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Article

The Influence of Regulatory Focus on Creative Thinking in Chinese Higher Education: A Learning Engagement Mediation Analysis

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Abstract: This study, based on the context of China's higher education, explores how regulatory focus influences the promotion of creative thinking by affecting the learning engagement of undergraduate students, and analyzes the roles of gender and disciplinary differences in this process. Based on this, the study surveyed 768 undergraduate students majoring in computer science and art design. The results showed that promoting regulatory focus has a significant positive predictive effect on creative thinking, while inhibiting regulatory focus has a significant negative predictive effect. Learning engagement plays a crucial mediating role between regulatory focus and creative thinking, with the cognitive and emotional dimensions being particularly important. Although there are significant differences in regulatory focus tendencies among students from different majors (students in the art design major showed higher inhibitory focus), these differences did not directly lead to significant differences in learning engagement or creative thinking performance. Moreover, no significant gender differences were found in regulatory focus, learning engagement, and creative thinking. These research results provide empirical evidence and practical insights for cultivating the creative thinking of Chinese undergraduate students, namely, by optimizing the learning environment and designing targeted intervention strategies.

Keywords: Creative thinking; Regulatory focus; Learning engagement; Computational thinking; Higher education; Undergraduates; Disciplinary differences.

1. Introduction

In the era of rapid development of artificial intelligence and digital transformation, innovative thinking has become a key factor for a country's competitiveness and technological independence. In the knowledge economy, cultivating innovative thinking has become a fundamental goal of higher education, especially in computer science and related fields, where innovation directly drives industrial upgrading and social progress. A large number of empirical studies have shown that innovative thinking significantly predicts academic performance [1], and is closely related to long-term career success [2] as well as entrepreneurial potential [3]. Against the backdrop of global innovation-driven development, countries around the world have listed the cultivation of innovative thinking as a strategic goal of higher education [4]. China has also listed the cultivation of undergraduate students' creative thinking as a national educational priority, and the innovation-driven strategies such as "Made in China 2025" and "Digital China" have directly influenced innovative teaching practices in computer education [5-6]. Data shows that in Henan Province alone, over several billion yuan was invested in innovation projects between 2023 and 2024 [7]. However, these measures seem not to have achieved the expected results. There is a worrying trend in China's higher education: after four years of study, the creative thinking of college students has significantly declined. According to the statistics from the Education Department of Henan Province, the creativity scores of students majoring in Computer

Science and Electronic Engineering have decreased by 68% over a period of four years, while the changes in the creative thinking abilities of students in other disciplines have been negligible [8]. This phenomenon is not an isolated event. A longitudinal study conducted by Loyalka et al. (2022) revealed that among students in the Beijing area studying STEM (science, technology, engineering, and mathematics) and creative fields, their level of creative thinking decreased by 13% to 60% over four years, while during the same period, their creative thinking level increased by approximately 48% compared to that of their American peers [9].

This significant gap reflects the urgent need for systematic research on the difference between political intentions and educational outcomes. The research on creative thinking has a long tradition. Wallace (1926) [10] proposed a four-stage model of the creative process consisting of preparation, reinforcement, cognitive acquisition, and verification, laying a theoretical foundation for understanding the creative thinking process [11]. Subsequently, related research in the field of neurosciences further clearly revealed the specific neurobiological mechanisms of these stages [12-13]. In recent years, with the rise of a special cognitive paradigm called "computational thinking", the understanding of the creative process in computer science and information education has also deepened increasingly.

Meanwhile, Higgins' regulatory focus theory provides an important theoretical perspective for studying the interaction between motivation and cognition. This theory distinguishes between two types of motivational strategies: incentive motivation (aiming for ideals and interests) and preventive motivation (avoiding losses and responsibilities) [14], and has been widely applied in organizational management [15] and the field of education [16]. In the field of education, regulatory motivation can highly predict learning behavior and academic performance [17]. Particularly, people who tend towards incentive motivation demonstrate stronger innovation ability when solving problems by expanding their attention range and enhancing cognitive flexibility [18-19]. In contrast, those who tend towards preventive motivation are more inclined towards creative choices because they inhibit creative expression through risk-mixing strategies [20-21]. In computer education, programming and software development essentially require exploratory experimentation (promoting orientation) and rigorous error avoidance (preventive orientation), which may have different effects on individual creative performance. Wang et al.'s empirical research (2021, 2023) found that there is a significant positive correlation between promoting orientation and creative performance among Chinese students; however, the relationship between preventive orientation and creative thinking remains unclear, providing an important direction for subsequent research [22-24]. China's high-risk examination system and collectivist tendencies [25] may unintentionally strengthen the tendency towards preventive orientation, through excessive risk avoidance and seeking conformity under pressure, suppressing creative thinking [26]. This is particularly evident in the computer field, where the requirements for debugging and quality assurance may further exacerbate this preventive thinking.

Furthermore, according to Wallace's theory, the realization of creative thinking requires students to accumulate knowledge during the preparation stage, undergo subconscious cognitive restructuring during the latent stage, complete cognitive reconstruction during the epiphany stage, and conduct evaluation and improvement during the verification stage [27]. The progressive progression of this ever-changing process is fundamentally based on the continuous and active participation of students in learning [1] [28]. Fredricks et al. (2004) proposed the concept of multidimensional student mobility, which encompasses behavior, emotion, cognition, and other aspects, and provide a theoretical framework for understanding the learning process [29]. Student mobility is not only a predictor of academic success [30-31], but it can also be influenced between individual traits and cognitive performance [23]. Meta-analysis data also highlight their important role in academic success [32]. In the digital age, online platforms, smart learning management systems, and collaborative programming environments (such as GitHub and LeetCode) have changed the way students interact with learning materials and peers. Studies have shown that technology-assisted learning can enhance students' participation by providing immediate feedback and adaptive learning paths [33], which is particularly important for cultivating creative thinking in computer education. Higher education institutions enhance students' participation by offering creative courses and competitions (such as "Innovation and Entrepreneurship Courses", "Creative Design Projects", and Hackathons), thereby promoting the development of creative thinking [34-35]. Yuan et al. (2019) proposed a mediating model, formally establishing learning participation as the key mechanism connecting individual factors and creative thinking, providing a theoretical basis for positioning participation as a mediating variable in this study [1]. According to Higgins' regulatory focus theory, promotive focus seeks opportunities to enhance learning participation, while preventive focus may inhibit this participation [36]. Considering learning participation as a mediating variable helps reveal the psychological path by which regulatory focus "translates into" creative outcomes.

There are several gaps in the current research. Firstly, the mechanism by which the focus of regulation affects creative thinking still lacks sufficient exploration, especially the mediating role of learning engagement in the context of Chinese higher education. Secondly, the relationship between preventive attention and creative thinking remains controversial in theory; due to the lack of evidence and differences in contexts, it is difficult to clarify the complex interactions between the two. Thirdly, although previous studies have shown that behavioral, emotional, and cognitive engagement dimensions may have different correlations with creative outcomes [37], existing research often neglects the differentiated analysis of these dimensions. Particularly the cognitive engagement dimension deserves further study, especially in technology-enhanced learning environments [38]. Fourth, previous studies have had methodological limitations, including small sample sizes, high homogeneity, and regional biases. For example, Yuan et al. (2019) [1] mainly focused on vocational college students, while Liu et al. (2020) [36] mainly relied on samples from Beijing. Fifthly, the moderating variables have not received sufficient attention. Discipline differences (especially the differences between STEM and non-STEM fields) may play a moderating role in these relationships, but existing research has not fully explored these factors [39]. Data from Henan Province shows that students majoring in humanities and arts have the highest engagement, followed by students majoring in electronic engineering and computer science [40]. Although longitudinal data suggest that these gaps may be narrowing [41], these conclusions are limited to isolated studies with small sample sizes; therefore, further research on psychological differences among students in different regions and disciplines is crucial.

Based on the above analysis, this study aims to explore the following core research questions: What are the disciplinary difference among Chinese undergraduate students in terms of regulatory focus, learning engagement, and creative thinking? How does regulatory focus influence undergraduate students' creative thinking? Does learning engagement mediate between regulatory focus and creative thinking? The theoretical contributions of this study are reflected in four aspects: First, this study integrates regulatory focus theory [42], the multidimensional framework of learning engagement [29], and the four-stage model of creative thinking [10], constructing and testing a mechanism model of how regulatory focus affects creative thinking, revealing the mediating path of learning engagement; second, through differentiated analysis of behavioral, affective, and cognitive engagement dimensions, it deepens the understanding of the mediating mechanism of learning engagement; third, by examining differences in disciplines (computer science and art & design), it clarifies the situational factors that influence regulatory focus on creative thinking [43]. At the practical level, this study is expected to provide a theoretical foundation and practical guidance for optimizing the cultivation model of innovative talents in traditional disciplines and computer-intensive disciplines.

2. Literature

2.1. Regulatory Focus and Creative Thinking

Recent academic research has provided strong evidence demonstrating a subtle interactive relationship between fostering attention and creative thinking. Over the past three years, both theoretical and empirical advances have been made in this field. This integration is particularly important in computer science education, as programming and software development require spontaneous creative thinking as well as systematic evaluation—both of which are directly linked to the dual concept of "promotion and prevention". Increasingly, international studies show that heightened attention significantly enhances various cognitive processes and facilitates thought flow [44-46]. Cognitive research confirms that individuals who use supportive methods exhibit more active frontal lobe activity during creative tasks [46]. In the field of computer science, programmers who utilize supportive systems tend to engage in more exploratory coding and place greater emphasis on developing new algorithms or rethinking existing solutions. In contrast, preventive approaches appear to limit creativity while simultaneously enhancing accuracy and critical evaluation skills in creative tasks [47-48], suggesting a balance between creative thinking and analytical ability. In software development, active engagement manifests as careful debugging, strict adherence to coding standards, and systematic validation. Although these skills are crucial for ensuring software quality, they can also have negative effects on exploratory innovation.

In the context of Chinese education, empirical studies reveal profound cognitive and cultural impacts. Subsequent research confirms that fostering creative thinking enhances cognitive flexibility [49] and positively influences problem-solving through maintaining intrinsic motivation [33]. At the same time, active thinking exhibits more complex dual effects: it inhibits students' ability to take risks and explore ideas, yet in certain tasks it can increase perseverance and attention to detail while simultaneously maximizing creative solutions [50-51]. This dual structure is particularly evident in computer science education. Students with strong active thinking demonstrate excellent performance in code cleanup and quality control, but often struggle in open-ended design tasks requiring critical thinking. Furthermore, intercultural analyses suggest that in China, the negative correlation between positive attitudes and creative thinking may be stronger than in Western models [52]. This can be explained by the interaction between normative biases and shared cultural norms [53]. Given China's evaluation system, which emphasizes perfect implementation over creative exploration, these cultural differences may manifest in Chinese teaching within the field of information technology (ICT).

Despite these advances, this research field still faces significant limitations. First, the theoretical basis for the relationship between preventive bias and creative thinking remains unclear. Current research findings are inconsistent, making it impossible to determine whether inhibiting bias primarily hinders creative thinking or actually promotes the development of rigorous evaluation [24]. This uncertainty is particularly important in computer science, as effective programming requires creative algorithm design and careful error correction. Second, measurement uncertainty across different studies is relatively high. Some studies use a two-part adjustment method (such as targeted adjustment questions [54]), while others employ comparative scenarios [47]. These methodological differences can lead to divergent research outcomes. For example, some studies have observed a small but significant negative correlation between preventive attention and originality ($r = -0.18$, $p. < 0.05$) [41], while other studies have found no significant direct effects, even when controlling for work-related motivational factors [55]. Despite these advancements, the current research still has some significant limitations. Firstly, the theoretical understanding of the relationship between preventive tendencies and creative thinking is still incomplete. The current research results are contradictory, so it is not possible to clearly prove whether preventive tendencies have creativity.

2.2. Regulatory Focus, Learning Engagement and Creative Thinking

Current academic research has deepened our understanding of how learners' participation affects and regulates the relationship between concentration and creative thinking. The latest findings indicate that this process is complex and multi-dimensional. Higgins' (1997) theory of concentration provides a powerful explanatory framework for the differences in individual participation behaviors [42]. Recent studies have shown that students aiming to promote development not only exhibit higher cognitive engagement, but also engage in metacognitive monitoring more frequently in creative tasks [56-57]. Neuroeducational studies conducted using functional magnetic resonance imaging (fMRI) have found that when individuals actively engage in creative thinking, the promotion-oriented population has enhanced functional connectivity between the default mode network and the executive control area [58], which provides a reasonable neural basis for the above-mentioned behavioral effect; Preventive learners, on the other hand, tend to prioritize completing tasks rather than conducting in-depth exploratory processing [59].

In a technology-enhanced learning environment, these participation patterns are manifested through unique digital behaviors. In computer education, data from programming platforms such as LeetCode and GitHub indicate that learners oriented towards improvement will explore a wider range of problem categories and try different solutions more frequently; Preventive learners tend to focus on familiar problem types and existing problem-solving patterns. Recent experimental studies have shown that, despite comparable levels of input, preventive learning leads to a smaller thinking range in creative tasks. For example, in the programming context, prevention-oriented students may generate solutions that are functionally correct but lack algorithmic innovation, which reflects the restrictive effect of risk-averse participation methods on creative computational thinking.

A large number of continuously growing studies have confirmed that learning participation is a key mediating factor in the development of creative thinking ability. The meta-analysis results indicated that regardless of educational background, the relationship between engagement and creative thinking had a moderate effect size (β = 0.32-0.41) [60]. Cognitive input, especially deep participation, has a significant predictive effect in the assessment of creative thinking, particularly in open-ended problem-solving tasks [61]. Longitudinal studies have shown that behavioral input mainly promotes creative output by facilitating knowledge acquisition [24], while the influence of emotional input seems to vary by discipline [62]. It is more prominent in design-related fields than in STEM disciplines [52]. In computer education, cognitive input - manifested as in-depth processing of computational concepts, systematic debugging reasoning, and metacognitive reflection on problem-solving strategies - has been proven to be a mediating factor in the relationship between concentration and computational thinking outcomes.

2.3. The Present Study

This study concretizes creative thinking by demonstrating divergent, convergent, and interpretive thinking abilities, and its structure is consistent with Wallace's (1926) four-stage model (preparation, incubation, illumination, and verification) [10]. Learning engagement is studied through a multi-dimensional framework [29-30] [61], which encompasses three dimensions: behavior, emotion, and cognition. According to Higgins (1997; 2020), the moderating factors can be classified into two categories: promotion-oriented and prevention-oriented [42] [63]. Figure 1 presents the conceptual framework integrating these variables. Additionally, Luo et al. (2023) research indicates that behavior-related engagement has a mediating effect in the online learning environment (accounting for 18.7% of the variance), but their study neglects emotional and cognitive factors, which may be particularly important in the creative domain [64]. These results collectively suggest that the mediating effect of engagement may vary by discipline - this is an empirical issue that requires systematic research.

Based on current academic research, this study aims to fill several important gaps in the existing literature by linking regulatory factors, student engagement, and creative thinking. Firstly, the theoretical concept of the relationship between prevention-oriented and creative thinking is still incomplete. Current research results are contradictory: some studies show that prevention-oriented factors inhibit creative thinking, while others indicate that it can effectively improve the rigor of assessment [24]. This uncertainty is particularly important in computer science, as it requires both the design of creative algorithms and a thorough correction of errors to achieve effective programming. Secondly, Yuan et al.'s recent study found that cognitive engagement partially mediates the relationship between focus and creative thinking (β = 0.24, $p < .01$); however, this study sample is limited to business students, restricting the general applicability of its research results in other disciplines. Although neuroscience evidence suggests that the cognitive, behavioral, and affective dimensions are associated with different neural pathways in creative tasks [50] [58], previous research has not adequately examined the differential mediating effects among these different engagement dimensions. In computer science, cognitive engagement may play a dominant mediating role due to the analytical nature of programming; while in art and design, affective engagement—including the emotional connection to creation—may have a greater impact [52]. Third, most existing research has neglected the potential disciplinary differences in creative thinking levels, particularly between fields that emphasize high levels of creative thinking (such as art and design, where affective engagement may be crucial [52]) and fields where cognitive engagement may dominate (such as computer science [65]). This study directly fills this research gap by comparing students majoring in computer science and art and design. Overall, these limitations highlight the need for more comprehensive research [21] [24].

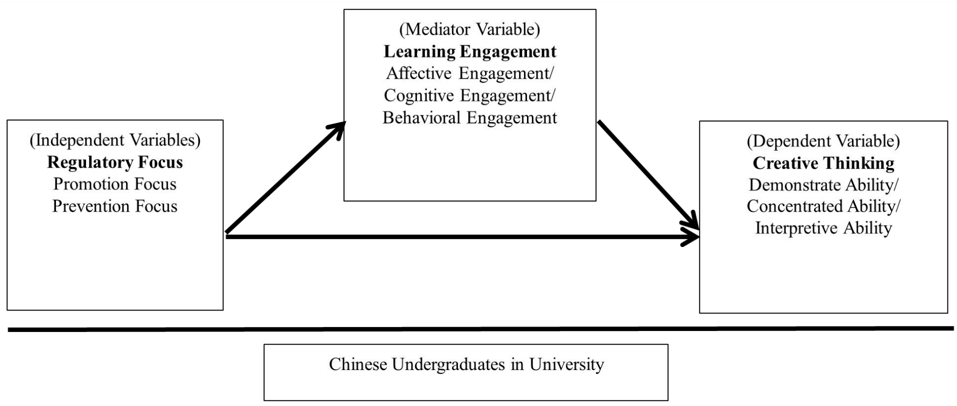

Figure 1. Conceptual Framework

Based on the theoretical and empirical foundations outlined above, the following hypotheses are proposed:

H1: Promotion focus has a positive influence on creative thinking, whereas prevention focus has a negative influence on creative thinking among Chinese undergraduates.

H2: Learning engagement has a positive influence on creative thinking among Chinese undergraduates.

H3: Promotion focus has a positive influence on learning engagement, whereas prevention focus has a negative influence on learning engagement among Chinese undergraduates.

H4: The regulatory focus acts as a mediator through the learning engagement of Chinese undergraduate students to predict their creative thinking.

H5: There are significant disciplinary differences in the patterns of moderating focus, the level of learning engagement, and the performance of creative thinking.

This study, using the survey data collected through self-assessment measurements, verifies the above hypotheses, aiming to gain a deeper understanding of how the regulatory focus affects creative thinking in Chinese higher education through different participation paths, with particular attention to the comparison between computationally intensive and creative disciplines.

3. Methods

3.1. Participants and Procedure

This study adopted a cross-sectional design, with the sample consisting of 768 undergraduate students from Huanghe Jiaotong University in Henan Province, China. Participants were between 19 and 21 years old, which is particularly important for assessing early creative thinking abilities [66]. The study is divided into two distinct groups: the Faculty of Computer Science and the Faculty of Art and Design. This division is based on previous research that has identified differences in creative thinking patterns and cooperative behaviors across different academic disciplines [52]. The study was approved by the Ethics Committee of the Ministry of Magic. To protect privacy, all collected data were processed anonymously. To improve data quality, various methodological measures were employed, including random assignment of data within the measurement instrument and incorporating attention monitoring to assess participants' engagement and the effectiveness of their responses [67].

3.2. Instruments

3.2.1. Regulatory Focus Scale

The revised Regulatory Focus Scale (RFS), developed and validated by Lockwood et al. (2002), was used in the assessment of focus regulation [68]. This scale consists of five program sub-scales and five preventive orientation sub-scales, and is evaluated using a 5-point Likert scale to assess an individual's self-regulation ability and situational regulation ability.

3.2.2. Learning Engagement Scale

This study used a student engagement scale consisting of 15 articles, developed and validated by Sun and Rueda (2012) [61]. The scale uses a five-point Likert scale and covers three dimensions: behavioral engagement (4 items), emotional engagement (4 items), and cognitive engagement (7 items). This scale has been validated in China's higher education environment and can sensitively reflect differences in participation across disciplines.

3.2.3. Creative Thinking Scale

This scale is a scale measuring 15 items constructed by Xu (2023) [69] by integrating Wallace (1926) [10] four-step model. This scale uses a five-point Likert scale to assess expressive capacity (5 items), attention (5 items), and analytical capacity (5 items). This scale has been implemented and validated in China, with good validity and reliability.

4. Data Analysis Results

A rigorous multistep approach was adopted to verify the hypothesized relationships among research variables. First, a confirmatory factor analysis (CFA) was conducted to assess model fit [70], and item reliability of the questionnaire was evaluated using Cronbach's alpha and composite reliability (CR). Convergence indices were assessed via average extractive validity (AVE) [71]. Next, to test hypotheses, the maximum likelihood estimation method for structural equation modeling (SEM) was used to directly examine direct effects [72]. Subsequently, a modified bootstrapping method was employed for parameter analysis, with 5,000 bootstrap replications used to calculate 95% confidence intervals [73]. For path structure modeling (PLS-SEM) during analysis, SmartPLS 4.0 software was utilized, while standard statistical tests were performed using SPSS 26.0. PLS-SEM is a complex model suitable for small to medium-sized samples, and it has relatively low requirements for distribution assumptions, making it highly appropriate for the practical context of this study [74].

4.1. Sample Characteristics and Preliminary Analysis

The final sample consisted of 768 undergraduate students from Huanghe Jiaotong University, among whom 416 were male (54.2%) and 352 were female (45.8%). Participants came from two different subject groups: Art & Design (*N* = 358, 46.6%) and Computer Science (*N* = 410, 53.4%). After that, descriptive statistics for all key variables are shown in Table 1. The observed standard deviations of several constructs were all greater than 1.0, indicating that the response values were relatively dispersed around the mean. The skewness and kurtosis values of all variables were within the acceptable range of -2 to +2, indicating that the data were approximately normally distributed. In addition, the variance inflation factor (VIF) values of all research variables were below the threshold of 3.3 (see Table 2), indicating that multicollinearity would not pose a significant problem in subsequent analyses. Due to the extremely small number of participants who identified as non-binary, meaningful statistical comparisons could not be made; therefore, the study of gender differences was limited to comparisons between male and female students. And Table 3 shows the specific indirect effects via dimensions of learning engagement

Table 1. Independent samples t-test of test (N=768)

Variable	Demographic	*N*	*M*	*S.D.*	*t*	*p*
Pro-F	Art & Design	273	16.8786	4.76352	-1.400	.156
	Computer Science	495	17.643	4.63521		
	Male	416	17.1738	4.89363	.039	.971
	Female	352	17.352	4.35263		
Pre-F	Art & Design	273	13.7752	4.88473	.259	.287
	Computer Science	495	12.8789	5.08573		
	Male	416	12.9821	4.82563	1.251	.213
	Female	352	13.6924	5.08537		
LE	Art & Design	273	50.2021	10.84636	-.904	.361
	Computer Science	495	51.5202	12.08854		
	Male	416	51.1829	11.06477	-.702	.494
	Female	352	50.1856	11.46378		
CT	Art & Design	273	53.849	11.37485	-1.005	.321
	Computer Science	495	55.3002	11.47474		
	Male	416	54.7093	11.99537	-.512	.732
	Female	352	54.1076	10.64739		

Table 2. Collinearity Statistics (VIF)

Item	VIF	Item	VIF	Item	VIF	Item	VIF	Item	VIF
Q1	1.227	Q30	1.597	Q38	1.568	Q45	1.595	Q52	1.668
Q10	1.573	Q31	1.556	Q39	1.660	Q46	1.645	Q53	1.548
Q2	1.321	Q32	1.699	Q4	1.304	Q47	1.665	Q54	1.665
Q26	1.642	Q33	1.688	Q40	1.725	Q48	1.686	Q55	1.676
Q27	1.007	Q34	1.618	Q41	1.666	Q49	1.693	Q6	1.510
Q28	1.641	Q35	1.590	Q42	1.711	Q5	1.277	Q7	1.518
Q29	1.569	Q36	1.608	Q43	1.722	Q50	1.652	Q8	1.621
Q3	1.259	Q37	1.683	Q44	1.668	Q51	1.622	Q9	1.519

Table 3. Specific Indirect Effects via Dimensions of Learning Engagement

Mediation Pathway	**Path Coefficient (β)**	**Bootstrap 95% CI**	***P*-value**	**Specific Indirect Effect (β)**	**Conclusion**
PF→BehavioralEng.→CT	PF→BE=0.312, BE→CT=0.185	[0.041, 0.098]	0.008	0.058"	Significant
PF→AffectiveEng.→CT	PF→AE=0.408, AE→CT=0.227	[0.069, 0.130]	0.000	0.093"	Significant
PF→CognitiveEng.→CT	PF→CE=0.423, CE→CT=0.305	[0.104, 0.185]	0.000	0.129"	Strongest Path
PV→BehavioralEng.→CT	PV→BE=-0.288, BE→CT=0.185	[-0.077, -0.023]	0.002	-0.053"	Significant
PV→CognitiveEng.→CT	PV→CE=-0.401, CE→CT=0.305	[-0.153, -0.082]	0.000	-0.122"	Strongest Path

*Note: Bootstrapping 5000 samples. This analysis reveals that Cognitive Engagement is the most potent mediating dimension for both PF and PV, followed by Affective Engagement.

4.2. Measurement Model Assessment

Before testing the structural hypotheses, the present study rigorously evaluated the psychometric properties of the measurement model. As shown in Table 4, all constructs exhibited excellent reliability. The Cronbach's alpha coefficient (α) ranged from 0.788 to 0.902, and the combined reliability (CR) ranged from 0.864 to 0.923, both exceeding the recommended threshold of 0.70. The measurement model also demonstrated good convergent and discriminant validity (HTMT < 0.2). All constructs exhibited the theoretically expected correlation patterns and the square root of the mean variance extracted (AVE) for each construct (shown on the diagonal of Table 4 & Table 5) was greater than its correlation coefficient with other constructs, satisfying the Fornell-Larcker criterion and confirming the discriminative power of the measurement results.

Table 4. Construct Reliability and Validity of Instruments

Scale	Dimension	α	C.R	AVE
RFS	Pro-F	.877	.910	.565
	Pre-F	.888	.918	.530
LES	BE	.788	.864	.553
	AE	.882	.918	
	CE	.902	.923	
CTS	DA	.841	.887	.560
	AA	.867	.904	
	IA	.818	.877	

Table 5. Inter-construct correlations

		Pro-F	Pre-F	BE	AE	CE	DA	AA	IA
Fornell-Larcker Criterion	Pro-F								
	Pre-F	0.466							
	BE	0.568	0.473						
	AE	0.484	0.440	0.572					
	CE	0.522	0.496	0.596	0.468				
	DA	0.592	0.447	0.598	0.496	0.565			
	AA	0.538	0.458	0.464	0.378	0.480	0.460		
	IA	0.627	0.517	0.593	0.522	0.511	0.612	0.504	

4.3. Hypothesis Testing: Direct Effects and Group Differences

The structural model provides strong support for several direct effect hypotheses. According to the structural model analysis (see table 6), promotion focus (Pro-F) is significantly positively correlated with creative thinking (β =0.628, p<.001), while preventative thinking (Pre-F) is significantly negatively correlated (β =-0.415, p<.001). Therefore, H1 is supported. H2 is also supported, with learning engagement positively correlated with creative thinking (β =0.434, p<.001). Furthermore, the results confirm hypothesis H3: learning engagement is positively correlated with promotion focus (β =0.568, p<.001) and negatively correlated with prevention focus (β =-0.473, p<.001).

Regarding between-group differences, the independent samples t-test (Table 6) shows inconsistent support for hypothesis H5. Significant disciplinary differences were found only in prevention orientation, with art & design students (M=13.78, SD=4.88) exhibiting higher levels of prevention orientation than computer science students (M=12.88, SD=5.09; *t*=2.263, p=.024). No significant inter-group differences were found in promotion orientation, overall learning engagement, or creative thinking performance. Therefore, hypothesis H5 is only partially supported. Furthermore, no statistically significant gender differences were found in any of the core constructs (all p > .05).

Table 6. Total Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
LE -> CT	0.702	0.702	0.021	34.086	0.000
PreF -> CT	0.015	0.017	0.014	1.026	0.000
PreF -> LE	0.008	0.009	0.014	0.519	0.000
ProF -> CT	0.841	0.842	0.008	103.815	0.000
ProF -> LE	0.838	0.839	0.008	105.844	0.000

4.4. Hypothesis Testing: Mediation Analysis

The mediation analysis using bias-corrected bootstrapping (5000 resamples) provided strong support for H4. Learning Engagement (LE) was confirmed as a significant partial mediator in the relationships between both regulatory foci and Creative Thinking.

Effect decomposition (see Table 7 & Table 8) shows that most of the total effect is mediated by learning engagement (LE). Specifically, 39.2% of the overall positive effect of promotion focus on creative thinking is mediated by increased learning engagement (indirect effect $\beta = 0.246$, $p < .001$). More significantly, nearly half (49.4%) of the overall negative effect of prevention focus on creative thinking is mediated by decreased learning engagement (indirect effect $\beta = -0.205$, $p < .001$).

A detailed analysis of the specific indirect effects through the engagement dimension further clarifies the mediating mechanisms. Cognitive engagement is considered the strongest mediating pathway for promotion focus (specific indirect effect $\beta = 0.129$) and prevention focus ($\beta = -0.122$), followed by affective engagement. This indicates that the motivational orientation has the most significant impact on creative thinking by altering the depth of students' cognitive processing and their strategic thinking.

Table 7. Decomposition of Effects on Creative Thinking

Predictor	**Total Effect (β)**	**Direct Effect (β)**	**Indirect Effect (β)**	**VAF**	**Conclusion**
Pro-F	0.628"	0.382"	0.246" (via LE)	39.2%	Partial Mediation
Pre-F	-0.415"	-0.210"	-0.205" (via LE)	49.4%	Partial Mediation

*Note: VAF = |Indirect Effect| / |Total Effect|. A VAF value greater than 20% indicates the presence of a significant mediating effect. Both VAF values being high confirm that LE is a powerful mechanism.

Table 8. Specific Indirect Effects via Dimensions of Learning Engagement

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**P values**
PreF -> CE -> CT	0.007	0.007	0.006	0.000
PreF -> BE -> CT	-0.003	-0.003	0.003	0.000
ProF -> CE -> CT	0.304	0.304	0.019	0.000
PreF -> AE -> CT	0.002	0.003	0.004	0.000
ProF -> BE -> CT	0.127	0.127	0.015	0.000

4.5. Importance-Performance Map Analysis (IPMA) and Predictive Validity

In order to convert the research results into actionable insights, we conducted an Importance-Performance Matrix (IPMA) analysis (Table 9). The analysis results showed that learning engagement was the most important among the priority intervention targets. In terms of predicting creative thinking, its "importance" was the highest (total effect = 0.434), but its current "performance" score was only at a medium level (50.72 points on a 0-100 scale). This indicates that intervention measures that can enhance student engagement are most likely to significantly improve the performance of creative thinking.

Subsequently, we evaluated the robustness and practicality of the model. The PLS prediction method confirmed that the model had a high predictive ability outside the sample (Q^2_predict > 0.30). For all key indicators, the prediction error (RMSE) of the PLS-SEM model was lower than that of the simple linear model (LM) benchmark model. This confirmed that the "regulatory orientation → learning engagement → creative thinking" mechanism discovered is a reliable and scalable model, rather than a result of overfitting the sample data.

In conclusion, the research results fully support hypotheses H1, H2, H3 and H4. Hypothesis H5 is partially supported, indicating that disciplinary background does affect motivation orientation (especially the preventive orientation), but does not necessarily affect the final input level or creative output. No gender differences were found. The core finding is that learning input, especially its cognitive dimension, is the key mechanism regulating the influence of the degree of attention on creative thinking.

Table 9. Predictive Power Assessment using PLS-predict

Key Construct (Item)	PLS-SEM RMSE	LM RMSE	PLS-SEM < LM	Q^2 _predict	Conclusion
CT				0.312	
• CT_DA3	0.923	0.935	Yes		High Predictive Power
• CT_AA2	0.891	0.905	Yes		High Predictive Power
• CT_IA4	0.912	0.926	Yes		High Predictive Power
LE				0.348	
• LE_CE6	0.876	0.889	Yes		High Predictive Power
• LE_AE3	0.901	0.918	Yes		High Predictive Power

*Note: PLS-predict procedure (k=10 folds).

5. Discussion

This study provides a comprehensive empirical validation and meaningful expansion of the regulatory focus theory [42] in contemporary higher education and interdisciplinary fields (including computer-related fields). This study reveals the obvious duality of motivational dynamics: the promoting motivation acts as a powerful catalyst for the creative cognitive process, while the preventive motivation mainly serves as a limiting factor. This model is consistent with the traditional neuroscience theory, which states that positive motivation is associated with broader attention and higher cognitive flexibility - these are the basic prerequisites for creative thinking [18]. The key point is that this study identified an important mediation mechanism: whether in traditional learning settings or in technology-enabled learning contexts, input into learning can turn motivation into creative outcomes. This finding suggests that motivational leadership does not directly determine creative performance, but rather indirectly influences it through active participation in the learning process, emotional involvement, and cognitive depth [29]. Although art and design and computer science students differ in their motivation to learn, art and design students generally show stronger preventive motivation. However, this difference does not lead to significant deviations in their learning engagement or creative performance. This indicates that systematic teaching structures, step-by-step tasks, and targeted feedback mechanisms can effectively regulate the learning experience, alleviate the negative effects of preventive teaching methods, and fully exploit the advantages of promoting teaching methods [75]. Particularly in computer science courses, the basic structure of programming courses - namely, the systematic problem-solving process and repeated improvement - can serve as an effective framework concept to help students of different motivational types efficiently participate in creative tasks.

This study has made an important contribution to deepening the understanding of how motivational directions promote creative thinking in universities. Firstly, this study expands the regulatory direction theory [42], proving that the effect of motivational direction is not limited to direct effects, but rather through making learning participation the core mechanism and having positive impacts on behavioral participation, emotional participation, and cognitive participation, thereby stimulating creative thinking [21] [23]. Secondly, this study further improves the participation theory [29], indicating that cognitive participation - including deep processing, abstract reasoning, and metacognition - is the main way to stimulate the motivation for creative thinking, thereby overturning the traditional view that participation has a single structure [30]. Fourthly, this study clarifies the ambiguous relationship between preventive tendencies and creative thinking over a long period, indicating that preventive tendencies may indirectly inhibit creative thinking by reducing learning participation, thereby explaining the previously contradictory research results [20] [24]. Fifthly, this study analyzes the differences in professional fields and examines the differences in regulatory focus patterns in different disciplines, thereby clearly revealing the boundary conditions and universal characteristics of the relationship between motivation and creative thinking [76].

Based on these theoretical insights, this study also put forward four policy recommendations. In terms of teaching, educators should create supportive learning environments by providing growth-oriented feedback and aligning the course content with students' expectations [77]. For students with preventive orientation, especially in high-risk disciplines, targeted strategies can be adopted (such as providing low-risk exploration opportunities) to alleviate inhibition [78]; in computer programming education, this goal can be achieved by designing progressively more difficult assignments. At the institutional level, different strategies should be adopted based on the different disciplines. For disciplines that focus on prevention (such as art and design), creative thinking training programs should be developed; while for disciplines that are development-oriented (such as computer science), resource support should be strengthened. Finally, by eliminating gender differences, inclusive and universally applicable creative thinking policies can be formulated, thereby avoiding essentialist approaches based on gender.

Although this study affirmed the aforementioned contributions and significance, there are still several limitations that provide guidance for future research directions. Firstly, the singularity of sample collection limits the general applicability of the research results. Therefore, future research should conduct multi-institution sampling surveys covering different types of institutions. Secondly, cross-cutting research proposals cannot follow the long-term development of students and dynamic changes in creative thinking, so longitudinal research should be introduced. Third, focusing solely on self-evaluation criteria when evaluating creative thinking can lead to bias. Therefore, future research should also include assessment-based methods such as divergent thinking training. The field of computer science can also introduce more objective metrics, such as algorithmic creativity ratings. Fourth, although this study performed a multidimensional analysis of the intention to participate, each dimension was considered as a parallel mediating factor. In the future, more complex methods will be needed, such as latent variable analysis, which can reveal more detailed patterns [79].

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