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The Relationship between Carl Jung's Eight Cognitive Functions and Social Entrepreneurial Intention: A Study Based on LLM Social Simulation

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Abstract: *This study focuses on the causal relationship between Social Entrepreneurial Intention (SEI) and personalities based on Carl Jung's Cognitive Function theory. The current research gaps in the field of SEI and the popularity of MBTI (based on Cognitive Function theory) make this article significant. There are two research questions in this article: "Does Cognitive Function predict SEI? If so, how does each function affect SEI specifically?" For our method, we used LLM social simulation to create 16 groups of the same 100 people assigned with 16 possible combinations of Cognitive Functions. Next, we simulated 1600 responses to a questionnaire measuring SEI on a scale of 1-7, with proper reasoning provided by LLM. Lastly, we used multiple linear regression tests to analyze the data and provide answers to our research questions. The results in the regression test suggest that Cognitive Function is a strong predictor of SEI, and each of the Cognitive Functions has distinct impacts on SEI. The outcome of this study fills existing research gaps and can be utilized in various ways that benefit society.*

Keywords: *Carl Jung; 8 Cognitive Functions; Social Entrepreneurial Intention; LLM Social Simulation*

1. Introduction

Starting a profitable company is tempting to many people. People admire wealthy entrepreneurs such as Elon Musk and Jeff Bezos. However, there are people who do not pursue wealth and power but rather behaviors that relate to their own value, such as helping a certain group of people in society or addressing existing problems. This leads us to the concept of social entrepreneurship, an approach to business that prioritizes social values over financial value.

Social entrepreneurship (SE) offers many advantages, such as directly solving problems, increasing sustainability for society (if solving environmental problems) [1], facilitating innovations [2], creating new markets, enhancing social resources, etc. Therefore, we think that by deepening the understanding of social entrepreneurial intention (SEI), the number of social entrepreneurships can be boosted. In this way, society can gain more of the benefits offered by SE.

According to an existing literature review [3] about existing studies of SEI, one of the research gaps is to find more factors that influence SEI. Initially, we were thinking of studying the impact of personality on SEI but discovered that there are already comprehensive studies about SEI and personality traits. For example, there is a study about Big Five personality [4], which is considered one of the most authoritative measures of personality. Alongside that is MBTI, a very popular personality test these days, and we decided to try Carl Jung's 8 Cognitive Functions. This is the underlying theory for MBTI; it is not academically suitable to use MBTI in our study, which we will discuss in detail in the literature review session. Dating to June of 2025, there are no existing papers that study the relationship between SEI and Cognitive Functions. Hence, we decided to discover Cognitive Functions' relationship with SEI.

We hypothesized that "Carl Jung's Cognitive Functions can predict SEI level, and each of the 8 functions impacts SEI in certain directions and strengths."

In this study, we used a sample group of 100 LLM-simulated (Large Language Model, also known as Generative-AI) subjects with specific demographic settings. We used this approach because of the significant advantages of using LLM social simulation in our case and our proper solutions to the potential concerns of AI simulation, which we will discuss in detail in the Justification of AI-simulated human subjects section. Next, we assigned each of the possible combinations of the Cognitive Functions, according to Jung's rule for function hierarchy (see Function stack section), to the same 100 people,

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creating 16 groups that each represents one combination of functions (personality). We then simulated 1600 response to a questionnaire measuring SEI level; each response contains a quantitative score by answering Likert scale and the justification for the score provided by AI. We then used a multiple linear regression test to find out the correlation of Cognitive Function versus SEI and the impacts of every 8 Cognitive Functions.

2. Literature review

Social Entrepreneurial Intention is a rapidly developing topic that gained increasingly more academic focus in the past decade, according to an overall literature review on the current academic field of SEI [3]. This literature review found 624 studies in the field published before April 2019 and then eliminated duplicate articles, analyzing the 36 articles left.

2.1 Current scope

The literature review [3] summarizes that the current studies of SEI can be categorized in 4 major categories: Core model, methodological, and theoretical issues; Personal-level variables; Context and institutions; and The social entrepreneurial intention-to-behavior process. The first category is related to the development, revision, and application of entrepreneurial models. Personal-level variables, which is the most relevant area to our paper, is the most researched area, and it focuses on how individual characteristics, such as personality and gender, influence SEI. Context and institutions examines how cultural and institutional factors influence SEI. The social entrepreneurial intention-to-behavior process, the least developed category in the field, identifies the connection between entrepreneurial intention and actual entrepreneurial action.

2.2 Research gaps

The literature review then highlights the areas of improvement for each category.

For the model-related area, the article recommends future studies to focus on models that examine the formation of SEI. Moreover, the impact of SEI in a larger sense, such as its relationship with economic growth and internationalization, is suggested to be further studied.

In terms of personal-level variables, the article suggests future studies to explore socially relevant factors, go deep into the existing variables, study the interaction between factors, and examine the barriers of SEI. We particularly reviewed articles in this category. We find that there are articles examining the relationship between specific personalities, such as Big Five [4], and SEI. However, we did not find any articles that relate MBTI 16-personalities or Cognitive Function to SEI.

Our study's focus on the Cognitive Functions' relationship with SEI acts as a deeper study into the existing variables (personality traits) and also demonstrates the interaction between factors (combination and interaction between Cognitive Functions). In addition, we also find barriers of SEI. We will go into more details in terms of the academic implication of our findings in the Implication section.

In terms of context and institutions, the role of culture in relation to SEI should be further clarified, and the effects of legal and political systems on SEI are recommended to be further studied.

The review conveys that the intention-to-action category is still under challenge, so it should receive more attention as a whole.

3. Cognitive Functions and Personality

We read the original works of Carl Jung and Isabel Briggs Myers: Jung's book Psychological Types (1921) [5] and the Myers' essay The Myers-Briggs Type Indicator: Manual (1962). We identified the commonalities and differences in terms of their utilization and explanation of Jung's Cognitive Functions.

3.1 Commonalities

3.1.1 Definition of the 8 Cognitive Functions

All of the information in this section is based on Carl Jung's original work Psychological types.

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There are 8 functions: Feeling, Thinking, Intuition, and Sensing, and each of the function has an extraverted and introverted form.

Feeling and Thinking are Judging Functions; they are related to the decision-making process.

Extraverted Feeling (Fe) is characterized by the pursuit of external harmony and connections; trying to fit in a group is a typical behavior of this function. Introverted Feeling (Fi) is characterized by the persistence of internal personal ethics and belief; prioritizing personal conviction over group harmony is a typical mentality of this function. Extraverted Thinking (Te) is characterized by the tendency to organize the external world towards maximum efficiency; creating a detailed group work plan is a typical behavior of this function. Introverted Thinking (Ti) is characterized by the pursuit of internal logic and one's own framework of understanding; spending time mentally to completely understand a problem and critiquing external arguments for precision are typical behaviors of this function.

3.1.2 Function stack

Though the expression "stack" is created by MBTI and modern works, it provides a clear sense of the hierarchy framework of Cognitive Functions.

Recognized by both Jung and MBTI are the Dominant Function, Auxiliary Function, and Inferior Function in the function stack (Jung did not use the term "stack" at his time but recognized order of functions).

The Dominant Function is the most developed, conscious, and preferred Cognitive Function that one uses. Auxiliary Function supports the Dominant Function. Dominant and Auxiliary Functions must make up both judging and Perceiving Functions, and they must have the opposite attitude (extraverted/ introverted). For instance, if one's Dominant Function is Fe, the person's Auxiliary Function must be either Ni or Si. In this way, Auxiliary Function complements the Dominant Function and ensures the individual has developed ways to both make decisions and perceive information. Inferior Function is one's least developed function among all 8 possible functions; it is primitive, so it can cause problems, especially under stress or dilemma. It has the opposite attitude to the Dominant Function and is in the other function type in the same Perceiving or Judging Function category. That is, Fe-dominated people must have Ti as their Inferior Function.

Though this evolved into the 16 MBTI types and is not explicitly mentioned by Jung, his hierarchy rules that connect the three functions, as mentioned above, meant that there would be 16 combinations.

The combinations are shown in the Figure 1.

	Dominant	Auxiliary	Inferior
INFJ	Ni	Fe	Se
INTJ	Ni	Te	Se
INFP	Fi	Ne	Te
ISFP	Fi	Se	Te
ISFJ	Si	Fe	Ne
ISTJ	Si	Te	Ne
INTP	Ti	Ne	Fe
ISTP	Ti	Se	Fe
ENTJ	Te	Ni	Fi
ESTJ	Te	Si	Fi
ENFJ	Fe	Ni	Ti
ESFJ	Fe	Si	Ti
ENFP	Ne	Fi	Si
ENTP	Ne	Ti	Si
ESFP	Se	Fi	Ni
ESTP	Se	Ti	Ni

Figure 1 The 16 combinations of Cognitive Functions (note that the name used on the left column is referencing the MBTI personalities' names just for clearer illustration)

3.2 Differences

3.2.1 Extended explanation to function stack

In addition to Dominant, Auxiliary, and Inferior Function, MBTI introduces Tertiary Function. In definition, this function is the third most preferred, developed, and conscious function. It is the Inferior

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Function for Auxiliary Function (e.g. the Tertiary Function for a Fe-auxiliary individual must be Ti).

Our study will not include this concept in our experimental process (methodology) for reasons mentioned in the following section.

3.2.2 MBTI as a "pseudo-science"

Though introduced later than Jung's original Cognitive Function theory, and provides extended explanations about the theory, MBTI is often considered as pseudo-science by the academic community.

Firstly, MBTI has poor retest reliability. People who take MBTI test often get different results. Specifically, 50% of the individuals get a different result as they retake the test, even after a short 5-week period [6]. This contradicts the MBTI's claim that each person has a fixed personality type.

Moreover, MBTI has dichotomous categories for its personality traits. MBTI holds that an individual is either E/I, N/S, F/T, and J/P. In comparison, Jung's theory describes personality traits as fluid and continuously developing, and major personality theories such as Big Five also state that traits have continuous spectrums instead of two extremes. This characteristic of MBTI is arbitrary and lacks validity.

Another reason that MBTI is considered unacademic is the lack of falsifiability. MBTI's descriptions of its personality types are vague, circular, and universal. This demonstrates the Forer effect [7], which states that individuals tend to believe that the general and widely applicable descriptions are unique to them. All of these flattering and ambiguous natures of the MBTI profiles make them unfalsifiable [6].

Overall, though MBTI is more popular and was established later than Jung's original theory, we will not involve any of MBTI's explanations of Cognitive Functions, such as Tertiary Function and dichotomous typology, in our study.

3.3 The challenges concerning LLM social simulation

3.3.1 Five challenges

Regardless of what reasons make AI-use compatible for our study, it is necessary to identify and deal with the challenges that this unconventional method has. We found an article by Jacy R. Anthis et al. [8] that identifies 5 typical challenges that LLM social simulation has. The 5 challenges, with their original definition by the article, are listed in Table 1.

Table 1 The five concerns of LLM social simulation

Challenge	Description	Promising Directions
Diversity	Generic and stereotypical outputs that lack human diversity	Inject humanlike variation in training, tuning, or inference (e.g., interview-based prompting, steering vectors)
Bias	Systematic inaccuracies when simulating particular human groups	Prompt with implicit demographic information; minimize accuracy-decreasing biases rather than all social biases
Sycophancy	Inaccuracies due to excessively user-pleasing outputs	Reduce the influence of instruction-tuning; instruct LLM to predict as an expert rather than roleplay a persona
Alienness	Superficially accurate results generated by non-humanlike mechanisms	Simulate latent features; iteratively conceptualize and evaluate; reassess as mechanistic interpretability advances
Generalization	Inaccuracies in out-of-distribution contexts, limiting scientific discovery	Simulate latent features; iteratively conceptualize and evaluate; reassess as generalization capabilities advance

3.3.2 Possible solutions towards the challenges

Despite specific solutions to each of the individual challenges, one common solution for the problems is well-designed prompts. Therefore, our study will elaborately create the prompts we use and attach the exact prompts in the appendix for reference.

In terms of diversity, the article suggests the AI-experimenter to use "context-rich" prompts, which means that they contain details that elaborate on the simulation of subjects. Moreover, injecting "steering vectors," which is adding variables that represent the diversity of people, such as race and gender, is also a practical approach. Other solutions, such as token sampling, are not suitable for our study.

In terms of bias, the solution depends on specific individual biases. Context-rich prompts are again suggested. What is noteworthy is that the article mentions that biases should not be completely eliminated but managed. For example, AI's stereotypical bias can reflect scientifically-reasonable patterns: one example of the patterns is that most CEOs are males because of social, environmental, and personal challenges faced by females [9].

In order to reduce the user-pleasing behavior, the user of LLM can select base or fine-tuning models, which are more underdeveloped and therefore have less flattering settings. In addition, the article suggests that changing the wording and perspective of prompts can effectively address the problem of sycophancy. For instance, instead of talking to AI as if it directly acts as the user's subject, the user should try to assign AI the identity of a third-party agent or expert.

Alienness and generalization are difficult to address in the short term; the priority related to these challenges is to get the more advanced LLM. We chose Gemini 2.5 Pro as our model, which is a relatively advanced model [10]. That said, the article does provide several additional solutions to these two challenges.

For alienness, users should prompt AI to consider the latent features, such as motivation and emotion, of the surface behaviors, which are again related to "context-rich" prompts. The article also recommends revision of AI models in technical terms, which is not possible in our study.

The solutions for generalization are mainly oriented towards the developers of AI. Encouraging AI to make reasonable predictions is a plausible approach for the users of AI.

Our study incorporated the solutions of this article [8] and created our comprehensive solutions for these concerns, seen in the upcoming section.

4 Methodology

4.1 Measurement method

In this study, we used LLM social simulation to create simulated human subjects, assign personality to the subjects, and simulate their response to a questionnaire that measures SEI level.

4.1.1 Justification for AI-simulated subjects and responses

The use of AI is necessary in our case. Firstly, SEI is not a concept that people tend to be familiar with, so finding a large sample group and educating every subject until they thoroughly understand the concept will be very unfriendly in terms of both time and expense. If we do not let them have a deep understanding about SEI, though, their answer to the questionnaire can be influenced by other factors that are unrelated to the traits that the items in the questionnaire are measuring. An LLM-simulated subject, on the other hand, has a good understanding of the fundamental factors underlying the questionnaire, such as risk-taking and innovation; therefore, the responses will be more accurate. Secondly, it is not possible for one single person to have different personalities (assuming there are no psychological disorders in the subjects). Hence, when it comes to real-life human subjects, to test another personality, the demographic characteristic, such as age and income level, will also change, acting as a confounding variable. By using AI simulation, we assigned the 16 possible combinations of Cognitive Functions (or personalities) to the same 100 subjects (resulting in 1600 distinct responses), making sure that personality is measured independently without other distractions. The third advantage of using AI is related to a common issue of personality tests for people in real life: the measurement of personality can be influenced by various factors when the person is doing the test, leading to inaccurate measurement of personality. Specifically, varying external conditions, internal mood, or context and social desirability bias cause up 40% of the personality test results to change after a few months [11]. By assigning personalities to simulated subjects, we can ensure that they are the ideal representatives of that personality.

Moreover, our study addressed every one of the five challenges of using LLM social simulation that we mentioned in the last Literature review section, referencing the solutions proposed by the original literature that also raised the challenges [8].

In terms of diversity, we created a large sample group of 100 subjects. Each subject contains 8 typical demographic variables (see Sample subject design). This not only addresses diversity but also decides the generalizability of our study (see population).

In terms of bias, we identified the overrepresentation bias, which states that AI tends to perform the behavior of white, educated subjects. We addressed this bias by prompting the AI to particularly consider the impact of varying demographic characteristics for each individual. Stereotypical portrayal bias, the phenomenon that AI mistakenly links certain characteristics with unrelated factors, such as linking female with the service industry, is also alleviated in our study: the demographic characteristics we used can provide a complete profile to reduce the arbitrary connections performed by AI.

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In terms of sycophancy, we made the AI conduct the experiment as a third party instead of directly talking to it in second-person perspective in our prompt; we also set the AI as a “strict and objective” third-party experimenter, which further reduces the inaccuracies caused by user pleasing.

In terms of alienness and generalization, our study is not affected by these two challenges. One typical characteristic that deviates from real-life humans (alienness) is that AI has an unreal amount of information and knowledge compared to humans. But in our case we need the subjects to fully understand SEI and show their most precise level of intention towards starting an SE, the god-like information will be beneficial for our study. Additionally, again, AI is the third party in this experiment, so the subjects are unlikely to have full information; only our “experimental assistant” has it. Another characteristic that shows alienness is the lack of human motivation for the simulated subjects [8]. In our case, we are simulating and measuring specifically motivation and intention, so motivation will not be ignored. Generalization does not appear in our study because SEI and Carl Jung’s Cognitive Functions are both existing concepts, and the process and methods we use are all inside the current circumvention of scientific understandings.

4.1.2 Sampling

1) Population

With the help of Large Language Model, the population of our study is unlimited—we are dedicated to making this study applicable to all humans because of the holistic demographic variables we assigned. That said, according to the Global Entrepreneurship Monitor 2019/2020 Global Report, entrepreneurs are aged between 18 to 60. To conclude, our population is global citizens within the age range of 18-60.

2) Sample subject design

To address the problem of diversity and overrepresentation bias of AI, we assigned each subject a distinct combination of 8 typical demographic characteristic categories. The variables are: age, geographic location, education level, income level, employment by sector, urban versus rural, and health status (see appendix for full categories and proportions for demographic variables).

We prompted Google Gemini 2.5 Pro to generate 100 subjects. We provided the demographic data and let Gemini randomly select among all 8 categories according to the categories and proportions we designed. The specific prompt and full subject list are in the appendix.

4.1.3 Assignment of personality

1) Avoid misconception

After the subjects are created, we reminded Gemini to differentiate Carl Jung’s definition of Cognitive Functions from MBTI’s, making sure it will not confuse these potentially similar concepts. This is an important step, as we discussed the drawbacks of MBTI in Cognitive Functions and Personality section. We will let AI be particularly cautious with flexibility and tendency (instead of strict typology), as well as the Tertiary Function, in the questionnaire responding process in order to keep this paper more academic.

2) Combining Cognitive Functions

Simply assigning one single function to the subjects is not how the theory of Cognitive Function works. As we mentioned, the functions work in combination, according to Jung. We prompted AI to create 16 duplicate groups of our existing 100 samples; each individual in a group is assigned the same combination of Cognitive Functions (personality).

However, we did not assign a full combination of dominant, auxiliary, and Fnferior Functions. Instead, we only included the dominant and Auxiliary Functions in each group. This is because the Fnferior Function, by definition, is very “unconscious,” and this property makes its weighting in the whole personality hard to assess, therefore hindering the process of regression testing.

4.1.4 Measurement of SEI

1) Questionnaire used

To measure the level of SEI of the subjects, we used an existing questionnaire established by Philipp Kruse et al [12]. The questionnaire has well-tested reliability and validity. In terms of reliability, the study has high Cronbach’s alpha scores for all three of its sample groups. In terms of validity, the study ensured its validity in three aspects: a comprehensive literature review was done for the content validity, Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were confirmed for the

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construct validity, and there is a reasonable correlation between SE-knowledge and SE-actions for both the countries involved, ensuring its criterion validity.

This is a 6-item questionnaire. Its items measure social mission, intention to combine SE with an income strategy, innovation ability, opportunity seeking, and management of tension between social and traditional entrepreneurship. All these constructs are directly related to SEI, according to previous studies. The higher the score for each item, the higher the level of SEI will be. The questionnaire is shown below [12], the graph from Table 2 in the essay.

Table 2 The 6-items questionnaire that measures SEI

Item (English version)
'I have the intention to found an enterprise that … '
1. ' … addresses social problems that have not been solved so far.'
2. ' … has a social mission (e.g. reducing poverty, improving education, helping disadvantaged people).'
3. ' … combines a social mission and an elaborated income strategy.'
4. ' … acts innovatively to solve problems in society.'
5. ' … is persistently looking for new opportunities and resources to fulfil its social mission'
6. ' … needs to deal with tensions arising from social and financial goals.'

2) Prompt and result

We prompted the AI to simulate the responses for all individuals in all groups (1600 in total); we particularly reminded it to emphasize the impact of demographics and personality while also forbidding it to consider MBTI definitions. Gemini has a limit for one-time generation, so we conducted 16 conversations (a prompt and a response) with it. The first prompt we included in this section is “Now you are a strict and objective research agent; please help me simulate the 100 responses to this questionnaire for each individual in each group, from a scale from 1-7 (1 is strongly disagree, and 7 is strongly agree). Be sure to consider demographic settings and personality, but do not apply MBTI definitions to personality, e.g. tertiary function. Explicitly state your reasoning and your consideration of these factors.” After that, we just prompted the AI to “Please continue the simulation for the next personality” fifteen times.

Here are several sample responses that show AI’s reasonable connection between the demographic and personality settings and the SEI score. Subject #1 is assigned ENFJ (Fe-Ni) and has a score of 6, 7, 4, 5, 6, 5. The AI’s reasoning is that “Fe is highly attuned to the community's needs. His auxiliary Ni gives him a vision for solving them. His low-income background makes the formal income strategy (Item 3) a conceptual hurdle, resulting in a lower score there.” When the same individual is assigned ENTP (Ne-Ti), it has 7, 5, 6, 7, 7, and 5 as its score, and the reasoning is that “Ne is constantly generating ideas to disrupt the inefficient service systems he sees. His auxiliary Ti enjoys creating the logical framework for a more clever solution. He is less driven by a ‘mission’ (Item 2) and more by the intellectual challenge. He may underestimate the human tensions (Item 6) his disruptive ideas could create.” We can see that AI connects the subjects’ traits with their scores to specific questions and shows diversity of subjects in its reasoning. In these cases, though both subjects have a high score for the first item, the reason for the ENFJ subject doing so is its connection with community (Fe), while the ENTP subject scores a 7 because it generates innovative ideas to solve problems (Ne). Similar patterns exist throughout every simulated response among the 1600 responses.

The mean score for each of the items for the 16 groups is shown; the rightmost column is the overall mean score for the personality. The personality that scores highest among all questions is INTJ (Ni-Te), while the lowest is ISTJ (Si-Te). (As shown in table 3)

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Table 3 The personalities' mean scores (1-7) for the items in the questionnaire

Personality	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Overall
ENFJ	6.55	6.88	5.23	5.89	6.07	5.92	6.09
INFJ	6.63	6.64	4.87	6.48	5.37	6.22	6.04
ENTJ	6.05	5.62	6.74	6.07	6.68	6.42	6.26
INTJ	6.64	5.56	6.60	6.81	5.86	6.61	6.35
ENFP	6.55	6.84	4.09	6.61	6.68	5.06	5.97
INFP	6.13	6.91	3.59	6.09	5.76	5.56	5.67
ENTP	6.45	4.86	5.39	6.89	6.85	5.48	5.99
INTP	6.19	4.01	5.25	6.71	5.46	5.25	5.48
ESFJ	4.39	6.79	4.97	3.39	5.16	5.20	4.98
ISFJ	3.42	5.68	4.71	2.37	4.10	4.60	4.15
ESTJ	4.95	5.09	6.63	3.43	5.95	5.85	5.32
ISTJ	3.01	4.07	4.82	2.13	3.93	4.21	3.70
ESFP	5.11	6.42	4.13	5.13	6.70	4.54	5.34
ISFP	5.31	6.90	4.15	5.30	5.46	5.49	5.44
ESTP	5.20	4.53	4.90	5.40	6.85	4.94	5.30
ISTP	5.09	4.23	5.04	6.03	5.71	5.10	5.20

The full chart for reasonings and scores is in the appendix.

The reliability test is performed using Cronbach's Alpha index. The overall Cronbach's Alpha is 0.783, which demonstrates acceptable consistency for the dataset. The code used is in the appendix.

The validity test is performed using Confirmatory Factor Analysis. For the model fit results, we have $\chi^2(9) = 187.34$, CFI = .921, TLI = .868, RMSEA = .078, and SRMR = .043. Overall, the dataset demonstrates reasonable results.

4.2 Regression test

4.2.1 Design

We used the Ordinary Least Squares method for our multiple linear regression test. The regressors for this test are the 8 Cognitive Functions, which are continuous variables in this case.

Firstly, we get the overall average score among the 6 items for each individual. Then, we assign a multiplier of 2 for the Dominant Function and a multiplier of 1 for the Auxiliary Function in each subject. This ensures that the Dominant Function remains the most significant function and does not make Auxiliary Function trivial. The design of hierarchy scoring is necessary according to neuroscience studies of personality [13]. Next, we input the "multipliers" and average scores to get the coefficient of the 8 Cognitive Functions. At last, we use standardized coefficients (Beta weights) to put all coefficients on a common scale.

4.2.2 Result

The result of the multiple linear regression test is shown in figure 2.

```
==============================================================================
Dep. Variable:            SEI_Overall   R-squared:                       0.781
Model:                            OLS   Adj. R-squared:                  0.780
Method:                 Least Squares   F-statistic:                     807.5
Date:                Mon, 04 Aug 2025   Prob (F-statistic):               0.00
Time:                        08:57:33   Log-Likelihood:                -831.14
No. Observations:                1600   AIC:                             1678.
Df Residuals:                    1592   BIC:                             1721.
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      4.2989      0.023    183.425      0.000       4.253       4.345
Ne             0.5843      0.015     39.866      0.000       0.556       0.613
Ni             0.5516      0.015     37.669      0.000       0.523       0.580
Se            -0.1257      0.015     -8.588      0.000      -0.154      -0.097
Si            -0.5330      0.015    -36.388      0.000      -0.562      -0.504
Fe             0.2107      0.013     15.845      0.000       0.185       0.237
Fi             0.0543      0.013      4.072      0.000       0.028       0.080
Te             0.1219      0.013      9.165      0.000       0.096       0.148
Ti            -0.0648      0.013     -4.858      0.000      -0.091      -0.039
==============================================================================
Omnibus:                       38.704   Durbin-Watson:                   1.502
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               54.832
Skew:                          -0.247   Prob(JB):                     1.24e-12
Kurtosis:                       3.766   Cond. No.                         16.4
==============================================================================
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Figure 2 Ordinary Least Squares (OLS) Regression Results for SEI and Cognitive Functions

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We conclude several key interpretations based on the result.

Firstly, our hypothesis that Cognitive Function is predictive for SEI is supported. The coefficient of determination is 0.781. This means that 78.1% of the variance of the SEI score can be explained by different personalities, which indicates a strong correlation between Cognitive Functions and SEI. Meanwhile, this supports our hypothesis that Carl Jung's Cognitive Function is a predictor of SEI.

Moreover, according to the hierarchy of influence, each of the Cognitive Functions has a different impact on SEI level, both in strength and direction, which also aligns with our hypothesis that individual Cognitive Functions have distinct effects on SEI. Specifically, Ni and Ne are the major stimulators of SEI, having the largest coefficient among all (0.55 and 0.58); Si is the function that inhibits SEI most significantly, having the lowest coefficient among all (-0.53). The full hierarchy of impact from positively stronger influence to negatively stronger influence is: Ne, Ni, Fe, Te, Fi, Ti, Se, and Si.

5. Discussion

5.1 Academical contribution

As mentioned in the literature review section, the academic field of SEI studies personal-level factors that impact SEI. In terms of this, our study not only expands the academic understanding of personality as a broad factor but also provides Carl Jung's Cognitive Function as an additional, independent factor that influences SEI. Moreover, we find certain Cognitive Functions, such as Si, Se, and Ti, are negatively correlated to SEI, which provides insight into the barriers of SEI, another area that is significant in the field of research.

5.2 Practical use

Since we find that Intuitive and Sensing Functions are the strongest stimulator and the strongest barrier of SEI, one further interpretation is that people who seek future possibilities and abstract patterns are more willing to engage in social entrepreneurship, but people who follow strict rules and concrete patterns are less likely to be social entrepreneurs. The difference between Feeling and Thinking functions may also imply that people who prefer ethical and non-rational decisions are more likely to establish SE companies compared to people who prefer efficiency and internal logical consistency.

Cognitive Functions, as a newly found factor, can contribute to the measurement of SEI. Take the 6-item questionnaire we used as an example; although it asks qualitative questions, it is essentially measuring the factors that are already identified to be correlated to SEI. Therefore, our findings can be used to create an 8-item questionnaire, measuring intuitive and sensing tendencies as stimulators and inhibitors of SEI. This increases the precision of the measurements.

When it comes to the manipulation of SE behaviors in society, our study also helps. When SE is desired by the society, educational institutions, for instance, can foster intuitive thoughts of students according to Cognitive Function's definition, thus increasing the amount of SE behaviors. In theory, if SE has to be controlled someday, strengthening sensing tendency or reducing intuitive tendency can also be possible strategies.

Our findings can also enhance the effectiveness and efficiency of social entrepreneurship. This is related to choosing partners or collaborators. When social entrepreneurs want to start their new company with a certain partner, according to this study, they can make a better decision on the selection of their partners. This can reduce the possibility of selecting someone that is potentially not suitable for SE, and this also increases the success rate of SE when finding the right people to work with.

On the consumer side of SE, investors of social entrepreneurial companies can also benefit from this study. By better understanding how well the entrepreneur suits SE, investors are able to make smarter investment decisions. This not only brings more profit to the investors but also supports the actually strong and powerful social enterprises, providing consistent benefit to the society.

6. Conclusion

To conclude, our study provides an extensive view into SEI by confirming that Carl Jung's Cognitive Function is a strong indicator of SEI. We also find that each Cognitive Function has different impacts on SEI. According to their regression coefficient, Ni and Ne are the strongest stimulators of SEI (0.55 and

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0.58), Fe and Te are mild predictors of SEI (0.21 and 0.12), Fi and Ti are not very influential to SEI level (0.05 and -0.06), Se is a mild inhibitor of SEI (-0.13), and SI is the strongest inhibitor of SEI (-0.53). In turn, these bring applicablility to measurement of SEI, manipulation of the amount of SE in society, success rate of starting SE, and effectiveness of financial investments in SE.

Our study can be mainly improved in terms of the use of the AI model. Better AI models, better prompting, and more information fed to the model can lead to more precise and more conclusive simulation results.

If the problems of using human subjects, such as letting all subjects have a clear understanding of the concept of SEI, controlling variables other than personality properly, and testing personality precisely, can be solved, a study using human subjects that looks into the same topic can be done and compared to our study, which can further deepen the understanding of LLM social simulation and provide support or opposition towards the relationship between Cognitive Functions and SEI.

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