitating and inhibitory factors into a single analytical framework will contribute to a more comprehensive understanding of users' technology adoption decisions.

## **1.2 Significance of the Study**

### **1.2.1 Theoretical significance**

The theoretical significance of this study is primarily reflected in the following three aspects:

Firstly, it extends the applicability of classical technology adoption theories to the context of AI creativity. By applying the core constructs of the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB) to the emerging technological context of AI image/video generation tools, this study tests their explanatory power within the specific domain of 'human-machine collaborative creation', thereby clarifying the boundary conditions and scope of application of classical theories.

Secondly, constructing a dual-pathway 'facilitating–inhibiting' analytical framework. This study incorporates both facilitating factors—such as perceived usefulness, perceived ease of use and subjective norms—and inhibiting factors—such as perceived risk and technology anxiety—in an attempt to provide a more comprehensive explanation of the symmetrical issues of 'why use' and 'why not use'.

Thirdly, we introduce social approval motivation and individual innovativeness as additional individual-level variables to explore the

boundary conditions of the influence mechanisms, thereby avoiding simplistic, 'one-size-fits-all' judgements regarding the roles of influencing factors.

### 1.2.2 Practical implications

At the practical level, the findings of this study can provide guidance in the following areas: firstly, they offer insights into user needs for AI tool developers, guiding the optimisation of product features and user experience design; secondly, they provide empirical evidence for AI literacy education in higher education institutions, helping educators understand students' motivations for use and their concerns; thirdly, they offer guidance for the design of communication strategies targeting young users, guiding the production of differentiated content and targeted outreach.

## 1.3 Research Objectives and Research Questions

This study aims to systematically investigate the key psychological and social factors driving young people's use of AI image and video generation tools. The specific research questions are as follows:

- (1) How does young people's perceived usefulness of AI-generated tools influence their willingness to use them?
- (2) Do perceived risks (such as copyright issues and uncertainty regarding quality) constitute barriers to use?
- (3) How do subjective norms (peer influence, social trends) promote usage behaviour?
- (4) Does the need for social approval drive usage behaviour?
- (5) Does the pleasure derived from use drive adoption independently of practical value?
- (6) Does technological anxiety inhibit the willingness to use these tools?

## 2. Theoretical Framework and Research Hypotheses

### 2.1 The Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), proposed by Davis in 1989, is one of the most influential theoretical frameworks in the field of information systems research [4]. Based on the Theory of Reasoned Action, this model aims to explain and predict individuals' acceptance of information technology.

The core logic of TAM is concise and compelling: an individual's use of a technology

is determined by their intention to use it; in turn, this intention is primarily influenced by two cognitive variables. The first variable is 'Perceived Usefulness' (PU), defined as 'the extent to which an individual believes that using a specific system can enhance their work performance'. When users believe that a particular technology can help them complete tasks more efficiently and to a higher standard, their attitude towards the technology tends to be positive, and their intention to use it consequently increases. The second variable is 'Perceived Ease of Use' (PEOU), defined as 'the extent to which an individual believes that using a specific system does not require excessive effort'. [4] The easier a technology is to master, the lower the barrier to entry for users, and the greater the likelihood of adoption.

The enduring relevance of TAM lies in the robust explanatory power of its variables across different technological contexts. Since its inception, the model has been extensively validated in numerous fields, including office automation, e-commerce, mobile applications and social media. However, when technology itself evolves from a passive 'tool' into an active 'creative participant', can perceived usefulness still effectively predict the use of AI creative tools, just as it does for the adoption of office software? This question remains to be empirically tested. This study adopts TAM as one of its core frameworks to examine the applicability of its core constructs in the context of AI-driven creativity and to critically assess its explanatory power.

### 2.2 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB), proposed by Ajzen in 1991, is an extension and refinement of the Theory of Rational Action [5]. This theory posits that human behavioural intentions are the result of careful deliberation and are influenced by three core variables.

The first variable is 'Attitude towards the Behaviour', which refers to an individual's positive or negative evaluation of performing a particular behaviour. The second variable is 'Subjective Norm' (SN), which refers to the social pressure an individual perceives from significant others or groups regarding whether they believe the individual should perform the behaviour [5]. The third variable is 'Perceived Behavioural Control', which refers to an individual's perception of the ease or difficulty

of performing a particular behaviour; it reflects an individual's assessment of their own capabilities and available resources.

Of these three variables, 'Subjective Norm' aligns closely with the social impact concerns addressed in this study. In decisions regarding the use of AI tools, subjective norm may play a role in various forms: the usage behaviour of peers, the intensity of discussions on social media, and the recommendations or objections of significant others may all shape an individual's perception of 'whether one should use AI tools'. Particularly amongst young people, the influence of peer effects and a sense of group belonging cannot be overlooked. This study incorporates subjective norms into the model to examine their role in promoting usage intention.

### 2.3 Social Norm Theory

Social Norms Theory provides a more refined analytical framework for understanding the mechanisms by which subjective norms operate. This theory distinguishes between two types of norms. The first is 'descriptive norms', which refer to individuals' perceptions of 'what others are actually doing'. When young people observe an increasing number of people around them using AI tools, this behaviour itself constitutes a form of social proof, suggesting that 'using AI tools is normal and acceptable'. The second type is 'injunctive norms', which refer to an individual's perception of 'what others think I ought to do' [6]. This involves expectations regarding social rewards and punishments—that is, doing so will be recognised, whilst not doing so may lead to marginalisation.

These two types of norms play distinct yet complementary roles in the social diffusion of AI tools. Descriptive norms answer the question 'Is everyone doing this?', thereby lowering the psychological barriers to the behaviour; injunctive norms, on the other hand, answer the question 'Does everyone think I should do this?', thereby reinforcing the legitimacy of the behaviour.

### 2.4 Formulation of Research Hypotheses

Based on the theoretical reasoning outlined above, this study proposes the following research hypotheses:

#### 2.4.1 Positive effect hypotheses

H1: Perceived usefulness has a significant positive influence on young people's behavioural intention to use AI tools [4].

The logical basis for this hypothesis lies in the core proposition of the Technology Acceptance Model (TAM): users believe that AI tools help to enhance creative efficiency and quality, thereby making them more likely to develop an intention to use them.

H2: Perceived ease of use has a significant positive effect on young people's behavioural intention to use AI tools [4].

The lower the barrier to entry for an AI tool, the easier it is for users to get to grips with it, and the stronger their intention to use it becomes.

H3: Subjective norms (peer usage, social trends) have a significant positive influence on behavioural intention [5–6].

Based on the Theory of Planned Behaviour (TPB) and social norm theory, perceived social pressure prompts individuals to conform to group behaviour patterns.

#### 2.4.2 Hypotheses regarding negative influences

H4: Perceived risks (copyright concerns, quality uncertainty) have a significant negative impact on behavioural intention [7].

When users believe that using AI tools may entail risks such as copyright disputes or unreliable quality, their intention to use is inhibited.

H5: Technological anxiety (concerns that AI will replace human creativity) has a significant negative effect on usage intention.

Deep-seated concerns that 'AI will eventually replace human creators' may lead some users to deliberately keep their distance in order to reduce cognitive dissonance.

## 3. Research Methodology

### 3.1 Questionnaire Design

This study employed a questionnaire survey as the primary means of data collection. All scales used in the questionnaire were derived from published academic literature to ensure content validity.

The specific sources of the scales for each variable are as shown in Table 1.

**Table 1. Questionnaire Used for the Variables**

| Variable              | Scale Source                                        |
|-----------------------|-----------------------------------------------------|
| Perceived Usefulness  | Davis (1989) original TAM scale [4]                 |
| Perceived Ease of Use | Davis (1989) original TAM scale [4]                 |
| Subjective Norm       | Ajzen (1991) TPB scale [5]                          |
| Perceived Risk        | Featherman & Pavlou (2003) Perceived Risk Scale [7] |

|                              |                                                                                                                                                                                       |
|------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Technological Anxiety        | Venkatesh et al. (2003) UTAUT Anxiety Subscale [8]                                                                                                                                    |
| Enjoyment of Use             | Davis et al. (1992) Intrinsic Motivation Scale [9]                                                                                                                                    |
| Social Approval Motivation   | Self-constructed (based on Social Approval Theory)                                                                                                                                    |
| Personal innovativeness      | Agarwal & Karahanna (2000) [10]                                                                                                                                                       |
| Behavioural Intention        | Venkatesh et al. (2003) UTAUT Scale (Unified Theory of Acceptance and Use of Technology) was proposed by Venkatesh, Morris, Davis, and Davis in 2003 and published in MIS Quarterly.) |
| Influence of opinion leaders | Self-constructed (based on two-step flow theory)                                                                                                                                      |

All scale items were measured using a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

### 3.2 Data Collection

#### 3.2.1 Survey participants

The participants in this study were young people who had used or were likely to use AI image/video generation tools, specifically university students aged 18–25 and young professionals aged 26–35. These two groups were selected primarily for the following reasons: university students are in a phase of rapid accumulation of knowledge and skills, are sensitive to emerging technologies, and have a wide range of usage scenarios; young professionals, on the other hand, face more direct pressure to improve work efficiency and have a more urgent need for AI tools.

#### 3.2.2 Survey process

The questionnaire was distributed online via the Credamo platform. Credamo is a specialised academic research platform in China, possessing a sample database covering all age groups and industries, and has been utilised in numerous academic studies. The questionnaire was distributed from May to June 2026, over a period of four weeks.

Prior to the formal distribution, a small-scale pilot study (N=30) was conducted. Based on the feedback from this pilot, the wording of some questions was slightly adjusted to ensure clarity and unambiguity. A screening question (Q1) was included in the formal survey to identify respondents who did not meet the study criteria.

#### 3.2.3 Sample composition

A total of 107 valid questionnaires were returned. The detailed composition of the sample is as follows:

Gender distribution: 38 males (35.5 per cent) and 69 females (64.5 per cent). The proportion of female respondents was significantly higher than that of males. This ratio may reflect a higher penetration rate of AI creative tools amongst women, or it may be related to gender bias in the sampling channels.

Age distribution: 33 respondents aged 18–25 (30.8 per cent), 35 aged 26–35 (32.7 per cent), and 39 aged 36 and over (36.4 per cent). It is worth noting that whilst this study operationally defined 'young people' as those aged 18–35, nearly 40 per cent of the respondents in the actual sample were over 35 years old. This discrepancy suggests that the actual user base for AI creative tools may be broader than anticipated, and that the group of middle-aged and older adults aged 36 and above should not be overlooked.

Distribution by status: 35 respondents were university students (32.7 per cent), 54 were working professionals (50.5 per cent) and 18 were in other categories (16.8 per cent). The fact that working professionals accounted for over half of the sample suggests that AI tools may already have penetrated professional settings quite deeply.

Distribution by academic/professional background: 30 respondents (28.0 per cent) were in creative fields, 13 (12.1 per cent) in science and engineering, 33 (30.8 per cent) in the humanities and social sciences, and 31 (29.0 per cent) in other fields. The distribution across these categories was relatively balanced, providing a foundation for subsequent inter-group comparative analysis.

### 3.3 Analytical Methods

This study utilised SPSS 27.0 for data analysis, comprising two stages.

Stage One: Descriptive statistical analysis. The mean and standard deviation of each variable were calculated to characterise the sample's overall performance across the core variables. The mean reflects central tendency, whilst the standard deviation reflects the degree of dispersion. For the 7-point scale, a mean above 5 indicates that respondents generally hold a positive attitude, around 4 indicates a neutral attitude, and below 3 indicates a negative attitude.

Stage Two: Multivariate linear regression analysis. With frequency of use (Q6) as the dependent variable, all scale items were included

as independent variables in the regression model to investigate the predictive role of various factors on actual usage behaviour. The regression model employed the 'enter' method, whilst controlling for the influence of demographic variables. A collinearity diagnosis was conducted prior to the regression analysis to ensure that the variance inflation factor (VIF) for each variable was below the threshold value of

10.

## 4. Research Findings

### 4.1 Descriptive Statistics

Descriptive statistics provide an initial 'snapshot' for understanding the psychological state of the respondents. The means and standard deviations of each core variable are shown in Table 2.

**Table 2. Descriptive Statistics of Core Variables**

| Variable                     | N   | Minimum | Maximum | Mean   | Standard deviation |
|------------------------------|-----|---------|---------|--------|--------------------|
| Perceived Usefulness (PU)    | 107 | 1       | 7       | 5.51   | 1.39               |
| Perceived Ease of Use (PEOU) | 107 | 1       | 7       | 21 May | 1.32               |
| Subjective Norm (SN)         | 107 | 1       | 7       | 5.35   | 1.31               |
| Perceived Risk (PR)          | 107 | 1       | 7       | 5.22   | 1.55               |
| Technology Anxiety (TA)      | 107 | 1       | 7       | 4.87   | 1.59               |
| Pleasure of Use (PE)         | 107 | 1       | 7       | 5.10   | 1.40               |
| Behavioural Intention (BI)   | 107 | 1       | 7       | 5.26   | 1.45               |

Note: The score for each dimension is the arithmetic mean of all items within that dimension.

The following provides a detailed analysis of several key findings.

#### 4.1.1 Highest perceived usefulness: efficiency is the primary driver

Perceived usefulness ranked first among the seven dimensions with a mean score of 5.51. This result indicates that the primary driver for young people's use of AI creative tools remains 'usefulness'-they believe these tools can enhance creative efficiency, improve the quality of their work, and help them accomplish tasks that would otherwise be difficult to achieve. Looking at the mean scores for individual items, 'Using AI tools improves my creative efficiency' scored the highest (5.67), followed by 'Using AI tools helps my creative work' (5.59), and then 'Overall, I find AI tools very useful for my creative work' (5.50).

This finding is not surprising, but it serves as a reminder of a fundamental truth: no matter how 'cool' or 'trendy' AI tools may be, if they fail to deliver on their functional promises, they are unlikely to retain users' favour in the long term. 'Usefulness' is the cornerstone of all technology adoption, and this has not changed in the age of AI.

#### 4.1.2 Perceived risks and technological anxiety: the 'other side' that cannot be ignored

Perceived risk (5.22) and technological anxiety (4.87) constitute the 'shadow side' of this picture. Users do not embrace AI unreservedly-they are concerned about unclear copyright ownership, unreliable output quality, the misuse of their

creative data, and even the prospect that AI will eventually replace human creators.

Specifically, all four items relating to perceived risk scored above 5: 'Concern about unclear copyright ownership of AI-generated content' (5.32), 'Concern that my creative data might be misused by AI tools' (5.23), 'Concern that using AI tools may raise ethical issues' (5.17), and 'Concern about the unreliable quality of AI-generated content' (5.14). This indicates that users' perception of risk is multidimensional, encompassing various aspects such as legal, ethical, quality and data security concerns.

In terms of technological anxiety, the item with the highest score was "I believe over-reliance on AI will undermine human creativity" (5.43)-a rather telling finding: although young people are using AI tools, deep down they remain wary of the "erosion of creativity". This was followed by "concern that AI tools will replace human creators" (4.83), "concern that I am losing my creative abilities when using AI tools" (4.72), and "feeling uneasy at the thought of AI entering the creative sphere" (4.49).

An average score of nearly 5 points for technology-related anxiety suggests that these concerns are not merely the 'groundless fears of a minority', but rather a fairly widespread psychological state. Relevant surveys corroborate this assessment: 46.99 per cent of university students are concerned that long-term use of AI will weaken their ability to construct arguments from scratch (China Youth Daily, 2026b). This contradictory mindset of 'both reliance and wariness' may be a key entry point for understanding user behaviour in the AI era

[11].

#### 4.1.3 Subjective norms: the permeating influence of social factors

Subjective norms (5.35) ranked second among the seven dimensions, second only to perceived usefulness. This indicates that social influence plays a significant role in young people's decision-making regarding the use of AI tools. The scores for "Many of my peers are using AI tools" (5.45) and "More and more people in my social circle are using AI tools" (5.49) were particularly high, illustrating the significant influence of descriptive norms-when young people perceive that "everyone is using them", adopting AI tools becomes a conventional choice.

"Everyone on social media is discussing AI creative tools" (5.37) also corroborates the shaping influence of the media environment on usage behaviour. By contrast, "People important to me think I should use AI tools" (5.07) scored slightly lower, suggesting that the pressure from prescriptive norms within close social circles is relatively mild.

#### 4.1.4 Pleasure of use: the independent contribution of intrinsic motivation

Although the enjoyment of use (5.10) was

slightly lower than perceived usefulness, it remained at a medium-to-high level. 'Using AI tools for creative work is fun in itself' (5.21) received the highest score, followed by 'I enjoy exploring the various functions of AI tools' (5.10), 'Using AI tools gives me pleasure' (5.08) and 'AI tools inspire my creativity' (5.00).

These results provide empirical support for the notion that 'AI tools are not only useful but also fun'. For younger users, fun and creative inspiration are in themselves driving forces independent of practical value. This implies that the design of AI tools must not focus solely on functional optimisation; it must also address the emotional dimensions of the user experience-ensuring that users feel enjoyment and satisfaction whilst using them.

## 4.2 Results of Regression Analysis

Whilst descriptive statistics answer the question of 'what users are thinking', regression analysis seeks to answer 'what factors truly distinguish frequent users from infrequent users'. The results of the multiple linear regression analysis, with usage frequency as the dependent variable, are shown in Table 3.

**Table 3. Results of Regression Analysis (Dependent variable: Frequency of use)**

| Variable                      | Unstandardised Coefficient (B) | Standardised Coefficient (Beta) | t      | Significance |
|-------------------------------|--------------------------------|---------------------------------|--------|--------------|
| (Constant)                    | 5.069                          | -                               | 4.729  | 0.000        |
| Q3. Age                       | 0.345                          | 0.209                           | 1.440  | 0.155        |
| Q4. Status                    | -0.118                         | -0.049                          | -0.329 | 0.744        |
| Q5. Field of study/profession | 0.389                          | 0.312                           | 2.395  | 0.020*       |

\*Note: Only significant and near-significant variables are listed; the full model comprises 44 independent variables;  $p < 0.05$

Of the 44 independent variables, only one reached statistical significance: 'Field of Study/Occupation' ( $\beta = 0.312$ ,  $p = 0.020$ ). This implies that, all other things being equal, respondents with a creative academic or professional background use AI tools significantly more frequently.

This finding, whilst not surprising, is highly significant. Creative professionals-such as designers, artists and media practitioners-face a higher demand for visual content production, and AI image and video generation tools are, in effect, efficiency tools 'tailor-made' for them. In other words, the use of AI tools depends not merely on an individual's attitude towards them, but more significantly on the 'task fit' between the tools and the individual's daily practices. The

deeper AI tools are embedded within a workflow, the higher the frequency of use-a factor that may be more explanatory than any psychological variable.

None of the psychological variables reached statistical significance. The regression coefficients for perceived usefulness, perceived ease of use, subjective norms, perceived risk and technological anxiety were all statistically insignificant ( $p > 0.05$ ). This finding does not fully align with theoretical expectations, but it is not inexplicable. Possible reasons include the following three aspects:

Firstly, insufficient statistical power. A sample size of 107 is clearly too small for a regression model comprising 44 independent variables. Statistically speaking, each independent variable requires at least 10–15 observations to obtain a stable estimate-meaning this study would have required at least 440 observations to achieve an

acceptable level of statistical power. The insufficient sample size may have led to increased standard errors, thereby causing effects that might otherwise have been significant to be 'drowned out' by noise.

Secondly, there is an issue with the choice of dependent variable. The dependent variable in this study is 'frequency of use' rather than 'behavioural intention'. The core logical chain of the TAM and TPB is 'cognition → attitude → intention → behaviour'; psychological variables more directly influence 'behavioural intention' rather than 'actual behaviour'. The transition from intention to behaviour is also influenced by mediating or additional individual-level variables such as situational factors, convenience, and the power of habit. This study bypassed the intermediate stage of 'intention' and directly examined the effects of psychological variables on 'behaviour'; this may have 'lengthened' the causal chain, leading to a weakening of the effects.

Thirdly, there is the issue of multicollinearity amongst the independent variables. Variables such as perceived usefulness, enjoyment of use and behavioural intention are moderately correlated with one another, which may have diluted their respective independent explanatory power to some extent.

## 5. Discussion

### 5.1 Theoretical Interpretation of Key Findings

#### 5.1.1 'Love-hate relationship': Understanding the ambivalent mindset in AI adoption

The most striking descriptive finding of this study is the 'coexistence' of perceived usefulness alongside perceived risk and technological anxiety—respondents both highly valued the usefulness of AI tools (5.51) whilst remaining vigilant about their potential risks (perceived risk 5.22, technological anxiety 4.87).

This contradictory 'love-hate' mindset reflects the complexity of users' technology adoption decisions in the AI era. The traditional TAM model implicitly assumes a 'rational economic agent': users' attitudes towards technology are a simple sum of positive and negative factors, and an intention to use arises when positive factors outweigh negative ones. However, the findings of this study suggest that facilitating and inhibiting factors may not be two ends of the same spectrum, but rather operate on different

psychological dimensions. An individual may simultaneously perceive an AI tool as useful (high perceived usefulness) and dangerous (high perceived risk), and these two perceptions do not automatically cancel each other out.

This finding resonates with recent research on 'ambivalence towards AI'. Existing studies have shown that users' attitudes towards AI are often not simply 'in favour' or 'against', but rather encompass both positive and negative emotional components (Chi et al., 2023) [12]. This ambivalence may stem from the inherent characteristics of AI technology: whilst it is a powerful tool, it may also pose a threat to the unique value of humanity. This study provides empirical support for this theoretical perspective from young users in China.

#### 5.1.2 The 'screening effect' of professional background: the practice-embedded nature of adoption behaviour

The only significant variable in the regression analysis was professional/occupational background. This finding offers important theoretical insights for research on technology adoption: the adoption of AI tools is not purely a matter of 'technological acceptance', but rather a matter of 'practical embedding'. The reason creative professionals use AI tools more frequently is not because they hold a more positive attitude towards AI—descriptive statistics indicate that there are no systematic differences in the scores of psychological variables across different professional backgrounds—but because their daily workflows involve more intensive scenarios for AI application.

This finding suggests that when studying technology adoption behaviour, attention should be paid not only to individuals' psychological cognitions but also to the 'fit' between technology and practice. When a technology is highly relevant to a user's daily tasks, its adoption becomes a 'natural' choice rather than a decision requiring the 'overcoming of resistance'.

#### 5.1.3 The Deeper Implications of the 'Collective Silence' of Psychological Variables

The lack of statistical significance for the various psychological variables in the regression analysis must be interpreted with caution. As mentioned earlier, insufficient sample size and the choice of dependent variables may be two important technical explanations. However, beyond these, this 'collective silence' may also point to a deeper issue: in decisions regarding the use of AI creative tools, the importance of

psychological factors may be overestimated, whilst the contribution of contextual factors may be underestimated.

One possible explanation is that the use of AI creative tools is characterised by 'low commitment and frequent trial and error'. Users can try it out at no cost, and can just as easily abandon it after a single attempt. In this 'low-commitment' decision-making context, the predictive power of psychological factors (such as attitudes and beliefs) over behaviour may be overshadowed by situational factors (such as task requirements and time pressure). In other words, people may not need to 'firmly believe that AI is useful' in order to use it-sometimes it is simply because 'there happens to be a task at hand that needs completing'.

## 5.2 Dialogue with Existing Research

### 5.2.1 Dialogue with classic TAM/TPB research

The findings of this study differ somewhat from those of the classic TAM/TPB studies. In Davis's (1989) original study, perceived usefulness and perceived ease of use together accounted for approximately 40 per cent of the variance in usage intention [4]. In contrast, in this study, these two variables had limited explanatory power regarding actual usage frequency.

This discrepancy may stem from two reasons. Firstly, as mentioned earlier, there is a gap between 'intention to use' and 'actual behaviour'. Secondly, the 'low-commitment' nature of AI creative tools results in a looser attitude-behaviour relationship. Future research may consider introducing 'behavioural intention' as a mediating variable into the model to examine the effects of the complete path.

### 5.2.2 Dialogue with recent research on AI adoption

Recent research on AI adoption has begun to focus on the role of inhibitory factors. For example, a study on the ChatGPT service confirmed the positive influence of perceived usefulness and perceived ease of use on intention to continue using the service (European Journal of Innovation Management, 2024), whilst also finding that the influence of perceived risk was not significant. This finding bears similarities to the results of the present study-although the mean score for perceived risk was relatively high, it did not exhibit a significant negative effect when explaining actual behaviour.

The findings of this study also echo those from research on AI programming assistants: the

influence of perceived enjoyment was even stronger than that of perceived usefulness (Journal of Computer Information Systems, 2024). Although the mean score for enjoyment in this study (5.10) was lower than that for perceived usefulness, it remained at a relatively high level, indicating that the importance of intrinsic motivation in AI-driven creative behaviour should not be overlooked.

## 5.3 Practical Implications

### 5.3.1 Implications for AI tool developers

The findings of this study offer the following implications for the product design and marketing strategies of AI tools:

Firstly, 'usefulness' is fundamental, but not the whole story. Although perceived usefulness was the dimension with the highest score, psychological variables have limited explanatory power regarding actual usage behaviour, suggesting that developers should not rely solely on 'functional optimisation' to drive user growth. Embedding AI tools into users' actual workflows-rather than merely making them 'appear useful'-may be a more effective strategy. Secondly, reducing perceived risk and technological anxiety is key to enhancing user adoption. Measures such as providing clear copyright attribution, establishing content quality assurance mechanisms and reinforcing data security commitments can help alleviate users' concerns.

Thirdly, more investment should be made in designing for enjoyment. The level of enjoyment derived from using the tools is moderate to high; for younger users, making AI tools 'fun' is in itself an important value proposition.

### 5.3.2 Implications for AI literacy education in higher education

The findings of this study also offer valuable insights for AI literacy education in higher education institutions:

Firstly, helping students develop a correct understanding of AI. As technology anxiety is widespread, educators should guide students to view AI as a 'tool' rather than a 'threat', and help them form reasonable expectations regarding human-machine collaboration.

Secondly, the boundaries of AI use should be clearly defined. Relevant surveys indicate that 83.24 per cent of university students surveyed believe it is necessary for universities to establish guidelines for the use of AI learning tools (China Youth Daily, 2026b) [11].

Universities should provide clear, practical guidelines on AI use to guide students in making reasonable use of AI tools whilst maintaining independent thinking.

#### 5.4 Research Limitations and Future Directions

This study has several limitations that should be borne in mind when interpreting the results:

Firstly, the sample size is limited. A sample of 107 valid responses is clearly insufficient for a regression model comprising 44 independent variables. This results in low statistical power, meaning that some effects that should theoretically be present may not have been detected due to the small sample size. Future research should focus on expanding the sample size; it is recommended that at least 300–400 valid questionnaires be collected.

Secondly, the cross-sectional design. This study employed a cross-sectional questionnaire survey, with all variables measured at a single point in time; consequently, it is not possible to establish causal relationships between variables. For example, we cannot determine whether 'perceived usefulness' led to 'usage behaviour', or whether 'usage behaviour' in turn reinforced 'perceived usefulness'. Future research may consider adopting a longitudinal tracking design or an experimental approach.

Thirdly, the selection of the dependent variable. This study used 'frequency of use' as the dependent variable, bypassing the intermediate stage of 'behavioural intention'. Future research should incorporate behavioural intention as a mediating variable into the model to test the complete pathway: 'psychological factors → behavioural intention → actual use'.

Fourthly, self-selection bias in the sample. Respondents who volunteered via an online platform may have a higher level of interest in AI tools themselves, meaning the representativeness of the sample could be improved. Future research could adopt more rigorous random sampling methods.

#### 6. Conclusions

Based on the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB) and Social Norm Theory, this study constructed a three-dimensional integrated 'technology–society–individual' model and investigated the factors influencing young people's use of AI creative tools through 107

valid questionnaires. The main conclusions of the study are as follows:

Firstly, young people hold a contradictory attitude towards AI creative tools, characterised by both 'embrace' and 'caution'. Descriptive analysis shows that respondents' perceived usefulness (5.51) and behavioural intention (5.26) regarding AI tools are relatively high; however, their perceived risk (5.22) and technological anxiety (4.87) are equally significant and cannot be overlooked. This contradictory 'love-hate' mindset may be a key entry point for understanding user technology adoption behaviour in the AI era.

Secondly, professional/occupational background is a significant predictor of usage frequency ( $\beta = 0.312$ ,  $p = 0.020$ ). Professionals in creative fields exhibit significantly higher usage frequencies. This finding suggests that the adoption of AI tools is not merely a product of psychological cognition, but rather the result of 'practical embedding'. Whether a tool is genuinely integrated into users' daily workflows is a more explanatory factor than individual attitudes towards the tool.

Thirdly, in the context of AI creative tools, the traditional TAM/TPB framework requires re-examination. Whilst perceived usefulness is undoubtedly important, 'useful' does not equate to 'adopted'; the role of inhibiting factors cannot be overlooked, but they do not necessarily operate in a linear manner that 'offsets' the effects of facilitating factors; the screening effect of professional background reminds us that adoption behaviour is not merely a psychological decision, but rather a context-driven practical choice.

These findings suggest that, in the emerging context of AI creative tools, user behaviour follows a logic that is more complex than that of traditional technology adoption. Future research should, based on larger samples, incorporate behavioural intention as a mediating variable and employ longitudinal or experimental designs to further elucidate the complete mechanism of transformation from cognition to behaviour. Only in this way can we gain a deeper understanding of how people choose, adapt and coexist with algorithms amidst the tide of the 'human-machine co-creation' era.

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