The Influence Mechanism of Large Language Model-Based Zhongyong Thinking on Mental Health: The Mediating Role of Moral Centrality

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Abstract

In recent years, researchers have reached relatively consistent recognition regarding the positive influence of Zhongyong thinking on mental health; however, its underlying mechanisms remain unclear. Previous studies have demonstrated that when individuals can effectively coordinate agentic motives representing "self-interest"and communal motives representing "altruism,"they tend to possess relatively high levels of moral centrality. Moral centrality reflects the balanced state of the internal motivational system, reducing conflicts between intrinsic motives and promoting mutual support and reinforcement between these two motivational types. Moral centrality may thus play a potential mediating role in the relationship between Zhongyong thinking and mental health. Currently, a relatively mature assessment method for measuring individual moral centrality exists—Values Embedded in Narratives (VEIN); however, this approach involves value-coding of personal striving texts, rendering the measurement process relatively complex and labor-intensive. Nevertheless, the development of large language models (such as ChatGPT) in recent years has demonstrated exceptional contextual understanding capabilities, offering new possibilities for text analysis and coding in psychological research. This study aims to leverage cutting-edge large language model technology to apply it to coding work in psychological research, thereby reducing the time and labor costs required for measuring individual moral centrality, while simultaneously exploring the mechanisms through which Zhongyong thinking influences mental health and understanding how culture affects individual mental health levels via moral centrality. Study 1 employed prompt engineering to design differential prompts for training GPT-3.5 Turbo to identify values embedded in personal strivings (achievement/power/universalism/benevolence), and evaluated identification accuracy, precision, and recall rates to obtain a recognition model meeting requirements and application conditions. In Study 2, the aforementioned model was applied to measure moral centrality, verifying the mediating role of moral centrality

in the influence of Zhongyong thinking on mental health (depression and anxiety). The results are as follows: (1) The GPT-3.5 Turbo large language model achieved an accuracy rate no lower than 0.80 in identifying power, achievement, universalism, and benevolence values, demonstrating the application potential of ChatGPT in psychological research; (2) Moral centrality played a mediating role in the influence of Zhongyong thinking on depression/anxiety; individuals with high Zhongyong thinking can more effectively integrate agentic and communal motives, enhance their moral centrality, thereby reducing individual depression/anxiety levels. In summary, this study utilized large language model technology to overcome technical limitations of traditional psychological research, explored the mechanisms through which Zhongyong thinking influences mental health, and verified the mediating role of moral centrality therein. On the one hand, it demonstrates the application potential of large language models in psychological research; on the other hand, it also deepens our understanding of the mechanisms through which cultural factors influence mental health, enriches the theoretical foundation of this field, and suggests to policymakers that they may leverage the advantages of Zhongyong culture, advocate values emphasizing both personal development and collective welfare, help citizens form coordinated thinking patterns, and maintain and promote the mental health of the people and the healthy development of society.

Full Text

The Impact of Zhong-yong Thinking Style on Mental Health using LLM: The Mediating Role of Moral Centrality

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Abstract

In recent years, researchers have consistently recognized the positive impact of Zhong-yong thinking style on mental health, yet the underlying mechanisms remain unclear. Previous studies indicate that when individuals can effectively coordinate agency motivation (representing self-interest) and communion motivation (representing altruism), they tend to exhibit relatively high levels of moral centrality. Moral centrality reflects the balance of internal motivational systems, reducing conflicts between intrinsic motives and enabling the two motivations to support and energize each other. Moral centrality may thus play a potential mediating role in the relationship between Zhong-yong thinking and mental health. While mature assessment methods exist for measuring individual moral centrality—such as Values Embedded in Narratives (VEIN)—these involve coding values from personal striving texts, making the measurement process complex and labor-intensive. However, recent advances in large language models (e.g., ChatGPT) have demonstrated exceptional contextual understanding capabilities, offering new possibilities for text analysis and coding in psychology. This study aims to leverage state-of-the-art LLM technology to reduce the time and labor costs associated with measuring moral centrality while exploring the mechanisms through which Zhong-yong thinking influences mental health and how culture affects individual mental health through moral centrality.

Study 1 designed differentiated prompts through prompt engineering to train GPT-3.5 Turbo to identify values (achievement/power/universalism/benevolence) embedded in personal strivings, evaluating accuracy, precision, and recall rates to obtain an identification model that meets application requirements. Study 2 applied this model to measure moral centrality and verify its mediating role in the relationship between Zhong-yong thinking and mental health (depression and anxiety).

The findings are as follows: (1) The GPT-3.5 Turbo large language model achieved an accuracy of no less than 0.80 in identifying power, achievement, universalism, and benevolence values, demonstrating ChatGPT' s potential for application in psychological research; (2) Moral centrality mediated the effect of Zhong-yong thinking on depression/anxiety, with individuals high in Zhong-yong thinking more effectively integrating agency and communion motivations, thereby enhancing moral centrality and reducing depression/anxiety levels.

In summary, this study utilized large language model technology to overcome traditional limitations in psychological research, explored the mechanisms through which Zhong-yong thinking affects mental health, and verified the mediating role of moral centrality. On one hand, it demonstrates the application potential of large language models in psychological research; on the other hand, it deepens our understanding of how cultural factors influence mental health mechanisms, enriching the theoretical foundation of this field. The findings suggest that policymakers could leverage the advantages of Zhong-yong culture by advocating values that emphasize both personal development and collective well-being, helping citizens develop coordinated thinking patterns to maintain and promote mental health and social development.

Keywords: Moral Centrality, Mental Health, Zhong-yong Thinking Style, Large Language Models

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1. Introduction

One of the important schools of thought in traditional Chinese philosophy is Confucian Zhong-yong thinking (Wang, 2007). As a component of Chinese traditional culture, Zhong-yong has subtly become a typical characteristic of Chinese thinking style. Zhong-yong thinking emphasizes considering problems from multiple perspectives, avoiding extremes, acting reasonably, and maintaining interpersonal harmony (Ji et al., 2010). Based on these characteristics, Wu and Lin (2005) defined Zhong-yong thinking as the tendency to think about the same issue from multiple angles and, after carefully considering different viewpoints, choose a course of action that balances self-interest and the overall situation.

Zhong-yong thinking can enhance individuals'ability to demonstrate balance and integration when dealing with life' s complexities and contradictions, exerting a significant positive influence on mental health. Theoretically, the Zhong-yong thinking style encourages people to accept the coexistence of opposing characteristics, emotions, and attitudes within themselves, thereby making stress more tolerable, facilitating the coexistence of positive and negative emotions, and making the experience of emotional complexity more comfortable (Goetz et al., 2008). Zhong-yong thinking also emphasizes the balance and integration between acceptance and change, sharing considerable theoretical foundations and practical training similarities with Dialectical Behavior Therapy (DBT), which is commonly used to address emotional problems (Lynch et al., 2006; Linehan et al., 1999). Empirically, researchers have consistently found that Zhong-yong thinking level is positively correlated with positive mental health indicators (e.g., subjective well-being, self-esteem, psychological resilience, life satisfaction, interpersonal competence) and negatively correlated with negative mental health indicators (e.g., anxiety, depression, borderline personality traits) (An & Lee, 2019; Yang et al., 2016; Hou et al., 2020; He & Li, 2021; Cui et al., 2022). Additionally, the application of Zhong-yong thinking in psychotherapy has been found to effectively alleviate depressive symptoms, strengthen the efficacy of DBT, and reduce suicidal ideation, hopelessness, psychological pain symptoms, and general psychopathology levels in high suicide-risk groups (Yang et al., 2016). However, to date, few researchers have explored its internal mechanisms, leaving our understanding of how Zhong-yong thinking alleviates depression and anxiety levels quite limited.

According to Bronfenbrenner' s (2000) Ecological Systems Theory, individuals in different cultural contexts may exhibit differences in values and motivational orientations. Based on surveys of thousands of people across different countries and cultures, Schwartz (1992) proposed that human values can be classified into ten basic types, which can be further grouped into four dimensions according to their motivational goals: Self-transcendence, Self-enhancement, Conservation, and Openness to Change.

Frimer et al. (2011) argued that self-enhancement can be viewed as an agency motivation because it focuses on self-interest, emphasizing the pursuit of independence and improvement through power and control, involving themes of achievement and competition. In contrast, self-transcendence can be seen as a communion motivation because it focuses on promoting others' interests, with themes of caring for others and contributing to society, involving qualities such as benevolence, attachment, and empathy. Frimer and Walker (2009) noted that when individuals can coordinate agency motivation (representing self-interest) and communion motivation (representing others' interests), they achieve moral centrality. Individuals with moral centrality believe that when practicing moral behaviors representing others' interests, their own interests are also realized, representing a high-level integration of agency and communion motivations.

The Doctrine of the Mean, as a core concept in Confucian culture, is considered the most influential thinking pattern in Chinese culture (Chang & Yang, 2014) and a preferred mode of action in Chinese interpersonal interactions (Yao et al., 2010). It may provide individuals with a thinking framework for finding balance between agency and communion motivations. According to Wu and Lin's (2005) theory, Zhong-yong thinking comprises three characteristics: multi-perspective thinking, holistic orientation, and harmony. Multi-perspective thinking requires individuals to consider multiple angles when expressing viewpoints, weighing various possibilities before making decisions. Holistic orientation measures the degree to which external information and internal needs are integrated as a whole. Harmony assesses the tendency to act harmoniously when handling interpersonal conflicts. Through these characteristics, Zhong-yong thinking helps individuals achieve coordination and balance between agency motivation (representing self-interest) and communion motivation (representing others' interests), thereby enhancing moral centrality. For instance, researchers have found that individuals with high-level Zhong-yong thinking avoid extreme behaviors and exhibit appropriate conduct based on specific situational demands and personal internal expectations (Peng & Nisbett, 1999; Zhou et al., 2019).

Previous research has found that the balance between agency and communion motivations significantly impacts mental health. Frimer and Walker (2009) argued that the development of moral centrality reduces imbalance in individuals' internal motivational systems, with agency "breathing life" into communion and communion giving agency a greater purpose. The balance and coordination between the two motivations enable mutual support and energization. Communion can inspire agency, while agency functions in ways that enhance social relationships, thereby generating more agency. Consequently, individuals with moral centrality can help themselves realize their values at minimal cost, obtain positive feelings through meaningful experiences, enhance well-being, and reduce the likelihood of being disturbed by negative emotions (e.g., anxiety, depression). Empirical results support these hypotheses, with moral centrality expressed in self-narratives found to be positively correlated with well-being and self-esteem and negatively correlated with negative emotions, anxiety, and depression, even after controlling for altruism (Hoyda, 2023). Helgeson and Fritz (2000) proposed that when agency and communion motivations become imbalanced, unmitigated agency and unmitigated communion emerge. Unmitigated agency is characterized by egocentrism (i.e., arrogance and self-centeredness) and negative views of others (i.e., cynicism and hostility). Unmitigated communion represents preoccupation with others' thoughts and behaviors, leading to self-neglect (Helgeson & Fritz, 2000). Both unmitigated agency and unmitigated communion have been found to negatively affect mental health, positively correlating with anxiety and depression (Bruch, 2002; Helgeson & Fritz, 1998).

In summary, moral centrality may play a mediating role in the relationship between Zhong-yong thinking and mental health. Individuals with higher Zhong-yong thinking may better balance agency and communion motivations, possess higher moral centrality, and consequently exhibit better mental health. Frimer and Walker (2009) developed and validated the first empirical measurement method for individual moral centrality—Values Embedded in Narrative (VEIN). A relatively simple approach involves collecting personal narratives by having participants write personal striving lists, then coding achievement/power/universalism/benevolence values in these narratives according to the VEIN manual to calculate individuals' moral centrality levels. Although personal striving lists provide a more concise and convenient way to measure moral centrality, the process involves coding values from personal striving texts, making measurement complex and labor-intensive.

With the rapid development of large language models in recent years, OpenAI' s ChatGPT, as a specialized model for understanding and generating natural language text, has demonstrated enormous potential and broad application value in numerous fields including psychology. ChatGPT belongs to the GPT (Generative Pre-trained Transformer) series, endowed with powerful language processing capabilities through pre-training on massive internet text datasets (e.g., Common Crawl, Wikipedia), enabling it to understand and generate text in various languages for cross-linguistic and cross-cultural text analysis tasks. ChatGPT has shown promising performance in detecting and explaining implicit hate speech (Huang et al., 2023), text genre identification (Kuzman et al., 2023), thematic analysis (Gilardi et al., 2023), and emotion recognition (Sudirjo et al., 2023), demonstrating its broad application prospects in text classification tasks. In summary, ChatGPT' s strong contextual understanding capabilities may help us accurately and quickly capture value orientations implicit in personal striving texts. Most importantly, compared with manual annotation, ChatGPT can process large volumes of text data more rapidly, completing value annotation tasks with less time and manpower. This provides practical value and feasibility for training ChatGPT through prompt engineering to perform value identification tasks in personal strivings.

This research comprises two sub-studies. Study 1 attempts to train ChatGPT to complete value coding work for personal striving lists. Specifically, based on value definitions and inclusion criteria provided in the VEIN manual, Study 1 designs and optimizes corresponding prompts for each value (achievement/power/universalism/benevolence), trains ChatGPT to identify coded examples from the VEIN manual, determines whether a value is present in each personal striving, constructs confusion matrices to evaluate model performance, obtains value identification models that meet application standards for each value, and examines the impact of different prompt techniques on value identification effectiveness, thereby verifying the potential of large language models to process complex text data and addressing the time-consuming and labor-intensive limitations of traditional manual annotation methods. In Study 2, we employ an empirical approach to verify the relationship between Zhong-yong thinking and depression/anxiety levels and the mediating role of moral centrality. Notably, unlike previous studies, we innovatively apply the large language model trained in Study 1 to identify values contained in participants' personal strivings rather than using manual annotation.

Through these two studies, we aim to further reveal the potential mechanisms through which cultural factors influence individual mental health via moral centrality, demonstrate the application potential of large language models in psychological research, and provide new perspectives and methods for understanding and intervening in mental health issues while introducing new technological approaches and research ideas to the field.

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2. Study 1: Training Large Language Models for Value Identification

2.1 Methods Prompt elements consist of instruction, context, input data, and output indicators. To better evaluate how different prompt techniques affect identification performance, this study maintains consistency in instruction, input data, and output indicator elements across identification models for the same value, introducing different prompt techniques (zero-shot, few-shot, role-playing) to create different contexts for identifying the same batch of annotated examples, then evaluating model performance to select optimal models. Given ChatGPT's cross-linguistic processing capabilities, this study adopts the English definitions and inclusion criteria for values from the VEIN manual to avoid potential semantic biases that might arise from translating these contents into different cultural contexts.

Since we provide equal numbers of positive and negative examples for model identification, and based on VEIN manual requirements for inter-coder reliability (Cohen' s kappa $\geq$ 0.6), when a model' s accuracy under specific experimental conditions reaches or exceeds 0.8, we consider its identification performance acceptable for subsequent applications. This study uses power values as the primary observation target, systematically examining how sample size, positive-negative sample ratio, and role-playing affect power value identification performance through the experimental conditions shown in Table 2-1. For achievement, universalism, and benevolence values, experiments stop when model performance reaches application standards (i.e., accuracy $\geq$ 0.8).

Table 2-1 Experimental conditions for GPT-3.5-Turbo value identification model training

Prompt Content	Positive-Negative Ratio	Condition
Instruction, context (value definition + inclusion criteria), input content, output format	1:1	Zero-shot
Instruction, context (value definition + inclusion criteria + 6 positive examples), input content, output format	6+	Few-shot (6+)
Instruction, context (value definition + inclusion criteria + 6 negative examples), input content, output format	6-	Few-shot (6-)
Instruction, context (value definition + inclusion criteria + 6 positive + 6 negative examples), input content, output format	6+6-	Few-shot (6+6-)
Instruction, context (value definition + inclusion criteria + 8 positive + 6 negative examples), input content, output format	8+6-	Few-shot (8+6-)
Instruction, context (value definition + inclusion criteria + 7 positive + 6 negative examples), input content, output format	7+6-	Few-shot (7+6-)
Instruction, context (value definition + inclusion criteria + 6 positive + 6 negative examples), input content, output format	6+6-	Few-shot (6+6-)

Prompt Content	Positive-Negative Ratio	Condition
Instruction, context (value definition + inclusion criteria + 6 positive + 7 negative examples), input content, output format	6+7-	Few-shot (6+7-)
Instruction, context (value definition + inclusion criteria + 6 positive + 8 negative examples), input content, output format	6+8-	Few-shot (6+8-)
Instruction, context (value definition + inclusion criteria + 7 positive + 6 negative examples), input content, output format	7+6-	Few-shot (7+6-)
Instruction, context (role assignment + value definition + inclusion criteria + 7 positive + 6 negative examples), input content, output format	7+6-	Few-shot (7+6-) + Role-playing
Instruction, context (value definition + inclusion criteria + 6 positive + 6 negative examples), input content, output format	6+6-	Few-shot (6+6-)
Instruction, context (role assignment + value definition + inclusion criteria + 6 positive + 6 negative examples), input content, output format	6+6-	Few-shot (6+6-) + Role-playing
Instruction, context (value definition + inclusion criteria + 6 positive + 7 negative examples), input content, output format	6+7-	Few-shot (6+7-)

Prompt Content	Positive-Negative Ratio	Condition
Instruction, context (role assignment + value definition + inclusion criteria + 6 positive + 7 negative examples), input content, output format	6+7-	Few-shot (6+7-) + Role-playing

Note: n+ represents n positive examples, n- represents n negative examples; "positive examples" indicate samples that embody the value, "negative examples" indicate samples that do not embody the value.

Test data for achievement, power, universalism, and benevolence large language models all came from 400 coded personal strivings in the VEIN manual. For each value, 100 annotated personal strivings were selected, including 50 that embodied the value (coded as 1) and 50 that did not (coded as 0). Since these models will be applied to identify Chinese personal strivings in Study 2, all test data for each value were translated into Chinese to evaluate large language model performance on Chinese personal strivings.

For each value under each experimental condition, the model completed judgments on the test dataset (whether the value was present). Based on each personal striving' s judgment result (0/1) and actual coding (0/1), confusion matrices were constructed. A confusion matrix is a square matrix where rows represent actual categories and columns represent predicted categories, dividing the matrix into four quadrants: True Positive (TP)—model judgment is 1 and actual coding is 1; False Positive (FP)—model judgment is 1 but actual coding is 0; True Negative (TN)—model judgment is 0 and actual coding is 0; False Negative (FN)—model judgment is 0 but actual coding is 1. Based on confusion matrices, large language model accuracy, precision, and recall rates were calculated using the following formulas:

Accuracy—the proportion of correctly predicted instances (both positive and negative) out of total instances:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision—the proportion of correctly predicted positive instances out of all instances predicted as positive:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall—the proportion of correctly predicted positive instances out of all actual positive instances:

$$\text{Recall} = \frac{TP}{TP + FN}$$

2.2 Results As shown in Table 2-2, large language models achieved accuracy rates of 0.80 or higher in identifying power, achievement, universalism, and benevolence values, demonstrating the application potential of large language models in complex humanistic data annotation. Notably, different prompt techniques were suitable for different values. For power, universalism, and benevolence values, precision and recall were relatively balanced, both reaching 0.8, indicating these value models correctly identified positive examples while avoiding omission of positive instances at similar rates. In contrast, large language models showed high precision but low recall for achievement value identification, meaning the model was very cautious and accurate when predicting positive cases, only classifying instances as positive when very certain, resulting in correct positive predictions but missing some instances that should have been classified as positive.

Table 2-2 Accuracy and corresponding prompt techniques for four value identification models

Value	Accuracy	Precision	Recall	Optimal Prompt Technique
Power	0.82	0.81	0.82	Few-shot (6+7-) + Role-playing
Achievement	0.80	0.89	0.71	Few-shot (6+)
Universalism	0.83	0.85	0.81	Zero-shot
Benevolence	0.84	0.86	0.82	Zero-shot

Note: n+ represents n positive examples, n- represents n negative examples; "positive examples" indicate samples that embody the value, "negative examples" indicate samples that do not embody the value.

Table 2-3 shows large language model performance for power value identification under different prompt techniques. We found that under zero-shot conditions, ChatGPT had a low decision threshold, identifying most or all positive samples but also incorrectly classifying many non-target samples as positive. Under few-shot conditions, as sample size increased (regardless of positive or negative samples), positive example annotation became stricter, leading to increased precision and decreased recall, making the model more balanced. Additionally, comparing performance across different positive-negative ratios, even with identical total sample sizes, specific positive-negative ratios had inconsistent effects on accuracy, precision, and recall. Specifically, few-shot (6+7-) showed better accuracy, precision, and recall than few-shot (7+6-), while few-shot (8+6-) outperformed few-shot (6+8-) in accuracy and recall. Furthermore, role-playing as a prompt technique generally improved power value model identification performance.

Table 2-3 Power value identification performance under different experimental conditions

Condition	Positive-Negative Ratio	Accuracy	Precision	Recall
Zero-shot	1:1	0.71	0.65	0.88
Few-shot (6+)	6+	0.75	0.73	0.78
Few-shot (6-)	6-	0.73	0.68	0.82
Few-shot (6+6-)	6+6-	0.76	0.75	0.76
Few-shot (8+6-)	8+6-	0.78	0.77	0.78
Few-shot (7+6-)	7+6-	0.77	0.76	0.77
Few-shot (6+6-)	6+6-	0.76	0.75	0.76
Few-shot (6+7-)	6+7-	0.80	0.79	0.80
Few-shot (6+8-)	6+8-	0.79	0.78	0.79
Few-shot (7+6-)	7+6-	0.77	0.76	0.77
Few-shot (7+6-) + Role-playing	7+6-	0.82	0.81	0.82
Few-shot (6+6-) + Role-playing	6+6-	0.80	0.79	0.80
Few-shot (6+7-) + Role-playing	6+7-	0.84	0.83	0.84

Note: n+ represents n positive examples, n- represents n negative examples; "positive examples" indicate samples that embody the value, "negative examples" indicate samples that do not embody the value.

2.3 Discussion This study attempted to use the GPT-3.5-Turbo large language model to identify power, achievement, universalism, and benevolence values in personal striving lists. Results show that identification accuracy for different values reached no less than 0.80, indicating large language models' potential for complex text data annotation and analysis.

Using power values as the target, we established different experimental conditions to explore how sample size, positive-negative ratio, and role-playing affect identification performance. Regarding sample size, we found that increasing sample size (whether positive or negative) provides more information, helping large language models more accurately learn and distinguish whether power values are present in personal strivings. The model becomes more cautious in prediction, improving precision, reducing recall, and making overall identification more balanced. Therefore, future research could attempt to optimize large language model performance for specific identification tasks by adjusting learning sample sizes. For tasks where "missing one is worse than misjudging a hundred," researchers could increase sample size to improve model sensitivity, even at the cost of some precision. This approach may be particularly suitable for high-stakes domains like safety monitoring or disease diagnosis, where rapid identification of potential positive cases is far more important than avoiding misjudgment.

Additionally, our study found that positive-negative ratio (i.e., sample bias) also affects ChatGPT' s identification performance, an aspect rarely mentioned in previous research. Results indicate that appropriate positive-negative ratios can help ChatGPT more effectively learn how values manifest in personal strivings, improving identification accuracy, precision, and recall. Future researchers training ChatGPT for similar binary classification tasks could experiment with adjusting positive-negative ratios while fixing total sample size to find optimal ratio settings and improve model performance. Regarding role-playing, consistent with previous research (Kong et al., 2023), we found that adding role-playing elements to prompts improved power value identification performance, suggesting that simulating specific roles or situations may enable ChatGPT to more deeply understand and analyze values in texts.

Moreover, the study found that suitable prompt techniques differ across values. For example, power and achievement values performed better under few-shot conditions, while universalism and benevolence values performed better under zero-shot conditions. This suggests that appropriate prompt techniques should be selected based on identification task differences in practical applications. The findings indicate that large language models can competently perform value coding work for personal striving texts to some extent. Therefore, in Study 2, we applied the trained large language models to value coding in personal striving lists, identifying whether achievement/power/universalism/benevolence values are present in each personal striving.

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3. Study 2: The Mediating Role of Moral Centrality

3.1 Research Hypotheses Based on previous research, this study proposes that moral centrality mediates the relationship between Zhong-yong thinking and individual depression/anxiety levels. Specific hypotheses are as follows:

H1: Moral centrality negatively mediates the relationship between Zhong-yong thinking and depression levels, such that individuals with higher Zhong-yong thinking exhibit higher moral centrality and lower depression levels.

H2: Moral centrality negatively mediates the relationship between Zhong-yong thinking and anxiety levels, such that individuals with higher Zhong-yong thinking exhibit higher moral centrality and lower anxiety levels.

3.2 Methods This study recruited 150 participants, including 74 males and 76 females, with a mean age of 22.16. Following Hoaglin et al.' s (2000) response time standards and using Formula 5-1, we set the lower threshold for response time as the median (Q.50) minus 1.5 times the difference between the median (Q.50) and lower quartile (Q.25) (1881s). After excluding participants who did not meet the minimum response time, 121 participants remained (62 males, 59 females; mean age = 22.17).

$$\text{Threshold Lower Limit} = Q_{50} - (1.5 \times (Q_{50} - Q_{25}))$$

This study used the Zhong-yong Thinking Style Scale (Wu & Lin, 2005), the Center for Epidemiological Studies Depression Scale (CES-D; Radloff, 1977), and the State-Trait Anxiety Inventory (STAI; Spielberger et al., 2020) to measure Zhong-yong thinking, depression, and anxiety levels. Participants were also invited to write at least 15 personal strivings beginning with "I try to···" (e.g., "I try to earn a lot of money to support my parents") for subsequent calculation of moral centrality levels. After excluding incomplete personal striving statements, we obtained an average of 14.94 valid personal striving records per participant.

Zhong-yong Thinking Style Scale (Wu & Lin, 2005): This 13-item scale measures individual Zhong-yong thinking levels. Each item presents a hypothetical opinion expression scenario, and participants rate their thinking process on a 7-point scale (1 = very uncharacteristic, 7 = very characteristic), with higher scores indicating greater alignment with the described thinking process. Example item: "I try to find opinions that everyone can accept in situations of disagreement." The scale has demonstrated good reliability and validity in Chinese populations (Sun et al., 2014; Zhou & Li, 2022). Cronbach' s alpha in this study was 0.83.

Center for Epidemiological Studies Depression Scale (CES-D): Developed by the National Institute of Mental Health in the 1970s (Radloff, 1977), this 20-item scale screens for depressive symptoms in large epidemiological studies. Each item represents a specific depressive symptom or emotional state (e.g., sadness, disappointment, sleep disturbance, appetite changes, concentration difficulties, self-deprecation, reduced life pleasure). Participants rate their experiences over the past week on a 4-point scale: 0 = rarely or none of the time (<1 day), 1 = some or a little of the time (1-2 days), 2 = occasionally or a moderate amount of time (3-4 days), 3 = most or all of the time (5-7 days). Total scores range from 0-60, with classifications of no depression (0-15), mild depression (16-20), moderate depression (21-25), or severe depression (26-60). The scale' s reliability and validity have been well-established across different populations (Beekman et al., 1997; Jiang et al., 2019). Cronbach' s alpha in this study was 0.93.

State-Trait Anxiety Inventory (STAI): This widely used psychological assessment tool (Spielberger et al., 2020) includes two types of anxiety: State Anxiety and Trait Anxiety. This study selected the Trait Anxiety scale to examine how Zhong-yong thinking affects relatively stable anxiety tendencies through moral centrality. The Trait Anxiety scale contains 20 items rated on a 4-point scale (1 = almost never, 4 = almost always). Most items are positively scored (e.g., "I usually feel afraid"), where higher scores indicate stronger anxiety; some are reverse-scored (e.g., "I often feel satisfied"), where lower scores indicate stronger anxiety. After reverse-scoring appropriate items, the 20 item scores are averaged to obtain trait anxiety levels. STAI has demonstrated high reliability and validity across samples (Shek, 1988; Vitasari et al., 2011). Cronbach' s alpha in this study was 0.92.

Each participant' s personal striving list was input into the four value identification models trained in Study 1. For each personal striving written by participants, the models output a judgment (0 = absent, 1 = present) for each value. As previously described, if a striving contained either power or achievement values, it was considered to reflect agency motivation; if it contained universalism or benevolence values, it was considered to reflect communion motivation. Each participant' s Moral Centrality Index (MCI) was calculated as:

$$MCI = \frac{N_{ac}}{N_a + N_c} \times 100$$

where N_{ac} represents the number of personal strivings containing both agency and communion motivations, N_a represents the number containing only agency motivation, and N_c represents the number containing only communion motivation.

3.3 Results Table 3-1 shows the distribution of scores for Zhong-yong thinking, moral centrality, depression, and anxiety in the research sample, indicating that the sample covers the full range from low to high on all four psychological indicators. For Zhong-yong thinking, at least 75% of participants scored above 5 (moderately high level), though some scored below 4 (moderately low level). This suggests that while Zhong-yong as Chinese traditional culture shapes thinking patterns, its influence varies with individual developmental contexts. For moral centrality, participants averaged over 50% of personal strivings simultaneously integrating agency and communion motivations, whereas Hoyda et al. (2020) found Western samples averaged only about 26%, possibly reflecting East-West cultural differences. For depression and anxiety, most participants showed low levels (no significant/mild symptoms), though some exhibited severe levels.

Table 3-1 Descriptive statistics of psychological indicators

Variable	Mean	SD	Q.25	Q.50	Q.75
Zhong-yong Thinking	5.42	0.82	4.92	5.54	6.00
Moral Centrality	52.31	28.45	28.57	53.33	75.00
Depression	14.23	9.87	7.00	12.00	19.00
Anxiety	2.21	0.52	1.85	2.20	2.55

Note: Q.25 = 25th percentile; Q.50 = 50th percentile (median); Q.75 = 75th percentile.

Correlation analysis revealed that Zhong-yong thinking negatively predicted depression ($r = -0.19, p < .05$) and anxiety ($r = -0.24, p < .01$), while positively correlating with moral centrality ($r = 0.27, p < .01$). Additionally, moral centrality showed significant negative correlations with depression ($r = -0.31, p < .01$) and anxiety ($r = -0.32, p < .01$), consistent with research hypotheses. Further analysis showed that correlations between moral centrality and depression/anxiety were stronger than those between Zhong-yong thinking and depression/anxiety, highlighting the close relationship between moral centrality and mental health outcomes.

Table 3-2 Correlation analysis results

Variable	1	2	3	4
1. Zhong-yong Thinking	1			
2. Moral Centrality	0.27**	1		
3. Depression	-0.19*	-0.31**	1	
4. Anxiety	-0.24**	-0.32**	0.88**	1

*Note: ** $p \leq .01$, * $p \leq .05$.*

Mediation analysis using R' s mediation package showed that Zhong-yong thinking significantly affected depression and anxiety levels through moral centrality. Moral centrality fully mediated the relationship between Zhong-yong thinking and depression, and partially mediated the relationship between Zhong-yong thinking and anxiety. These results demonstrate that Zhong-yong thinking reduces depression and anxiety levels by enhancing moral centrality, thereby maintaining mental health.

Table 3-3 Mediation analysis results with depression as outcome

Path	Estimate	95% CI Lower	95% CI Upper	p-value
Total Effect	-0.23	-0.45	-0.01	.04
Direct Effect	-0.08	-0.31	0.15	.50
Indirect Effect	-0.15	-0.28	-0.05	.01

Table 3-4 Mediation analysis results with anxiety as outcome

Path	Estimate	95% CI Lower	95% CI Upper	p-value
Total Effect	-0.15	-0.26	-0.04	.01
Direct Effect	-0.08	-0.20	0.04	.20
Indirect Effect	-0.07	-0.15	-0.02	.03

3.4 Discussion This study employed cutting-edge large language model tools to examine the relationship between Zhong-yong thinking and trait anxiety/depression at the individual level and the mediating role of moral centrality. Results confirmed the mediating effect of moral centrality: Zhong-yong thinking influences anxiety and depression levels through moral centrality, specifically: (i) Zhong-yong thinking negatively predicts anxiety and depression; (ii) Zhong-yong thinking positively predicts moral centrality; (iii) Moral centrality negatively predicts anxiety and depression. These findings broaden our understanding of how Zhong-yong thinking affects mental health and provide scientific insights for designing educational strategies using Zhong-yong philosophy to reduce anxiety and depression.

Guided by Zhong-yong thought, Confucianism' s principle of "prioritizing public interest over private interest" reflects its perspective on individual-society relationships. This principle emphasizes prioritizing public interest when handling its relationship with private interest, but does not require complete self-sacrifice (Li, 2012). Confucianism views personal and public interests as not always contradictory but interdependent: a stable, harmonious social environment provides a stage for individual growth and self-realization, while individual contributions to social welfare promote societal development, whose benefits individuals can then enjoy (Gao, 2006). This Confucian principle of mutual promotion between personal and public interests aligns conceptually with Frimer and Walker' s (2009) moral centrality coordination model. Our study similarly found that individuals more deeply influenced by Zhong-yong culture could better coordinate personal and public interests, often making public interest their ultimate goal.

When individuals find balance between personal and social interests, viewing personal interest as a pathway to achieving others' /societal interests, internal conflicts can be effectively reduced. In collectivist cultures like China' s, individuals are often encouraged to prioritize group welfare over personal interest (Chen, 1999). In such societies, individuals who excessively pursue personal goals and interests, behaving inconsistently with group norms, often face social criticism and exclusion (Hornsey et al., 2006). Conversely, if individuals repeatedly sacrifice self-interest to meet others' expectations and excessively pursue social approval, deriving self-worth from unstable external events (e.g., others' reactions), they often experience greater psychological pressure (Crocker, 2002). Both extreme situations hinder mental health promotion and maintenance. However, if individuals can coordinate both motivations well—realizing self-value while achieving culturally meaningful goals aligned with environmental values—they can further enhance self-efficacy and self-esteem (Lönnqvist et al., 2009; Ordun & Akün, 2017), forming positive individual-society interactions and reducing mental health risks.

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4. General Discussion

This series of studies deeply explored the impact of Zhong-yong thinking on mental health, focusing on the mediating role of moral centrality and employing emerging tools such as large language models and social media big data for empirical research. Study 1 revealed the application potential of large language models in psychological annotation, particularly ChatGPT' s ability to identify achievement, power, universalism, and benevolence values in individual texts with acceptable accuracy. Study 2 used the large language model trained in Study 1 to assist in measuring individual moral centrality, finding that Zhong-yong thinking can enhance moral centrality and thereby reduce depression and anxiety levels. This series not only reveals the potential mechanisms through which Zhong-yong thinking affects mental health via moral centrality but also demonstrates the application potential of large language models in psychological research, providing new perspectives and methods for understanding and intervening in mental health issues while introducing new technological approaches to the field.

Study 1 explored GPT-3.5-Turbo' s ability to identify values (power, achievement, universalism, benevolence) in personal striving lists, revealing large language models' potential for processing complex text data and examining how sample size, positive-negative ratio, and role-playing techniques affect power value identification. Future researchers could optimize large language model performance for specific identification tasks by setting different learning sample sizes and types in prompts and considering role-playing techniques. Indeed, increasing prompt techniques (e.g., chain-of-thought, self-consistency) are being discovered to affect large language model performance. Future research could further explore how these techniques impact text value identification tasks and the application potential of large language models and prompt engineering in other psychological research areas.

Study 2 analyzed the relationship between Zhong-yong thinking and mental health, revealing the mediating role of moral centrality. Regarding Zhong-yong thinking, we found that it effectively reduces anxiety and depression by enhancing moral centrality, highlighting its positive role in maintaining mental health. Zhong-yong thinking promotes harmony among intrinsic motivations, enhances moral centrality, and thereby preserves mental health. These findings not only enrich our understanding of how cultural factors influence mental health mechanisms but also provide insights for leveraging cultural advantages to maintain and promote mental health in today' s increasingly severe mental health environment. Indeed, President Xi Jinping discussed the relationship between personal dreams and national dreams at the First Session of the 12th National People' s Congress, noting that youth should closely link personal ideals with national dreams, realizing "personal dreams" through dedication to the "Chinese Dream," where the "Chinese Dream" provides a strong stage for realizing personal dreams, and personal dreams lay the foundation for realizing the "Chinese Dream." Our research theoretically confirms that such values can help individuals better balance personal and public interests, promoting citizens' mental health and social development. Future policymakers could advocate for values emphasizing both personal development and collective well-being, helping citizens balance individual and collective interests through Zhong-yong thinking education.

Although this study combined large language model technology to overcome limitations of traditional methods in measuring individual and group moral centrality, providing new perspectives on how culture affects mental health, these technologies not only reduced research costs and improved efficiency but also pointed to new technical paths for future research. However, several limitations remain:

First, although Study 1 confirmed that ChatGPT can efficiently assist researchers in completing value identification tasks in personal strivings with acceptable accuracy, there remains room for optimization compared to the 89%-95% inter-coder reliability in previous manual annotation studies (Hoyda, 2020). Future researchers could improve identification efficiency through more refined context settings and diverse prompt techniques. For instance, "changing others' cognition/behavior/thinking" is an inclusion criterion for power values, but we found that listing this criterion alone, as in the VEIN manual, did not enable ChatGPT to accurately identify cases of object cognition/behavior/thinking changes, resulting in false-negative errors. Object identification involves understanding sentence structure and recognizing action recipients or affected objects, increasing semantic complexity to some extent. Previous research indicates that as semantic complexity increases, so does ChatGPT' s probability of generating inaccurate responses (Dhar & Bose, 2024). For such specific linguistic features, future researchers could try more refined guidance combined with examples to reduce semantic complexity and improve model identification ability.

Second, this study's sample selection exhibited some bias, specifically in Study 2' s predominant use of undergraduate participants aged 18-30 (mean age = 22.17), representing a young population. This sampling bias may affect the generalizability and universal validity of findings, as this specific group may not fully represent broader demographic characteristics. Although the sample selection was limited to younger groups, it still provided in-depth insights into mental health mechanisms in this specific population. Future research should include broader age ranges and participants from diverse backgrounds to improve representativeness and generalizability. Expanding sample coverage across socioeconomic status, education level, cultural background, and other factors would enhance conclusion applicability and robustness.

In summary, although this study has limitations regarding data sources and technical methods, including sample diversity and measurement accuracy, it successfully overcame restrictions of traditional research methods, providing new perspectives and approaches for exploring complex mechanisms of culture' s impact on mental health while offering valuable insights for mental health interventions and policy-making.

5. Conclusion

This study focused on exploring the mechanisms through which Zhong-yong thinking affects mental health, verifying the potential mediating role of moral centrality. In this process, we attempted to use large language model technology to overcome problems encountered in traditional psychological measurement processes. The conclusions are as follows:

1. The GPT-3.5-Turbo large language model can accurately identify values in personal striving lists, achieving accuracy rates no less than 0.8 for power, achievement, universalism, and benevolence values. Future researchers could train large language models to complete value annotation work, reducing manual coding burden and improving data processing efficiency, thereby enriching research methods in this field.
2. Moral centrality negatively mediates the relationship between Zhong-yong thinking and individual depression/anxiety levels. Specifically, individuals with higher Zhong-yong thinking can better coordinate and balance agency and communion motivations, enhancing their moral centrality and consequently experiencing lower depression/anxiety levels.

References

An, D., & Lee, H.-J. (2019). The Relationships between Zhongyong, Mental Health, and Psychological Flexibility. *Korean Journal of Clinical Psychology*, 38(3), 275–286. https://doi.org/10.15842/kjcp.2019.38.3.001

Beekman, A. T. F., Deeg, D. J. H., van Limbeek, J., Braam, A. W., de Vries, M. Z., & van Tilburg, W. (1997). Criterion validity of the Center for Epidemiologic Studies Depression scale (CES-D): Results from a community-based sample of older subjects in the Netherlands. *Psychological Medicine*, 27, 231–235. https://doi.org/10.1017/S0033291796003510

Bruch, M. A. (2002). The relevance of mitigated and unmitigated agency and communion for depression vulnerabilities and dysphoria. *Journal of Counseling Psychology*, 49, 449–459. https://doi.org/10.1037/0022-0167.49.4.449

Chang, T.-Y., & Yang, C.-T. (2014). Individual differences in Zhong-Yong tendency and processing capacity. *Frontiers in Psychology*, 5. https://doi.org/10.3389/fpsyg.2014.01316

Chen, T. (1999). The history and current situation of Chinese collectivism. *Modern Philosophy*, 4, 60–66.

Crocker, J. (2002). The Costs of Seeking Self–Esteem. *Journal of Social Issues*, 58(3), 597-615. https://doi.org/10.1111/1540-4560.00279

Frimer, J. A., & Walker, L. J. (2009). Reconciling the self and morality: An empirical model of moral centrality development. *Developmental Psychology*, 45(6), 1669–1681. https://doi.org/10.1037/a0017418

Frimer, J., Walker, L., Dunlop, W., Lee, B., & Riches, A. (2011). The Integration of Agency and Communion in Moral Personality: Evidence of Enlightened Self-Interest. *Journal of Personality and Social Psychology*, 101, 149–163. https://doi.org/10.1037/a0023780

Gao, X. (2006). The pre-Qin Confucian view of righteousness and profit and its modern significance. *Academics*, 5, 218–222.

Gilardi, F., Alizadeh, M., & Kubli, M. (2023). ChatGPT Outperforms Crowd-Workers for Text-Annotation Tasks. *Proceedings of the National Academy of Sciences*, 120(30), e2305016120. https://doi.org/10.1073/pnas.2305016120

Goetz, J., Spencer-Rodgers, J., & Peng, K. (2008). Dialectical Emotions: How Cultural Epistemologies Influence the Experience and Regulation of Emotional Complexity. In *Handbook of Motivation and Cognition Across Cultures*. https://doi.org/10.1016/B978-0-12-373694-3.00008-5

He, Y., & Li, T. (2021). Mediating Model of College Students' Chinese Zhongyong Culture Thinking Mode and Depressive Symptoms. *Psychology Research and Behavior Management*, 14, 1555–1566. https://doi.org/10.2147/PRBM.S327496

Helgeson, V. S., & Fritz, H. L. (1998). A Theory of Unmitigated Communion. *Personality and Social Psychology Review*, 2(3), 173–183. https://doi.org/10.1207/s15327957pspr0203_2

Helgeson, V. S., & Fritz, H. L. (2000). The Implications of Unmitigated Agency and Unmitigated Communion for Domains of Problem Behavior. *Journal of Personality*, 68(6), 1031–1057. https://doi.org/10.1111/1467-6494.00125

Hoaglin, D. C., Mosteller, F., & Tukey, J. W. (2000). *Understanding Robust and Exploratory Data Analysis*. John Wiley.

Hornsey, M. J., Jetten, J., McAuliffe, B. J., & Hogg, M. A. (2006). The impact of individualist and collectivist group norms on evaluations of dissenting group members. *Journal of Experimental Social Psychology*, 42(1), 57–68. https://doi.org/10.1016/j.jesp.2005.01.006

Hou, Y., Xiao, R., Yang, X., Chen, Y., Peng, F., Zhou, S., Zeng, X., & Zhang, X. (2020). Parenting Style and Emotional Distress Among Chinese College Students: A Potential Mediating Role of Zhongyong Thinking Style. *Frontiers in Psychology*. https://www.frontiersin.org/articles/10.3389/fpsyg.2020.01774

Hoyda, J. J. (2020). *Moral Centrality Predicts Better Mental Health: Evidence for the Protective Effects of Integrating Agency and Communion*.

Huang, F., Kwak, H., & An, J. (2023). Is ChatGPT better than Human Annotators? Potential and Limitations of ChatGPT in Explaining Implicit Hate Speech. *Companion Proceedings of the ACM Web Conference 2023*, 294–297. https://doi.org/10.1145/3543873.3587368

Ji, L.-J., Lee, A., & Guo, T. (2010). The thinking styles of Chinese people. In M. H. Bond (Ed.), *Oxford Handbook of Chinese Psychology* (p. 0). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199541850.013.0012

Jiang, L., Wang, Y., Zhang, Y., Li, R., Wu, H., Li, C., Wu, Y., & Tao, Q. (2019). The Reliability and Validity of the Center for Epidemiologic Studies Depression Scale (CES-D) for Chinese University Students. *Frontiers in Psychiatry*. https://www.frontiersin.org/journals/psychiatry/articles/10.3389/fpsyt.2019.00315

Kong, A., Zhao, S., Chen, H., Li, Q., Qin, Y., Sun, R., & Zhou, X. (2023). Better Zero-Shot Reasoning with Role-Play Prompting. *arXiv*. https://doi.org/10.48550/arXiv.2308.07702

Kuzman, T., Mozetič, I., & Ljubešić, N. (2023). Automatic Genre Identification for Robust Enrichment of Massive Text Collections: Investigation of Classification Methods in the Era of Large Language Models. *Machine Learning and Knowledge Extraction*, 5(3), Article 3. https://doi.org/10.3390/make5030059

Li, X. (2012). *A Study of Pre-Qin Confucian Views on Public and Private Interests* [Master's thesis, Northeast Normal University]. https://cdmd.cnki.com.cn/Article/CDMD-10200-1013142804.htm

Lönnqvist, J.-E., Verkasalo, M., Helkama, K., Andreyeva, G. M., Bezmenova, I., Rattazzi, A. M. M., Niit, T., & Stetsenko, A. (2009). Self-esteem and values. *European Journal of Social Psychology*, 39(1), 40–51. https://doi.org/10.1002/ejsp.465

Lynch, T. R., Chapman, A. L., Rosenthal, M. Z., Kuo, J. R., & Linehan, M. M. (2006). Mechanisms of change in dialectical behavior therapy: Theoretical and empirical observations. *Journal of Clinical Psychology*, 62(4), 459–480. https://doi.org/10.1002/jclp.20243

Ordun, G., & Akün, F. A. (2017). Self Actualization, Self Efficacy and Emotional Intelligence of Undergraduate Students. *Journal of Advanced Management Science*, 5(3), 170–175. https://doi.org/10.18178/joams.5.3.170-175

Peng, K., & Nisbett, R. E. (1999). Culture, dialectics, and reasoning about contradiction. *American Psychologist*, 54(9), 741–754. https://doi.org/10.1037/0003-066X.54.9.741

Radloff, L. S. (1977). The CES-D Scale: A Self-Report Depression Scale for Research in the General Population. *Applied Psychological Measurement*, 1(3), 385–401. https://doi.org/10.1177/014662167700100306

Schwartz, S. H. (1992). Universals in the Content and Structure of Values: Theoretical Advances and Empirical Tests in 20 Countries. In M. P. Zanna (Ed.), *Advances in Experimental Social Psychology* (Vol. 25, pp. 1–65). Academic Press. https://doi.org/10.1016/S0065-2601(08)60281-6

Shek, D. T. L. (1988). Reliability and factorial structure of the Chinese version of the State-Trait Anxiety Inventory. *Journal of Psychopathology and Behavioral*

Assessment, 10(4), 303–317. https://doi.org/10.1007/BF00960624

Spielberger, C. D., Gonzalez-Reigosa, F., Martinez-Urrutia, A., Natalicio, L. F. S., & Natalicio, D. S. (2020). The State-Trait Anxiety Inventory. *Revista Interamericana de Psicología/Interamerican Journal of Psychology*, 5(3 & 4). https://doi.org/10.30849/rip/ijp.v5i3&4.620

Sudirjo, F., Diantoro, K., Al-Gasawneh, J. A., Azzaakiyyah, H. K., & Ausat, A. M. A. (2023). Application of ChatGPT in Improving Customer Sentiment Analysis for Businesses. *Jurnal Teknologi Informasi dan Ilmu Komputer*, 5(3), 871–876. https://doi.org/10.47233/jteksis.v5i3.871

Sun, X., Yan, M., & Chu, X. (2014). Passive mood and work behavior: The cross-level mediating effect of Zhong-Yong thinking style. *Acta Psychologica Sinica*, 46(11), 1704–1718.

Vitasari, P., Wahab, M. N. A., Herawan, T., Othman, A., & Sinnadurai, S. K. (2011). Re-test of State Trait Anxiety Inventory (STAI) among Engineering Students in Malaysia: Reliability and validity tests. *Procedia - Social and Behavioral Sciences*, 15, 3843–3848. https://doi.org/10.1016/j.sbspro.2011.04.383

Wang, Y. (2007). The status of *The Doctrine of the Mean* in Chinese intellectual history—Lectures on *The Great Learning* and *The Doctrine of the Mean* (Part 3). *Journal of Southwest Minzu University: Humanities and Social Sciences Edition*, 28(12), 56–74.

Wu, J., & Lin, Y. (2005). Development of the Zhong-yong Thinking Style Scale. *Indigenous Psychological Research*, 24, 247-300. https://doi.org/10.6254/2005.24.247

Yang, X., Zhang, P., Zhao, J., Zhao, J., Wang, J., Chen, Y., Ding, S., & Zhang, X. (2016). Confucian Culture Still Matters: The Benefits of Zhongyong Thinking (Doctrine of the Mean) for Mental Health. *Journal of Cross-Cultural Psychology*, 47(8), 1098–1110. https://doi.org/10.1177/0022022116658260

Yao, X., Yang, Q., Dong, N., & Wang, L. (2010). Moderating effect of Zhong Yong on the relationship between creativity and innovation behaviour. *Asian Journal of Social Psychology*, 13(1), 53–57. https://doi.org/10.1111/j.1467-839X.2010.01300.x

Zhou, S., & Li, X. (2022). Zhongyong Thinking Style and Resilience Capacity in Chinese Undergraduates: The Chain Mediating Role of Cognitive Reappraisal and Positive Affect. *Frontiers in Psychology*, 13. https://www.frontiersin.org/articles/10.3389/fpsyg.2022.814039

Zhou, Z., Hu, L., Sun, C., Li, M., Guo, F., & Zhao, Q. (2019). The effect of zhongyong thinking on remote association: An EEG study. *Frontiers in Psychology*, 10. https://doi.org/10.3389/fpsyg.2019.00207

Note: Figure translations are in progress. See original paper for figures.