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ARTICLE

Development of a Mental Health Scale for College Students

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ABSTRACT

The purpose of this study is to explore the mental health status of college students in Beijing and develop a scientific assessment scale. First, a systematic review of domestic and international literature related to college students' mental health was conducted, and a three-dimensional model covering adaptation, distress, and resilience was proposed. Then, open-ended questionnaire surveys were carried out based on the literature review to collect data, and a preliminary scale was developed through factor analysis. This study further tested and optimized the preliminary scale to ensure its reliability and validity, so as to form a formal scale. As a result, a formal scale is devised after three testing processes that consist of 134 items. The scale primarily consists of three subscales: adaptation, distress, and resilience. The adaptation subscale covers six points: interpersonal relationships, learning, career choice, emotions, self-adaptation, and satisfaction. The distress subscale includes seven aspects: depression, anxiety, somatization, compulsion, Internet addiction, withdrawal and aggression. The resilience subscale consists of four features: self-confidence, positive cognition, problem-solving, and social support. The results show that all three subscales have good reliability and validity. This scale enables mental health assessment from three distinct levels: adaptation, distress, and resilience, thus objectively reporting the developmental characteristics of college students' mental health. The division of these three levels not only remedies the deficiencies of previous mental health measurements but also meets the practical needs of developmental psychological counseling in universities, clarifying the tasks of mental health education.

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1. Introduction

College students in their late teenage years experience a transition from student life to becoming responsible adults. They face developmental and psychological issues such as separation from their families, adaptation to new environments, and rebuilding interpersonal relationships. A study of 4,799 college students in Spain found that the overall psychological condition of 47.4% of the students exceeded the clinical threshold of psychological well-being, 63.8% of them had subjective well-being distress, and 4.3% had the risk of self-harm or attacking others, indicating that college students' psychological distress was universal [1]. A meta-analysis integrating data from 2010 to 2020 found that the prevalence of sleep problems (23.5%), depression (20.8%), and self-harm (16.2%) among Chinese college students was particularly high. The prevalence of anxiety, depression, sleep problems, and suicide attempts has shown a significant upward trend over the past decade [2].

Through the literature review of previous studies on college students' mental health, it is found that there are some deficiencies, which are mainly manifested in the following three aspects:

1. Mental Health Connotation and Standard Issues

Mental health connotations and standards are the core of research, and different countries, generations and scholars have different views. Although the contending theory promotes the prosperity of theory, the lack of consensus also leads to the suspension of relevant research. This question involves deep content such as outlook on life and values, and it is difficult to have a unified answer, and the theoretical discussion is often disconnected from the practical needs of mental health education in colleges and universities.

2. Problems in the Assessment of Mental Health

In the past, mental health assessment scales were mainly divided into two categories. One was based on overall assessment, covering positive and negative emotions and pathological symptoms; the other was a single positive or negative assessment. The existing problems are: quantitatively, few measurement tools focus on positive mental health (positive), and most of them are evaluated from a pathological perspective (negative), such as depression, anxiety, etc. In terms of applicability, most of the scales are suitable for adults, and few scales have been localized and verified for the development characteristics of college students. Research and application are often disconnected, and most previous research on measurement tools has focused on theoretical discussions, failing to fully consider their applicability and operability in the practice of psychological counselling in colleges and universities.

3. The Orientation of Psychological Counselling at Educational Institutes

Nowadays, psychological counselling in universities is often oriented toward correction, exhibiting three tendencies: the focus on adaptive counselling and resolving psychological crises; the emphasis on correcting psychological disorders while neglecting the management of general psychological issues; and the adult model is practically applied in the analysis and discrimination, ignoring the age characteristics of students. This approach, which "sees the symptoms but not the individual," is difficult to adapt for achieving the goal of modern college education, where it is needed to promote the all-around development of students. Therefore, mental health counselling in colleges and universities urgently needs to shift from focusing on correction to a developmental, preventive and corrective model.

This study aims to address these challenges by creating a new mental health assessment model and developing a more scientific and practical assessment system that can provide a basis for developmental psychological counselling in colleges and universities. Its basic objective is to precisely define the connotation and standards of mental health applicable to college students. Research suggests that college students should have no serious emotional distress, adapt well, show age-appropriate developmental characteristics, and have the potential to self-recover in case of setbacks and failures. Based on this, this study proposes a comprehensive assessment of college students' mental health across three interrelated yet distinct dimensions: adaptation, distress, and resilience. This multidimensional model provides a more objective and comprehensive overview of the characteristics of mental health and the development of college students. It clarifies the objective of mental health education in universities and addresses the shortcomings of previous single-perspective assessment models. It directly serves the practical needs of developmental psychological counselling in universities.

2. Materials and Methods

2.1. Subject

In a preliminary assessment, a total of 363 college students in Beijing were randomly selected, including 161 boys and 202 girls, aged 19–26 years old, with an average age of 21.77 years (SD = 1.31). 83.5% of the subjects were undergraduates, and two-thirds of the subjects were juniors and seniors.

In the second test, 136 college students (including 39 boys, 96 girls, and 1 unindicated gender) were randomly selected from Beijing, aged 17–30 years, with an average age of 20.62 years (SD = 2.69). 82.26% of the subjects were undergraduates, and more than half of the subjects were freshmen and sophomores.

In the third trial, a stratified random sampling method was used to randomly select 675 college students from colleges and universities in Beijing by grade (freshman to senior, master's and doctoral). Among them, 114 were freshmen, 103 were sophomores, 119 were juniors, 127 were seniors, 159 were master's, and 53 were doctoral students; 326 were male and 349 were female.

2.2. Theoretical Modeling

The study is based on the previous theoretical models and refers to relevant items in similar scales at home and abroad. The main reference is the China College Student Adjustment Scale (CCSAS) and the Symptom Checklist 90 (SCL-90) compiled by Fang and Derogatis, and other tools [3,4].

Combined with the definition of college students' mental health and developmental counseling needs, a topic system containing three major levels of adaptation, distress and resilience was preliminarily formulated: adaptation includes seven aspects: interpersonal adaptation, learning adaptation, campus life adaptation, career choice adaptation, emotional adaptation, self-adaptation and satisfaction; Troubles include depression, anxiety, somatization, compulsion, paranoia, Internet addiction, sexual psychology, dependence, impulsivity, withdrawal, aggression, psychotic tendencies, etc. Resilience includes four aspects: self-confidence, positive cognition, problem-solving, and social support.

2.3. Development of the Formal Scale

This study went through three stages: preliminary test, second test, and third test. The test items were screened and modified based on the data analysis results, and finally a formal questionnaire was formed.

Preliminary Test: The preliminary questionnaire consists of 356 items, including three subscales, with 56 reverse questions. Items are scored on a scale of 1–5 (1 = not at all, 5 = completely compliant). Project analysis and exploratory factor analysis were carried out on the preliminary test data. Based on the analysis results, items with low distinction degree and cross-load in the adaptation, distress, and resilience subscales were excluded. After adjustment, the adaptation subscale was limited from 7 factors to 5 factors, the distress subscale was adjusted from 12 factors to 10 factors, and the resilience subscale maintained a 4-factor structure.

Second test: The second test questionnaire has a total of 357 items. The scoring method is the same as the initial test. The project analysis and confirmatory factor analysis were carried out on the second test data to test and optimize the factor structure model formed after the initial test. Items with low discrimination and cross-loadings were further removed from the adaptation, distress, and resilience subscales. Following these adjustments, the adaptation subscale was optimized from 5 factors to 6 factors, the distress subscale was adjusted from 10 factors and its dimensionality was refined, and the resilience subscale continued to be optimized.

Third test: It was aimed to form and validate the final formal questionnaire on mental health among college students. Based on the results of the previous two tests, the questionnaire was reviewed again, the rationality and balance of each subscale dimension were deeply considered, and optimization and adjustment were made, and finally a formal scale containing 134 items was formed. The scale was divided into three subscales: adaptation, distress, and resilience, and is rated on a scale of 1–5. According to gender and grade, they were randomly divided into exploratory factor analysis group (339 students) and confirmatory factor analysis group (336 students).

3. Results

3.1. Results and Analysis of Adaptation Subscales

This study defines adaptation as the ability of individuals to maintain a dynamic balance with the environment in interpersonal relationships, learning, career choice, emotion, and self-domain [5]. Keeping this in view, a seven-dimensional framework based on the classical College Student School Adaptation Scale (CCSAS) was formulated.

3.1.1. Discrimination and Discriminatory Power Analysis

In this study, item-total score correlation coefficient was used to measure the degree of discrimination, and the discrimination power was measured by the high and low group discrimination index.

In the preliminary test, the total score of the item-total correlation coefficient is in the range of 0.18–0.67, and the MD value is between 0.392 and 1.794. According to the standard of discrimination less than 0.3 and MD value less than 0.8, a total of 5 items were eliminated due to two shortcomings in some questions at the same time. In the second test, five items with a discrimination of less than 0.3 were excluded, and nine items with an MD of less than 0.8 were excluded. The corresponding questions with insufficient discrimination were deleted, and a total of 10 items were removed, which enhanced the relevance of the questions and made the assessment more focused on the core content, and improved the quality of the assessment. In the third test, all items had an MD value greater than 0.8, which was at a high level, and no items were excluded. This indicates that after the optimization of the first two tests, the scale's dimensional structure is stable and its overall quality is high.

3.1.2. Reliability Analysis

In this study, the Cronbach's α coefficient of consistency was used to test the reliability index of the scale.

For the preliminary measurement, the Cronbach's α coefficient of the adaptation subscale was 0.897, and the internal consistency coefficients of the five factors were 0.853, 0.796, 0.810, 0.675 and 0.795, respectively, showing high internal consistency reliability as a whole.

In the second test, the Cronbach's α coefficient of the adaptation subscale was 0.890, and the internal consistency coefficients of the six factors were 0.826, 0.651, 0.778, 0.472, 0.762, and 0.827, respectively, and the reliability remained at a good level.

For the third test, Cronbach's α coefficient for the adapting subscales is 0.864. The specific results are shown in **Table 1**. The reliability of the career adaptation dimension is low ($\alpha = 0.485$), which may be related to the fact that there are only 3 questions in this dimension. From the perspective of reliability principle, when the number of questions is small, the degree of correlation between questions may be unstable, and it is difficult to fully cover the content area of this dimension, resulting in increased measurement errors and thus reducing reliability [6]. The reliability of the remaining dimensions (interpersonal, learning, self, emotion, satisfaction) is within the acceptable range ($\alpha > 0.65$), and the relatively reasonable reliability level of these dimensions provides a guarantee for the stability of the scale.

Table 1. Reliability Analysis of Adaptation Subscales and Sub-Dimensions.

Adaptation Subscale	Interpersonal	Study	Self	Career Adaptation	Mood	Satisfaction
0.864	0.658	0.697	0.771	0.485	0.782	0.652

3.1.3. Structural Validity Analysis

During preliminary assessment, all questions were limited to 7 factors, and exploratory analysis was conducted. It was found that the learning adaptation dimension still overlapped with the interpersonal relationship and campus life dimensions. For example, the question "I often ask people who have already started working about their work situation" should mainly belong to the learning adaptation dimension, but it also has high loadings on the interpersonal relationship dimension and the campus life dimension, resulting in unclear boundaries between the dimensions. Therefore, all questions were limited to 5 factors for analysis. After continuously deleting items with low loadings and cross-loadings, and balancing the number of questions, the KMO value was 0.891, the cumulative variance explained rate reached 52.878%, and the loading values of each item on the corresponding factor ranged from 0.426 to 0.779.

In the second test, all questions were limited to 7 factors, and exploratory analysis was conducted, which showed that the self-adaptation dimension and interpersonal relationships still intersected. Therefore, all items were further analyzed within the six-factor framework. After removing items with low or cross-loadings and balancing the number of items, the KMO value was 0.765, with a cumulative variance explained of 51.49%. The loadings of each item on the corresponding factor ranged from 0.458 to 0.789.

In the third assessment, all questions were limited to 6 factors, exploratory analysis was carried out, and items with low or cross-load were continuously deleted. After balancing the number of items, the KMO value was 0.869, the cumulative variance explained rate reached 53.77%, and the loading values of each item on the corresponding factor ranged from 0.458 to 0.789.

Confirmatory factor analysis further confirmed the structural validity, and the fitting results are shown in **Table 2**.

Table 2. Overall Fit Index of the Confirmatory Factor Analysis Model of the Adaptation Subscale.

	$\chi 2$/df	GFI	IFI	NNFI	CFI	RMSEA
Adapt to the model	1.483	0.92	0.97	0.97	0.97	0.038

According to the criteria for good model fitting, the values of GFI, IFI, NNFI and CFI should generally be greater than 0.900, and the values of RMSEA should be less than 0.080. The results show that all indicators are up to excellent standards [7]. The estimation results of factor loading showed that the standardized factor load values of each item in the adaptation subscale ranged from 0.38 to 0.72, which indicated that the items in the questionnaire were well correlated with each adaptation dimension, indicating that the adaptation subscale had good structural validity.

The correlation analysis between the various dimensions was carried out on the adaptation subscale, and the results are shown in **Table 3**. The total score of the adaptation scale was significantly and positively correlated with each dimension ($p < 0.01$). There are different degrees of significant correlation between each dimension, which reflects that each dimension is both interrelated and independent, which provides a reference for the structural validity of the scale.

Table 3. Correlation Analysis Between the Dimensions of the Adaptation Subscale.

	Adaptation Scale	Interpersonal Adaptation	Learn to Adapt	Self-Adaptation	Choose a Career to Adapt	Emotional Adaptation	Satisfaction
Adaptation scale	1						
Interpersonal adaptation	0.698**	1					
Learn to adapt	0.730**	0.399**	1				
Self-adaptation	0.737**	0.563**	0.505**	1			
Choose a career to adapt	0.556**	0.233**	0.375**	0.215**	1		
Emotional adaptation	0.622**	0.367**	0.278**	0.361**	0.169**	1	
satisfaction	0.689**	0.348**	0.426**	0.394**	0.230**	0.281**	1

**: $p < 0.01$.

3.2. Results and Analysis of Distress Subscales

The operational definition of distress in college students is a multidimensional psychosomatic symptom cluster triggered by stress, encompassing cognition (e.g., obsession, paranoia), emotion (e.g., depression, anxiety), behavior (e.g., aggression, withdrawal), and somatization [8]. Based on the six core dimensions of the SCL-90, six high-incidence dimensions, such as internet addiction and sexual psychology, were added to create a preliminary 12-dimensional theoretical framework.

3.2.1. Discrimination and Discriminatory Power Analysis

This study used the item-total correlation coefficient score to measure discrimination and the high-low group discrimination index to measure discrimination.

During preliminary assessments, the correlation coefficient of the total item-dimension score of the distress subscale ranged from 0.135 to 0.770, and the MD value ranged from 0.34 to 2.24. According to the standard of discrimination less than 0.3 and MD value less than 0.8, a total of 8 items were eliminated due to two shortcomings in some questions at the same time. In the second assessment, 10 items with a discrimination of less than 0.3 were excluded, and 18 items with an MD of less than 0.8 were excluded. Delete the corresponding questions with insufficient distinction and discrimination, and remove a total of 27 items. In the third assessment, 2 items with MD values below 0.8 were excluded. In general, the structure of each dimension of the distress subscale is stable, and the overall quality is high.

3.2.2. Reliability Analysis

In this study, the Cronbach's α coefficient of consistency was used to test the reliability index of the scale.

The Cronbach's α coefficient of the troubled subscale was 0.952, indicating that the overall internal consistency reliability of the scale was extremely high for the preliminary measurement. The internal consistency coefficients of the 10 factors were 0.855, 0.834, 0.837, 0.816, 0.795, 0.788, 0.641, 0.725, 0.610, and 0.693, respectively, but the internal consistency coefficients of the aggression (0.610), dependence (0.641) and paranoia (0.693) dimensions were relatively low.

For the second test, the Cronbach's α coefficient for the distressed subscale was 0.928, and the overall internal consistency was still high. However, the internal consistency coefficients of the 10 factors were 0.499, 0.829, 0.608, 0.624, 0.710, 0.819, 0.639, 0.820, 0.781, and 0.831, respectively, and the internal consistency of impulsivity (0.624), compulsion (0.608), and dependence (0.639) dimensions was relatively low, especially the depression dimension was only 0.499, which was not very consistent.

During the third assessment, the Cronbach's α coefficient of the adapted subscale was 0.898, and the overall internal consistency was good, indicating that the homogeneity between the items of the scale was high and the measurement results were more reliable. The specific results are shown in **Table 4**; most of the dimensions have good internal consistency and can stably measure psychological distress traits, but the coefficient of the obsessive dimension is only 0.521, the correlation of questions is weak, and the fit with the core concept is not good, so it needs to be optimized.

Table 4. Internal Consistency Analysis of Each Dimension of the Troubled Subscale.

Distress Total Scale	Depression	Anxiety	Somatization	Forced	Attack	Flinch	Addiction
0.898	0.808	0.757	0.704	0.521	0.701	0.742	0.712

3.2.3. Structural Validity Analysis

During preliminary assessment, all questions were limited to 12 factors, and exploratory analysis was conducted. After deleting the items with a load of less than 0.4 and cross-load, it was finally found that 10 factors were the most suitable, and after balancing the number of questions, the KMO value was 0.943, the cumulative variance explanation rate reached 62.586%, and the load value of each item on the corresponding factors was between 0.401 and 0.841.

In the second test, all questions were limited to 12 factors, and exploratory analysis was conducted to find that anxiety and depression intersect, psychosis and somatization, and paranoia intersect with aggression/hostility. Dimensions such as withdrawal, Internet addiction, psychosexuality, impulsivity, aggression, and somatization are better. After deleting the questions with a load of less than 0.4 and cross-load, it was finally found that 10 factors were the most suitable, and after balancing the number of questions, the KMO value was 0.810, the cumulative variance explanation rate reached 60.947%, and the load value of each item on the corresponding factors was between 0.418 and 0.794.

In the third test, according to the analysis of the distribution of options, it is found that the distribution trend of all questions and the options in the dimension is relatively consistent. Only Q019 (I am very taboo to talk about sex-related topics with others) and Q057 (I think "sex" is a difficult topic) The proportion of people who choose to match (the sum of basic and complete matches) has reached more than 15%, indicating that college students still cannot accept such a direct discussion of sex, so this dimension is deleted. In the end, the two dimensions of psychopathy and psychosexuality were deleted according to the distribution of options. After three test items were optimized by exploratory factor analysis, the items with low load and cross-load were continuously deleted, and the number of questions was balanced. The KMO value was 0.902, the cumulative variance explanation rate reached 60.941%, and the load value of each item on the corresponding factors was between 0.558 and 0.819.

The results of exploratory factor analysis showed that only two questions could be retained in the obsessive dimension. Therefore, the two questions were included in the model for confirmatory factor analysis, and the confirmatory results of the following three models were compared. In Model 1, Q011 and Q087 were retained; in Model 2, Q011 was deleted; and in Model 3, Q087 was deleted. The fitting results are shown in **Table 5**.

Table 5. Overall Fitting Index of the Confirmatory Factor Analysis Model of the Troubled Subscale.

	$\chi 2$/df	GFI	IFI	NNFI	CFI	RMSEA
Model 1	1.516	0.91	0.99	0.98	0.99	0.039
Model 2	1.525	0.91	0.99	0.98	0.99	0.039
Model 3	1.59	0.91	0.98	0.98	0.98	0.042

After comparing the three models and considering the balance of the number of items across the dimensions and the diversity of item presentation, Q011 and Q087 were ultimately retained. All indicators were within the acceptable range for a good-fit model. Therefore, overall, the data fit the defined model well, and the assumptions of the seven-factor model were accepted. Factor loading estimates showed that the standardized factor loadings for each item in the distress subscale ranged from 0.36 to 0.74, indicating a good correlation between each item and the corresponding dimension, indicating that the distress subscale has good structural validity.

The correlation analysis between the various dimensions was performed on the adaptation subscale, and the results are shown in **Table 6**. The total score of the adaptation scale was significant and positively correlated with each dimension ($P < 0.01$). There are different degrees of significant correlation between each dimension, which reflects that each dimension is both interrelated and independent, which provides a reference for the structural validity of the scale.

Table 6. Correlation Analysis Between the Dimensions of the Distress Subscale.

	Distress Subscale	Depression	Anxiety	Somatization	Forced	Attack	Flinch
Distress subscale	1						
depression	0.755**	1					
anxiety	0.712**	0.413**	1				
Somatization	0.725**	0.538**	0.417**	1			
forced	0.725**	0.482**	0.527**	0.420**	1		
attack	0.620**	0.386**	0.270**	0.423**	0.298**	1	
flinch	0.710**	0.521**	0.509**	0.377**	0.429**	0.321**	1
Internet addiction	0.683**	0.472**	0.364**	0.345**	0.463**	0.337**	0.354**

**: $p < 0.01$.

3.3. Results and Analysis of the Resilience Subscale

In this study, resilience is defined as the stress resistance mechanism formed by individuals through trait-environment interactions, which is manifested in the ability to maintain self-control and develop adaptive coping in the face of setbacks [9]. Based on the characteristics of college students, this study divides resilience into four dimensions: self-confidence (self-affirmation and acceptance), positive cognition (tendency to recognize things from a positive perspective), problem solving (taking the initiative to adopt effective strategies to solve problems), and social support (support obtained from social relationships).

3.3.1. Discriminative Analysis

In this study, the discriminative power was measured by the high and low group discrimination index.

In the preliminary assessment, the discriminative analysis results of the resilience subscale showed that the MD value was between 0.22 and 1.80, and the three items were excluded because the MD value was lower than 0.8 and the discriminative power was low. During the second test, twelve items with an MD below 0.8 were excluded. In the third assessment, all items had an MD value greater than 0.8, which was at a high level, and no items were excluded. The results showed that after the optimization of the first two tests, the structure of each dimension of the scale was stable, and the items in the resilience subscale had good discriminative power, which could effectively distinguish the performance of subjects at different levels in this dimension.

3.3.2. Reliability Analysis

In this study, the Cronbach's α coefficient of consistency was used to test the reliability index of the scale.

For the preliminary assessment, the Cronbach's α coefficient of the resilience subscale was 0.890, and the internal consistency coefficients of the four factors were 0.782, 0.687, 0.789, and 0.784, respectively.

In the second test, the Cronbach's α coefficient of the resilience subscale was 0.850, and the internal consistency coefficients of the four factors were 0.719, 0.690, 0.678 and 0.782, respectively.

After the third test, the Cronbach's α coefficient of adaptation subscale was 0.833, indicating that the subscale had good internal consistency. The specific results are shown in **Table 7**, which shows that after three optimizations, the resilience subscale Cronbach's α coefficient gradually decreases, and the internal consistency of each sub-dimension also fluctuates. It may be that the reliability does not rise but decreases due to the lack of homogeneity in the adjustment of the questions, and the subsequent optimization and adjustment strategy needs to be optimized to increase the reliability.

Table 7. Internal Consistency Analysis of Each Dimension of the Resilience Subscale.

Resilience Total Scale	Assertive	Positive Perception	Problem Solving	Social Support
0.833	0.643	0.697	0.656	0.738

3.3.3. Structural Validity Analysis

During the preliminary assessment, all questions were limited to 4 factors, and exploratory analysis was conducted, and it was found that the dimensions of self-confidence and positive cognition intersected, such as "I can always find several different ways to solve problems". After continuously deleting the items with low load and cross-load, and balancing the number of questions, the KMO value was 0.891, the cumulative variance interpretation rate reached 52.878%, and the load value of each item on the corresponding factor was between 0.419 and 0.749.

In the second test, all questions were limited to 4 factors and exploratory analysis was conducted. After continuously deleting the items with low load and cross-load, and balancing the number of questions, the KMO value was 0.822, the cumulative variance interpretation rate reached 57.443%, and the load value of each item on the corresponding factor was between 0.435 and 0.785.

In the third assessment, after three test items were optimized by exploratory factor analysis, the items with low load and cross-load were continuously deleted, and the number of questions was balanced. The KMO value was 0.860, the cumulative variance explanation rate reached 51.729%, and the load value of each item on the corresponding factors was between 0.496 and 0.817.

After confirmatory factor analysis, the fitting results are shown in **Table 8**.

Table 8. Overall Fit Index of the Confirmatory Factor Analysis Model of the Resilience Subscale.

	$\chi2$/df	GFI	IFI	NNFI	CFI	RMSEA
Resilience model	1.906	0.93	0.96	0.95	0.96	0.052

As shown in **Table 8**, all indicators are within an acceptable range for a good fit model. Therefore, overall, the data fit the defined model well, supporting the assumptions of the four-factor model. Factor loading estimates show that the standardized factor loading values for each item in the resilience subscale range from 0.30 to 0.75, indicating a certain degree of correlation between each item in the subscale and the corresponding dimension, reflecting, to some extent, the good structural validity of the resilience subscale.

The correlation analysis between the resilience subscales (**Table 9**) showed that the total score of the scale was significantly positively correlated with each dimension ($P < 0.01$), indicating that the overall scale was consistent with the measurement objectives of each dimension, and the correlation coefficient between each dimension was between 0.255–0.498 ($P < 0.01$), which not only reflected the correlation between the dimensions, but also showed a certain degree of independence. Support the rationality of the structural validity of the scale.

Table 9. Correlation Analysis Between the Dimensions of the Resilience Subscale.

	Restore The Score	Assertive	Positive Perception	Problem Solving	Social Support
Restore the score	1				
assertive	0.689**	1			
Positive perception	0.792**	0.375**	1		
Problem solving	0.725**	0.255**	0.498**	1	
Social support	0.722**	0.261**	0.492**	0.422**	1

**: $p < 0.01$.

4. Discussion

4.1. Adaptation Subscale

Based on theoretical assumptions, this study categorized college students' adaptation into the dimensions of interpersonal relationships, campus life, academics, career choices, emotions, self-adaptation, and satisfaction. Initial data analysis revealed significant cross-loadings between the campus life adaptation dimension and academic adaptation, with freshmen scoring significantly higher on this dimension than those from other grades, indicating grade-specific content. Consequently, this dimension was removed. Reliability and validity testing of the resulting adaptation subscale revealed an internal consistency reliability of 0.864 for the total scale, with reliability coefficients ranging from 0.658 to 0.782 for the interpersonal relationships, academics, self, emotions, and satisfaction dimensions, and a reliability coefficient of 0.485 for the career choice dimension, likely due to the small number of items and the significant differences in career pressure experienced by students across grades. Confirmatory factor analysis demonstrated a good fit, with the six-dimensional model effectively distinguishing core adaptation domains such as interpersonal relationships and academics. This scale confirms its ability to effectively reflect theoretical dimensions of college students' adaptation and provides a reliable tool for measuring their adaptation.

4.2. Distress Subscale

Based on the research on the mental health of college students, this study draws on the core dimensions of the SCL-90 scale and combines the characteristics of college students, and preliminarily constructs a mental health measurement tool containing 12 dimensions. After three screenings, due to the low detection rate of five dimensions such as psychopathy and psychosexuality, the seven dimensions of high detection rate of depression, anxiety, somatization, withdrawal, aggression, compulsion, and Internet addiction were finally retained, which was consistent with the conclusions of previous studies [10,11]. The reliability and validity test of the distress subscale formed by the study showed that the internal consistency reliability coefficient of the total scale was 0.898, and the reliability coefficient of depression, anxiety and other dimensions was between 0.701 and 0.808, and only the obsessive-compulsive dimension covered different levels such as compulsive behavior and thinking due to the questions, and the internal consistency coefficient was 0.521. The confirmatory factor analysis has excellent fit and good structural validity, which confirms that the scale can effectively measure the psychological distress of college students, and its theoretical concept is acceptable.

4.3. Resilience Subscale

This study defines college students' resilience as the ability and resources to recover quickly from stress. Based on theoretical construction, it is divided into four factors: self-confidence, positive cognition, problem-solving, and social support. Three tests were administered to develop a resilience subscale. Reliability and validity tests revealed an internal consistency coefficient of 0.833 for the total scale, with individual subscales ranging from 0.643 to 0.738, both within acceptable ranges. Confirmatory factor analysis demonstrated good construct validity, confirming that the scale effectively reflects the theoretical dimensions of college students' resilience and supports its theoretical conception.

5. Conclusions

This study assessed college students' mental health across three dimensions: adaptation, distress, and resilience. The internal consistency reliability of the three subscales of adaptation, distress and resilience was 0.864, 0.898 and 0.833, respectively. The results of confirmatory factor analysis showed that the structural validity of the three subscales of adaptation, distress and resilience was good. This provides a scientific tool for college students' mental health assessment. However, the career choice and compulsion dimensions exhibited relatively lower reliability in the study, so future research should optimize sampling methods and item design to further enhance the measurement accuracy of the tool.

Author Contributions

Conceptualization, S.L.; methodology, J.L., J.W. and M.T.; validation, J.L., M.T. and S.L.; formal analysis, J.L. and M.T.; investigation, J.L., J.W. and M.T.; data curation, J.L., J.W. and M.T.; writing—original draft preparation, J.L. and S.L.; writing—review and editing, S.L.; supervision, S.L. and J.W. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Ethical review and approval were waived for this study due to the exclusive use of anonymized, non-identifiable human data, no intervention or interaction with participants, no collection of sensitive personal information or involvement of commercial interests, and no foreseeable risk of physical or psychological harm.

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

For access to the data of this study, please contact the corresponding author with a reasonable request.

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Conflicts of Interest

The authors declare no conflict of interest.

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REVIEW

Images That Think: Theoretical Conflicts in Cognitive Psychology

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ABSTRACT

This paper explores the theoretical and empirical foundations of mental imagery and inductive reasoning within cognitive psychology, with a particular focus on their epistemological tensions and functional complementarities. The first part examines the longstanding debate between pictorial and propositional theories of mental representation, highlighting pivotal contributions by Kosslyn, Pylyshyn, Paivio, Shepard, and Cooper. Drawing on neuroimaging, behavioral experimentation, and computational modeling, the paper argues that mental images preserve spatial and perceptual properties and are manipulated in ways that mirror actual perception, thereby supporting the analogical view. These findings are contrasted with symbolic or propositional accounts, which emphasize the abstract, language-like structure of thought. The Kosslyn–Pylyshyn debate is analyzed as a paradigmatic conflict that shaped subsequent empirical methodologies and conceptual assumptions in the field. The second part focuses on inductive reasoning as a probabilistic, experience-driven process that underpins concept formation, categorization, and adaptive learning. The paper investigates the interplay between attention, perception, and memory in constructing conjunctive, disjunctive, and relational concepts. Inductive reasoning is shown to support decision-making in dynamic, uncertain environments through flexible cognitive strategies. Both imagery and induction are examined in their applied dimensions, ranging from clinical psychology and education to AI and neuroscience, where they inform therapeutic tools, instructional design, and cognitive modeling. Methodological insights from neuropsychology and qualitative introspection are integrated to underline the dynamic, multimodal nature of these processes. The paper concludes by proposing that imagery and inductive reasoning are not only theoretically

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interdependent but also crucial for advancing cognitive science and its practical applications.

Keywords: Mental Imagery; Inductive Reasoning; Cognitive Processes

1. Introduction

Mental imagery has long been a subject of theoretical contention in cognitive psychology, tracing back to classical philosophical inquiries into the nature of thought and representation. From Aristotle's idea that "the soul never thinks without an image" (*De Anima*, Book III) to Descartes' dualist speculations about mental picturing, the issue of how humans mentally simulate reality has remained pivotal in debates over the architecture of cognition. Contemporary psychological research inherits this tension, crystallizing it into two dominant perspectives: the pictorial and propositional approaches to mental representation.

The pictorial approach posits that mental images function analogously to visual perception, they retain spatial structure, metric properties, and a sense of visual continuity. This model is closely linked to the work of Stephen Kosslyn, who proposes that visual imagery operates through quasi-perceptual processes and relies on mechanisms similar to those involved in actual vision [1,2]. In contrast, the propositional view, advanced notably by Zenon Pylyshyn, argues that cognition is mediated by abstract, language-like codes that do not necessarily preserve sensory or spatial features [3,4]. These propositions, akin to syntactic representations in logic or computer programs, are assumed to be amodal, operating independently of perceptual systems.

This theoretical divide has significant implications for understanding cognitive processes, including memory, reasoning, language, and problem-solving. Kosslyn's experiments, which utilized mental scanning and rotation tasks, demonstrated that response times were proportional to the physical characteristics of the imagined stimuli, such as distance or angle [5]. These findings support the analogical nature of mental images. Conversely, Pylyshyn's critique emphasized the possibility that "tacit knowledge" influences participants' expectations, thereby mimicking perceptual effects without necessitating pictorial representation [4].

Mental imagery refers to the generation of sensory-like experiences in the absence of direct external stimuli. These experiences may span across multiple modalities, visual, auditory, olfactory, gustatory, and tactile, but the visual modality has received the most empirical attention [6,7]. Visual imagery allows individuals to mentally simulate objects, scenarios, or spatial transformations, playing a central role in knowledge acquisition, memory encoding, and creative reasoning [8,9].

Cornoldi, De Beni, and Giusberti [6] argue that mental images preserve key sensory characteristics of absent stimuli, allowing individuals to "reconstruct" perceptual experiences internally. Kosslyn, Thompson, and Ganis [7] further define mental imagery as a perceptual representation in the mind that can evoke subjective experiences similar to direct perception. These insights are supported by neuroimaging studies, which demonstrate that visual imagery activates overlapping regions in the visual cortex, particularly areas V1 and V2, suggesting a shared neural substrate for perception and imagery [10,11].

Allan Paivio's Dual Coding Theory [12,13] offers a complementary perspective by positing that cognition involves two semi-independent subsystems: one for verbal information and another for imagery. The interaction between these channels enhances learning and memory by providing multiple encoding routes. Empirical evidence from education and multimedia learning supports this claim, showing that information presented with congruent verbal and visual elements is retained more effectively than when either format is used alone [14,15]. This evidence has led to practical applications in instructional design, particularly in online learning and textbook development.

Complementary evidence comes from Shepard and Cooper's mental rotation studies [16], which found that individuals mentally manipulate three-dimensional objects in a manner that reflects physical transformations. Response times increased linearly with the angular disparity between objects, suggesting that mental images preserve geometric properties and are processed via mechanisms akin to motor planning.

Kosslyn's computational model of imagery conceptualizes the brain as a visual information processor, comprising a visual buffer, an image processor, and long-term memory for symbolic encoding [5]. The visual buffer, located in the primary visual cortex, acts as a mental screen where images are projected. The image processor manipulates these inputs, while long-term memory provides the syntactic rules for generating and interpreting visual scenes. This tripartite architecture has become a foundational model for understanding how visual representations are formed, transformed, and integrated into broader cognitive functions.

Recent perspectives have sought to bridge the pictorial–propositional divide through hybrid models. For example, the embodied cognition framework suggests that cognitive processes, including imagery, are grounded in bodily experience and sensorimotor contingencies [17]. These models propose that mental images are not mere static snapshots but dynamic simulations that recruit perceptual, motor, and affective systems. Neuroscientific studies support this view, showing that motor areas are activated during mental rotation tasks or when imagining grasping actions [18].

Mental imagery has also been examined in clinical and developmental contexts. For instance, individuals with aphantasia, an inability to voluntarily generate visual imagery, provide unique insight into the variability of imagery abilities across populations [19]. Conversely, individuals with highly vivid imagery may excel in tasks that require visualization, such as architectural design or advanced mathematics. Understanding these individual differences has implications for diagnosis and intervention in cognitive training, educational scaffolding, and therapy.

From a methodological standpoint, the study of mental imagery has employed a range of tools, including functional magnetic resonance imaging (fMRI), electroencephalography (EEG), transcranial magnetic stimulation (TMS), and eye-tracking. These techniques allow researchers to map the neural correlates of imagery and assess its temporal dynamics and spatial fidelity. For example, TMS applied to the occipital cortex can disrupt visual imagery, suggesting that early visual areas are functionally necessary for image maintenance [20].

The present paper adopts a dual-structured approach, first analyzing the theoretical foundations and empirical validations of the mental imagery debate, with a focus on analogical versus symbolic representations. Second, it investigates inductive reasoning as a complementary cognitive mechanism that operates probabilistically and empirically to form generalizations from specific instances. This second axis enables the exploration of how cognitive systems structure experience, construct meaning, and navigate uncertainty, thereby enriching the study of mental imagery with a broader lens on human cognition.

2. The Kosslyn–Pylyshyn Debate: Mental Imagery and Cognitive Architecture

A central controversy in cognitive psychology is the imagery debate between Stephen Kosslyn and Zenon Pylyshyn, which reflects broader tensions about the nature of mental representation and the architecture of thought. This debate is not merely academic but forms the epistemological axis upon which much of the empirical research on mental imagery is designed and interpreted. It centers on a deceptively simple yet deeply consequential question: When we imagine a visual scene, does the mind generate picture-like representations, or are these experiences epiphenomenal outputs of underlying symbolic processes?

Kosslyn, a prominent advocate of the pictorial (analogical) model, argues that mental imagery preserves spatial and visual characteristics akin to those found in actual perception. His neuroimaging studies using Positron Emission Tomography (PET) and fMRI techniques show that visual mental imagery activates early visual cortices (for example, area V1), reinforcing the idea that such imagery is functionally grounded in the perceptual system itself[1,7,10,11]. According to Kosslyn's theory, the brain constructs images on a "visual buffer", a mental screen within the visual cortex, on which transformations such as rotation, scanning, and resizing can occur [5].

In stark contrast, Pylyshyn contends that imagery is epiphenomenal, meaning that what feels like a picture in the mind is the byproduct of propositional cognitive processes. These propositions are abstract, amodal, and syntactically structured, comparable to language or computer code, without intrinsic spatial properties [3,4]. For Pylyshyn, the appearance of analogical behavior (for example, longer response times with increased mental distance) can be attributed to tacit knowledge or learned expectations about the physical world, rather than to genuinely pictorial representations.

2.1. Empirical Grounding: Classic Experiments

One of the most cited bodies of evidence in favor of the analogical view comes from Kosslyn's mental scanning tasks, in which participants are asked to form a mental image of a previously memorized map. The time it takes to scan from one point to another correlates linearly with the imagined distance, mimicking real-world spatial navigation [5]. Similarly, mental rotation tasks, originally conducted by Shepard and Cooper [16] and extended by Kosslyn, demonstrated that response times increase with angular disparity between imagined objects, again suggesting that mental images behave analogously to perceptual input.

Another widely discussed experiment involved imagining a rabbit next to either a fly or an elephant. Participants were quicker to identify features of the rabbit when imagined next to the fly than next to the elephant, implying that relative size and spatial granularity were preserved in the mental image [2,5,21]. These findings are difficult to reconcile with propositional theories, which do not predict such perceptual-like scaling effects.

In support of Pylyshyn's critique, however, some researchers have shown that strategic or task-related factors, such as the wording of instructions or contextual framing, can significantly alter results in imagery experiments. These effects suggest that cognitive strategies, rather than perceptual mechanisms, may drive some aspects of performance [22].

2.2. Cognitive and Neural Dissociations

Additional insights into the debate can be acquired from clinical neuropsychology. Studies of patients with brain lesions affecting occipital or parietal lobes show selective impairments in spatial imagery tasks, even when verbal reasoning remains intact [23]. For example, patients with damage to the right posterior parietal cortex often exhibit difficulties with mental rotation or spatial reconstruction, but can perform logical reasoning and semantic tasks normally. This fact supports the idea that imagery and symbolic processing are partially dissociable, both anatomically and functionally.

Kosslyn and colleagues used TMS (transcranial magnetic stimulation) to temporarily disrupt the occipital cortex during imagery tasks. They found that performance on visual imagery tasks decreased significantly during stimulation, suggesting a causal role for perceptual regions in the construction of imagery [20]. Such findings undermine the proposition that imagery is merely a symbolic epiphenomenon.

2.3. Multimodal Imagery and Embodied Extensions

Although much of the debate has focused on visual imagery, recent work emphasizes that mental imagery is a multimodal phenomenon, extending across auditory, tactile, olfactory, and motor domains. For example, individuals who are blind from birth can generate tactile or auditory mental representations that serve similar cognitive functions, such as spatial navigation, memory retrieval, or simulation of experiences, demonstrating that visual experience is not a prerequisite for mental imagery [24].

Embodied theories of cognition further challenge the dichotomy by proposing that imagery arises from sensorimotor simulations rooted in bodily experience [17]. For instance, imagining an action (for example, lifting a cup) activates overlapping neural circuits with those involved in the actual action itself [18]. This convergence suggests that mental imagery is not solely a symbolic construct, nor is it reducible to pictorial codes. It may instead emerge from integrated perceptual-motor systems, giving rise to what Barsalou calls "grounded simulations" [17].

2.4. Symbolic Representation Revisited

It is important to note that even Kosslyn acknowledged the limitations of a purely analogical model. In tasks involving abstract reasoning, ambiguous stimuli, or complex conceptual manipulation, propositional strategies may dominate. For instance, interpreting reversible figures (like the duck–rabbit illusion) or constructing mental representations of logic-based problems often involves symbolic encoding, hypothesis testing, and rule-based processing [4,25].

Thus, a hybrid account may offer a more plausible resolution to the imagery debate. Contemporary frameworks suggest that mental imagery engages multiple representational formats depending on task demands, individual differences, and domain-specific expertise. Some researchers propose that the brain dynamically toggles between analogical and symbolic systems, leveraging each according to efficiency and context [26].

2.5. Implications for Cognitive Architecture

The implications of this debate go beyond theoretical speculation. They influence how we understand memory consolidation, problem-solving, creativity, and even artificial intelligence (AI). In AI, for example, visual reasoning models attempt to simulate human-like perception-based inference, while symbolic systems focus on formal rule encoding. A comprehensive theory of cognition must therefore account for how both modalities contribute to flexible, adaptive intelligence [27,28].

In summary, the Kosslyn–Pylyshyn debate remains one of the most generative theoretical divides in cognitive science. Rather than resolving the controversy in favor of one model, recent research suggests that mental imagery is a composite process, sometimes perceptual and at other times symbolic, and often interactive. Ongoing studies in neuroscience, Human Computer Interaction (HCI), and computational modeling continue to refine our understanding of this core dimension of human cognition.

3. Applications of Imagery and Inductive Reasoning in Cognitive Psychology

Mental imagery is a powerful cognitive function with extensive applications across various domains, including clinical, educational, technological, and scientific fields. Far from being a theoretical curiosity, imagery processes are actively harnessed to enhance motor coordination, emotional regulation, memory consolidation, decision-making, and learning outcomes [9]. The increasing integration of neurocognitive tools and applied frameworks has provided empirical support for the practical benefits of imagery in diverse settings.

3.1. Clinical Psychology

In clinical psychology, mental imagery has emerged as a versatile tool used across both neurorehabilitative and psychotherapeutic frameworks. One of the most well-documented applications is Motor Imagery Practice (MIP), in which individuals imagine executing motor actions without actually moving their bodies. This method is particularly valuable for patients recovering from stroke, traumatic brain injury, or neurodegenerative conditions like Parkinson's disease. Empirical studies demonstrate that MIP activates the motor cortex, supplementary motor area, and cerebellum, areas also involved during actual movement, indicating its potential to preserve and enhance motor pathways during periods of physical inactivity [29].

In parallel, mental imagery plays a transformative role in trauma-focused therapies, especially within Eye Movement Desensitization and Reprocessing (EMDR). In this context, guided imagery is employed to evoke traumatic memories in a structured setting, allowing clients to reconsolidate these experiences with reduced emotional intensity. The visualization of safe spaces, protective figures, or empowering narratives is used to reframe cognitive appraisals and attenuate distress responses [30].

Beyond trauma, imagery-based cognitive restructuring is also highly effective in the treatment of anxiety disorders, depression, and obsessive-compulsive disorder (OCD). For instance, patients may be guided to visualize feared situations and mentally rehearse adaptive responses, or to imagine more realistic, compassionate interpretations of self-defeating thoughts. This process enhances emotional processing, supports exposure techniques, and strengthens self-efficacy, particularly in clients with high verbal reasoning skills but low emotional insight [31,32]. Overall, mental imagery serves as both a diagnostic probe and a change agent in psychotherapy, offering access to preverbal representations, implicit memory, and nonverbal affective schemas that are often difficult to reach through verbal dialogue alone.

3.2. Sports Psychology

Mental imagery is a cornerstone of performance enhancement and psychological training in sports psychology. Athletes routinely engage in visual, kinesthetic, and auditory imagery to mentally rehearse athletic movements, game strategies, and even emotional states under pressure. This type of mental simulation is widely recognized for improving motor coordination, reaction time, focus, and self-regulation. It is particularly effective when combined with physical practice, as it enables athletes to rehearse precision tasks repeatedly without the fatigue or injury risk associated with physical overtraining [33].

Neuroimaging studies [34,35] have confirmed that motor imagery activates neural structures, such as the premotor cortex, basal ganglia, and cerebellum, which overlap with those engaged during physical execution. This shared circuitry supports the idea that mental rehearsal strengthens sensorimotor representations, accelerates motor learning, and enhances automatization of complex skills.

Elite athletes often use scripted imagery protocols developed in collaboration with sports psychologists. These scripts may incorporate motivational components (for example, imagining successful outcomes), strategic simulations (for example, adapting to a competitor's unexpected move), and recovery scenarios (for example, bouncing back from errors). Imagery is also used pre-competition to regulate arousal levels, reduce performance anxiety, and maintain optimal attentional focus. For example, visualizing the execution of a penalty kick in front of a hostile crowd prepares athletes to maintain composure under stress.

Beyond individual sports, team-based disciplines utilize collective imagery sessions to improve coordination, communication, and tactical execution. As a cognitive training tool, mental imagery has become an integral part of performance psychology programs for Olympic teams, military athletes, and professional leagues worldwide.

3.3. Education

Educational psychology has long benefited from the application of mental imagery, particularly through frameworks like Dual Coding Theory, which posits that information is encoded more robustly when presented in both verbal and visual formats [12–14]. In classrooms and digital learning environments, this principle supports the use of diagrams, illustrations, mind maps, and interactive visuals to reinforce complex or abstract content.

Imagery facilitates not only memory retention but also conceptual clarity, especially in domains such as mathematics, science, engineering, and foreign language acquisition. For example, visualizing geometric transformations, atomic structures, or grammatical sentence trees can reduce cognitive load and scaffold schema construction [15,36]. The use of graphic organizers and imagery cues is particularly effective for students with learning difficulties, such as dyslexia or Attention-Deficit/Hyperactivity Disorder (ADHD), as it provides multisensory input and supports working memory.

Emerging technologies have further amplified the instructional potential of imagery. Augmented reality (AR) and simulation-based learning environments enable learners to interact with 3D models of anatomical systems, historical reenactments, or molecular structures [37]. These immersive experiences utilise spatial cognition and embodied learning, fostering a deeper understanding through visual manipulation and exploratory engagement [38].

Additionally, mental imagery plays a crucial role in developing reading comprehension, mathematical reasoning, and creative writing. When students are encouraged to "form a picture in their mind" while reading or solving problems, they engage with the material more actively and meaningfully. Overall, imagery-based strategies are essential tools for enhancing meaning-making, retention, and transfer of learning in both traditional and technology-enhanced educational settings.

3.4. High-Risk Professions and Training

In high-stakes environments, such as aviation, surgery, firefighting, and military operations, the stakes for human error are significant. In these fields, mental imagery is deployed as a core element of simulation-based training, allowing professionals to rehearse tasks, contingencies, and decision trees in controlled, low-risk settings. By mentally simulating the procedural and emotional demands of critical scenarios, individuals can pre-activate the neural and cognitive systems essential for successful real-world performance [39].

Virtual Reality (VR), Augmented Reality (AR), and 3D simulation platforms replicate realistic task environments and stress conditions. For instance, in aviation, pilots undergo flight simulator training that incorporates not only technical maneuvers but also emergency response protocols, often guided by scripted imagery. Similarly, military units train with VR-based mission walkthroughs that prepare personnel for combat unpredictability, helping to desensitize threat responses and enhance cognitive flexibility.

In medical education, imagery-based simulation is integral to surgical training. Residents practice complex procedures using haptic feedback systems and VR interfaces that mimic anatomical variability, time pressure, and instrument handling. Studies show that mental walkthroughs improve procedural recall, precision, and team coordination, even when physical resources are limited [40].

Importantly, these applications extend beyond technical training to emotional regulation and situational awareness.

Visualising a successful response in a high-stress emergency or anticipating complications during surgery not only improves competence but also enhances confidence, resilience, and decision-making speed. Mental imagery thus functions as a bridge between cognitive rehearsal and real-time adaptability, enhancing both performance and safety in critical settings.

3.5. Artificial Intelligence and Neuroscience

In the fields of artificial intelligence (AI) and neuroscience, mental imagery has inspired the development of computational models that attempt to simulate human reasoning, perception, and internal representation. Contemporary AI systems—particularly those focused on visual question answering (VQA), image captioning, and scene understanding—increasingly incorporate architectures that emulate perceptual-symbol systems [27,28]. These systems are designed not merely to process visual data but to interpret and generate inferences from imagined or hypothetical scenarios, mimicking the simulation-based reasoning seen in human cognition.

For instance, models like CLEVR or neural-symbolic reasoning frameworks integrate symbolic logic with deep learning to answer questions about visual scenes. Such models reflect how the human mind links perceptual input with conceptual structure, aligning with theories of grounded cognition and dual-process reasoning [41].

Simultaneously, in neuroscience and neuroengineering, mental imagery underlies critical innovations in brain-computer interface (BCI) technology. These systems translate imagined motor commands into digital signals that control prosthetic limbs, communication devices, or robotic systems. Successful implementation depends on the brain's ability to generate distinct neural activation patterns during motor imagery, which can be detected using EEG, MEG, or fMRI and then interpreted by machine learning algorithms [42].

Beyond motor control, BCIs are now exploring affective imagery for emotion regulation and visual imagery for neurofeedback-based treatments in anxiety or ADHD. This bidirectional relationship, where mental imagery both informs and is decoded by AI, demonstrates its centrality in bridging human and machine cognition, offering promising avenues for assistive technologies and the future of human–AI symbiosis.

3.6. Methodologies in Imagery Research

The scientific investigation of mental imagery relies on a diverse array of quantitative and qualitative methodologies, each providing distinct insights into the nature, function, and variability of internal representations.

On the quantitative side, neuroimaging tools such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and transcranial magnetic stimulation (TMS) allow researchers to explore the neural correlates and causal mechanisms underlying imagery processes. For instance, fMRI has shown that imagining a visual scene activates regions in the occipital cortex, particularly area V1, similar to those recruited during actual perception [10,20]. EEG provides high temporal resolution for analyzing the time course of imagery generation, while TMS can disrupt specific cortical areas to assess their functional necessity during imagery tasks.

Behavioral experiments complement these neural methods by assessing response time, accuracy, and task interference during classic tasks such as mental rotation, image scanning, and size comparison [5,16]. These experiments provide evidence for the analogical nature of mental images and reveal how imagery is manipulated in real time, often in a spatially structured manner.

Qualitative methods contribute essential insights into the subjective experience of imagery. Approaches like introspective verbal reports, think-aloud protocols, and imagery-based drawing tasks help uncover individual differences in vividness, modality dominance (e.g., visual, auditory, kinesthetic), and phenomenological richness [19]. Such methods are especially valuable in clinical and educational contexts, where imagery ability varies widely across populations.

More recently, mixed-methods research has begun to integrate these approaches, linking neurophysiological data with self-report measures and performance outcomes, thereby creating a more holistic understanding of imagery as both a neural process and an experiential phenomenon.

3.7. Inductive Reasoning: From Specifics to Generalizations

Inductive reasoning represents a fundamental form of human cognition through which individuals derive general principles from specific instances. Unlike deductive reasoning, which produces logically necessary conclusions from given premises, induction is probabilistic, experience-based, and often domain-sensitive. This makes it particularly well-suited to environments characterized by uncertainty, variability, and incomplete information [43,44].

Historically, the philosophical foundation of inductive reasoning was laid by Francis Bacon, who advocated for the systematic accumulation of empirical observations followed by the gradual formulation of hypotheses. This legacy underpins not only the scientific method but also modern approaches to machine learning, clinical inference, and concept development in psychology.

In contemporary cognitive science, induction is seen as the mechanism behind categorization, analogy formation, pattern recognition, and decision-making. It allows humans to learn from experience, generalize beyond data, and adapt flexibly to new or complex situations. Importantly, inductive reasoning is not purely logical, it is deeply integrated with perception, attention, and memory, making it an embodied, context-sensitive process [45,46].

Moreover, computational models of induction, including Bayesian reasoning, connectionist networks, and case-based reasoning systems, have further elucidated how humans approximate optimal inference using limited cognitive resources, highlighting both the power and limitations of inductive thought.

3.8. Cognitive Components of Induction

The success of inductive reasoning hinges on the coordinated activity of several core cognitive faculties, each contributing a specific function to the process of generalization:

- **Attention** acts as a filter and amplifier, selecting relevant features from sensory input while suppressing irrelevant or distracting stimuli.
- **Perception** structures incoming data, detecting patterns and organizing stimuli into meaningful categories that support early generalizations.
- **Memory** serves as a repository for exemplars and experiences, enabling comparisons across instances and aiding the abstraction of common features [47].

These faculties are dynamically engaged in the processing of different concept types:

- **Conjunctive concepts** (for example, "red and circular") are relatively straightforward, requiring identification based on simultaneous features.
- **Disjunctive concepts** (for example, "red or circular") demand attentional flexibility and greater working memory to handle multiple rule sets.
- **Relational concepts** (for example, "larger than", "left of") necessitate spatial reasoning and the ability to manipulate mental representations of relationships [47,48].

To navigate these challenges, individuals rely on strategic reasoning approaches such as:

- **Successive scanning**—testing one feature or hypothesis at a time,
- **Conservative focus**—limiting comparisons to one dimension,
- **Comparative analysis**—weighing similarities and contrasts to find general patterns.

These strategies reflect an adaptive toolkit that adjusts to task demands, prior experience, and cognitive load. Crucially, they highlight how inductive reasoning is not simply a logical function but an adaptive, contextually driven process influenced by individual differences and environmental affordances.

3.9. Integration of Imagery and Induction

While often studied independently, mental imagery and inductive reasoning are deeply interconnected in real-world cognition. Their interaction is particularly evident in domains such as scientific hypothesis generation, clinical diagnosis, design thinking, and problem-solving. In these contexts, imagery supports the simulation of scenarios, while induction helps extract patterns and derive rules or explanations from those simulations.

For example, a scientist may visualize a molecular interaction before forming a generalized hypothesis; a physician may mentally simulate a disease progression based on symptom patterns and then infer a diagnosis; a designer may prototype mental models of functionality and iteratively refine them through inductive reasoning based on feedback. In each case, visual simulation scaffolds abstraction, and inductive inference informs model updating.

This integration also plays a central role in learning environments, where visual analogies or conceptual metaphors enhance inductive category learning. In therapy, clients may visualize emotionally salient situations and derive new interpretations or relational patterns, reinforcing cognitive change.

Theoretical models increasingly recognize this dynamic interaction, advocating for hybrid frameworks that combine simulation-based and probabilistic reasoning systems. Empirically, studies using dual-task paradigms, neuroimaging, and computational modelling provide converging evidence that imagery and induction co-activate in problem-solving contexts, contributing to creative and flexible cognition.

Understanding this synergy is crucial for developing educational tools, clinical interventions, and intelligent systems that capture the full complexity of human thought. The scientific investigation of mental imagery relies on a diverse array of quantitative and qualitative methodologies, each providing distinct insights into the nature, function, and variability of internal representations.

On the quantitative side, neuroimaging tools such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and transcranial magnetic stimulation (TMS) allow researchers to explore the neural correlates and causal mechanisms underlying imagery processes. For instance, fMRI has shown that imagining a visual scene activates regions in the occipital cortex—particularly area V1—similar to those recruited during actual perception [10,20]. EEG provides high temporal resolution for analyzing the time course of imagery generation, while TMS can disrupt specific cortical areas to assess their functional necessity during imagery tasks.

Behavioral experiments complement these neural methods by assessing response time, accuracy, and task interference during classic tasks such as mental rotation, image scanning, and size comparison [5,16]. These experiments provide evidence for the analogical nature of mental images and reveal how imagery is manipulated in real time, often in a spatially structured manner.

Qualitative methods contribute essential insights into the subjective experience of imagery. Approaches like introspective verbal reports, think-aloud protocols, and imagery-based drawing tasks help uncover individual differences in vividness, modality dominance (e.g., visual, auditory, kinesthetic), and phenomenological richness [28]. Such methods are especially valuable in clinical and educational contexts, where imagery ability varies widely across populations.

More recently, mixed-methods research has begun to integrate these approaches, linking neurophysiological data with self-report measures and performance outcomes, thereby creating a more holistic understanding of imagery as both a neural process and an experiential phenomenon.

4. Conclusions

Mental imagery and inductive reasoning are foundational constructs in cognitive psychology, shaping our understanding of internal representation, simulation, learning, and adaptive behavior. Theoretical debates surrounding these processes, most prominently the one between Kosslyn and Pylyshyn, have not only crystallized divergent philosophical positions but also driven a robust empirical legacy. These debates have inspired the development of neuroimaging protocols, behavioral paradigms, and computational models that collectively reveal how the mind generates, manipulates, and evaluates mental content [49–52].

Mental imagery is no longer regarded as an epiphenomenal by product of thought. Instead, it is recognized as a neurologically grounded and functionally significant process, implicated in visual perception, memory retrieval, motor planning, and decision-making. Inductive reasoning, through its probabilistic, experience-based nature, complements imagery by elucidating how abstract categories and generalizations emerge from concrete perceptual input. Together, these two systems provide a rich and interactive account of cognition, one that is both symbolically expressive and perceptually embodied.

The convergence of empirical methodologies, from fMRI and TMS to behavioral experimentation and introspective techniques, underscores that neither imagery nor induction is a static construct. Rather, they are dynamic processes, modulated by developmental stage, task context, cultural background, and technological mediation [53]. This flexibility renders them especially relevant for real-world applications in therapy, education, professional training, and artificial intelligence.

Recent advances in immersive and simulation-based technologies, particularly in educational and clinical contexts, underscore the applied value of these cognitive mechanisms. As Soares[54] has noted, technologies such as virtual reality, serious games, and visualization tools can activate core imagery and reasoning processes, fostering experiential learning, metacognition, and adaptive expertise. These tools enable learners and practitioners to rehearse, reflect, and generalize in controlled yet realistic environments, thereby enhancing both conceptual understanding and the transfer of learning[55].

Future Directions

Despite the significant progress outlined above, several questions remain unanswered, indicating fertile ground for future research. One key direction involves investigating the developmental trajectory of imagery and induction, how these capacities emerge, interact, and differentiate across childhood, adolescence, and aging. Longitudinal and cross-sectional studies that integrate neurocognitive and educational assessments could provide valuable insights into sensitive periods and cognitive plasticity.

Another avenue concerns the individual differences in imagery ability and inductive reasoning. Emerging evidence suggests that factors such as vividness, modality dominance, working memory capacity, and even affective traits (for example, anxiety, optimism) may influence how individuals engage in and benefit from imagery-based or inductive tasks. Future studies should explore how to tailor interventions and learning strategies to these differences, particularly in clinical populations, neurodiverse groups, and aging adults.

Additionally, the integration of imagery and induction in computational models remains a largely unexplored frontier. Bridging symbolic AI systems with perceptual-simulation architectures could enhance machine reasoning, particularly in areas such as decision-making, causal inference, and human–AI collaboration. Research that translates insights from cognitive neuroscience into machine learning architectures, such as integrating image-based simulation with rule learning, could advance both theoretical and applied AI.

Ultimately, the study of contextual and cross-cultural influences on imagery and reasoning remains in its infancy. Cross-linguistic and cross-cultural research could reveal how social environments, educational systems, and cultural norms shape the development and deployment of these cognitive tools.

In sum, imagery and induction remain at the heart of some of psychology's most pressing questions and most promising solutions. Their continued study offers not only theoretical enrichment but also transformative potential across various fields, including science, health, education, and technology.

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