Exploring the Impacts of HEXACO Personality Traits on Text Composition and Transcription

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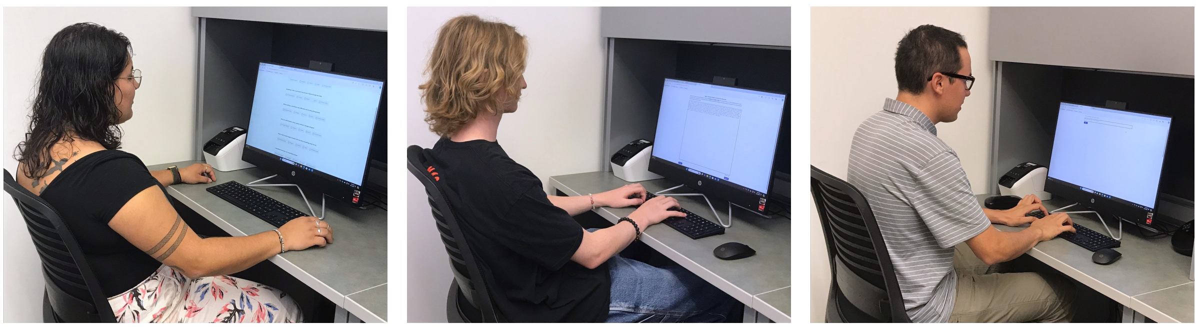

(a) HEXACO-PI-R **(b) Composition task** **(c) Transcription task**

Figure 1: Three participants taking part in the study: (a) completing the personality questionnaire, (b) performing the composition task, and (c) performing the transcription task.

Abstract

This study investigates the relationship between the HEXACO personality traits and text entry behaviors in composition and transcription tasks. By analyzing metrics such as entry speed, accuracy, editing efforts, and readability, we identified correlations between specific traits and text entry performance. In composition, honesty-humility and agreeableness were the strongest predictors, correlating significantly with composition time, text length, and editing efforts. In transcription, openness, honesty-humility, and agreeableness influenced performance, though no single trait consistently predicted all metrics. Interestingly, extraversion did not show strong correlations in either task, despite its established link to composition performance in academic contexts. These findings suggest that personality traits affect text entry behavior differently depending on the task, with creative tasks like composition being shaped by distinct traits compared to repetitive tasks like transcription. This research provides valuable insights into the relationship between personality and text entry, opening avenues for personalizing interaction systems based on individual traits.

CCS Concepts

• **Applied computing** → *Psychology*; • **Human-centered computing** → **Text input**; **Empirical studies in HCI**.

Keywords

Text Entry, Transcription, Composition, Texting, Writing, Data Entry, HEXACO

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1 Introduction

We spend a significant amount of time entering text on computers. A recent survey revealed that US office workers spend, on average, six hours a day on computers at work, with an additional hour spent on computers at home [124]. The global average for computer usage exceeds this, reaching more than 6.5 hours [122]. In a separate survey, Howarth [72] showed that even non-office workers spend around 3.5 hours a day on computers, with a significant portion of this time dedicated to text entry-related activities[1]. As a result, much attention has been given to providing users with effective tools, widgets, and advanced word processors powered by sophisticated language models and, more recently, generative AIs, to assist the text entry process [6, 64]. However, outside of academic writing among students and language learners, limited research has investigated the relationships between personality traits and text entry on computers (§ 2.2). Addressing this gap is critical for two reasons.

First, given the ubiquity of text entry on computers, this activity could serve as a continuous and unobtrusive way to detect users' personality traits. This information could, in turn, be used to personalize computer systems. Traditional methods for determining personality types usually rely on lengthy questionnaires, which are impractical for frequent use and cannot easily account for evolving personalities [63]. Alternative determination methods rely on additional hardware such as eye trackers [27], cameras [63], or biometric sensors [140], which are not always practical. Therefore, a method that observes users' text entry patterns and predicts their personality traits could offer a promising alternative, potentially simplifying the adaptation of the systems to users' changing needs and requirements, providing personalized services [38]. Enhancing users' interaction experiences is a common goal of software systems [33], which can be achieved by aligning interactions with users' mental models [102]. Section 2.5 presents examples from the literature that demonstrate the effectiveness of personalization across various application domains, further strengthening the motivation for this work.

Second, personalizing text entry systems and other software based on individual personality traits could lead to more efficient, user-friendly, and tailored experiences [127, 141]. By understanding user preferences, needs, and priorities during text entry, tools such as grammar checkers, autocorrect systems, and generative AI platforms could deliver more personalized suggestions and recommendations [110]. These tools could adapt to individual writing styles and preferences, offering support that enhances productivity and satisfaction without disrupting a user's natural flow or voice. By reducing intrusive corrections and tailoring assistance to fit unique user approaches, personalization could significantly improve the usability and effectiveness of text entry systems and composition tools.

Therefore, we take an exploratory step to bridge this gap by investigating the relationships between personality traits and text entry behaviors, aiming to highlight the merit of such studies and inspire further research. Our work differentiates itself from previous studies in several ways. First, we analyze both composition and transcription tasks, which are fundamentally different: composition requires complex planning and hierarchical processes (§ 2.2), while transcription is more mechanical and involves parallel processes (§ 2.3). As a result, findings from one task may not be directly applicable to the other. Second, much past research focused on academic writing among students, which might have been influenced by institutional guidelines and the goal of meeting academic expectations (§ 2.2). While this focus can enhance external validity by reflecting realistic educational scenarios, it may also reduce internal validity due to the influence of uncontrolled variables. Lastly, many studies use crowd-sourced platforms, which can pose challenges regarding data integrity and generalizability due to the diversity in text editors, devices, and settings [25, 96]. Classroom-based studies face similar limitations. In contrast, we conducted a controlled laboratory study, ensuring consistent settings, apparatus, and instructions to improve our findings' internal validity and reliability.

The remainder of this paper is structured as follows. First, we discuss related work in the field, focusing on studies that explore connections between personality traits and text composition, academic writing performance, and task performance. Next, we discuss and justify our choice of personality test, followed by an explanation of the study procedure and design. We then present and analyze the results. Finally, we conclude by discussing the implications of our findings and suggesting directions for future research.

2 Related Work

There is a substantial body of research on methods for determining personality and the correlations between various personality traits and human behavior, performance, and well-being. In this section, we focus only on the studies most relevant to our work, specifically those that examine the connections between personality traits and the user experience, text composition, academic writing performance, and cognitive processes involved in these tasks.

2.1 Personality Models

To effectively classify individuals according to their personality, a model is required that allows for the identification of distinct personality groups by applying thresholds to its metrics. There are numerous theories and models, each offering unique perspectives on specific aspects of personality constructs [45].

Personality encompasses habitual behaviors, cognitive patterns, and emotional responses that arise from biological and environmental influences [45], highlighting that personality can affect a user's perceptions of user interface design efficiency, and also influences technology use [85, 88, 113] and technology acceptance [50, 139].

Trait theory, introduced by Allport [8] in the late 1920s, remains a foundational concept in personality psychology. It defined personality traits as stable tendencies that guide an individual's behavior and categorized them into cardinal, central, and secondary traits. Cardinal traits are rare but dominant, central traits are fundamental and consistent, and secondary traits emerge in specific situations. Following Allport, theorists like Eysenck and Eysenck [57], Cattell et al. [34], and Goldberg [65] developed various models to refine and categorize personality traits. Eysenck's PEN model included Psychoticism, Extraversion, and Neuroticism, while Cattell's work

[1]In this paper, we use the following terms to differentiate between various modes of writing and text entry processes:
Writing refers to the general act of composing text using either computers or pen and paper.
Composition specifically refers to the process of organizing words and ideas to convey a clear message, performed on a computer system.
Transcription involves copying a source text using a computer system.
Text entry encompasses both text composition and transcription.

identified 16 factors through factor analysis. Other notable models include the Learning Style Inventory [87], which classifies personalities based on learning styles, and the Myers–Briggs Type Indicator (MBTI) [105], which assesses personality through dichotomies such as Extraversion/Introversion and Thinking/Feeling.

Several models aim to capture the dimensions of the personality. One such model is the Locus of Control (LoC) [94], which has been used to explore how users evaluate their experiences [77]. Another prominent model is the Five-Factor Model (FFM), also known as the OCEAN model or the Big Five [46]. This model assesses five key traits: Neuroticism, Extraversion, Openness to Experience, Agreeableness, and Conscientiousness, and has been extensively studied in the context of personality and technology [24]. More recently, the HEXACO model, which adds an Honesty-humility dimension to the Big Five, has gained attention [18, 136]. Our work utilizes this model, discussed in more detail in § 3.

2.2 Personality & Composition

Writing and text composition is the process of organizing words and ideas to convey a clear message [29]. While the composition-rhetoric research community recognizes different writing modes, such as description, narration, exposition, and argumentation [43, 112], this work views all forms of writing as inherently creative, as suggested by McVey [103]. Flower and Hayes [60] described the writing process as a cognitive task shaped by evolving goals and sub-goals. They, along with others [40, 60, 133], argue that effective writers actively manage the constraints of their knowledge, plans, and the developing text.

The relationship between personality traits and writing performance has not been widely studied. However, several studies have examined how traits, particularly extraversion, relate to essay writing and second language learning. Eysenck and Eysenck [57] theorized that introverts may be better learners because they possess "greater mental concentration" and can focus more effectively. However, the findings in this area are mixed. Some studies report a negative correlation between extraversion and academic writing performance [56, 120, 146], while others show a positive correlation [99]. Interestingly, some research does not find a correlation between personality traits and academic writing abilities [7, 109].

In an early study, Jensen and DiTiberio [78] investigated how personality impacts academic writing. Extraverts described their writing style as "quick and dirty" or taking the "easy way," preferring freewriting to develop ideas. They tend to write quickly and impulsively, with pauses caused more by difficulty generating ideas than planning. In contrast, introverts found writing less challenging, likely because they adhered more closely to traditional composition methods. Other studies suggest that extraverts excel in language learning, as they actively seek opportunities to practice using external input [32, 120]. Furthermore, there is evidence of positive relationships between openness to experience and performance in creative writing and essays [52, 81, 82, 144], as well as creativity in general [100, 131].

However, these studies all focused on academic writing under institutional guidelines, with subjective evaluations by instructors based on various criteria which means that the results may not directly apply to our work that investigates writing more generally. Furthermore, most of these studies were conducted on handwritten documents rather than computer-mediated text.

2.3 Personality & Transcription

Text transcription is fundamentally different from text composition. In transcription, users simply copy the presented text without contemplating what to type, so it does not involve the same complex, goal-directed processes as composition. Instead, Salthouse [126] described transcription as a series of parallel processes: converting text into chunks, decomposing these chunks into sequences of characters, converting characters into movement specifications, and performing those movements in a rapid and automated manner. As a result, previous studies have not found a significant relationship between text transcription performance and comprehension of the presented text [125]. Furthermore, in transcription tasks, editing mainly involves correcting spelling mistakes, and unlike composition, users tend to correct errors almost immediately after they occur [15].

To our knowledge, no previous work has investigated the potential relationships between personality traits and text transcription. A study examined a triplet number test in which participants were shown three one-digit numbers on a computer screen and asked to determine if they matched a specific rule by pressing the Yes/No buttons, somewhat similar to reading and understanding a phrase and then copying it. In this task, extraverts demonstrated a lower error rate compared to introverts [59].

2.4 Personality & Task Performance

Numerous studies have investigated correlations between personality traits and task performance across various fields. Here, we focus on studies relevant to our work.

Chamorro-Premuzic [36] examined the relationship between personality traits and students' academic performance over four years, based on written exams, continuous assessments, and a final-year dissertation. This work found that openness significantly and positively correlated with creative thinking scores, while conscientiousness was positively linked to all academic performance indicators, including exam grades. Similarly, Chamorro-Premuzic and Furnham [37] reported that conscientiousness often leads to higher academic achievement.

Several studies showed that different personality traits significantly influence information-seeking behaviors. For example, some studies [5, 62, 70] suggest that aligning the design of the interface with the personality of the user can improve performance. Kostov and Fukuda [89] found that users performed better when using interfaces tailored to their personality type. Al-Samarraie et al. [5] examined how personality traits affect performance in different task types: factual, exploratory, and interpretive. They discovered that individuals high in conscientiousness process information more quickly in factual tasks, those high in agreeableness have fewer fixations but longer durations in exploratory tasks, and extraverted individuals are faster. In interpretive tasks, both conscientious and extraverted individuals use similar strategies. These findings suggest that interface features should vary to accommodate different personality types. Devaraj et al. [50], on the other hand, examined the impact of personality on perceived usefulness and subjective norms toward technology, finding that traits such as conscientiousness, extraversion, and agreeableness influenced these relationships. Svendsen et al. [139] discovered that extraversion and conscientiousness were positively related to the intent to use technology, mediated by beliefs within the Technology Acceptance Model (TAM) [48]. Meanwhile, Barnett et al. [24] found that conscientiousness positively affected technology use, while neuroticism had a negative effect. McElroy et al. [101] found that personality, particularly openness and neuroticism, significantly predicted Internet use, with openness positively linked to general internet use and neuroticism strongly predicting online sales.

Research has also shown that extraversion enhances engagement and motivation in various goal- and plan-oriented tasks, such as video games [116, 118], job performance [147], technological innovation [73], and artistic creativity [68]. Furthermore, conscientiousness has been consistently linked to better academic and job performance [36, 44].

2.5 Personalization via Adaptive User Interfaces

Numerous studies have shown that personality traits significantly influence user preferences for interface and interaction designs. In a comprehensive review, Alves et al. [9] investigated the relationship between personality traits and interface preferences, revealing substantial evidence that these traits influence users' choices in design elements such as color schemes [42], font styles and sizes [17, 128], button placement [128], element styling [80], icon usage [128], information density [2, 138], navigation structures [138], and the overall look and feel [17, 80, 128]. Kostov and Fukuda [89] found that users perform better with interfaces adapted to their personality type. Similarly, Nass et al. [108] demonstrated that users find interactions more enjoyable, useful, and satisfying when a system aligns with their personality.

Adapting interfaces and interactions to personality traits has shown benefits across diverse application domains. Mampadi et al. [98] showed that e-learners exhibit better perception of structural clarity and logical sequencing using a learning interface adapted to their personality. Similarly, Sarsam and Al-Samarraie [128] found that adapting the design of a mobile learning interface to specific personality traits significantly improves the visual experience and engagement of users. Arazy et al. [10] showed that modeling social recommender systems to users' personalities boosts engagement, such as more frequent and higher ratings.

Elkin [55], on the other hand, demonstrated that using adaptive difficulty models based on dominant personality traits of players can improve their enjoyment of playing a game. In a follow-up study, Nagle et al. [106] showed that adjusting the difficulty level of a first-person shooter game to players' personality traits improves both the enjoyment and duration of the game. Karpinskyj et al. [79] conducted a comprehensive review of personalization approaches in computer games that adapt gameplay to individual players for enhanced entertainment, learning, and communication, including various models based on personality traits.

Kovbasiuk et al. [90] found that personality traits significantly influence users' interactions with chatbots. They recommended tailoring artificial intelligence (AI) technologies to better align with user psychological profiles to enhance engagement and improve task performance. Likewise, Ait Baha et al. [4] systematically reviewed personality-adaptive chatbots and concluded that customizing the chatbot vocabulary to suit the users' personality significantly improves their effectiveness. In a recent study, Weng et al. [143] explored how personality traits influence the three stages of self-regulated learning (forethought, performance, and self-reflection) when using ChatGPT. The study revealed that different personality traits affect each stage differently. Based on this, they recommended adapting generative AI (GenAI) learning environments to students' personality traits to support specific stages of self-regulated learning effectively.

These studies suggest that personalizing software systems by dynamically adjusting design elements, content, and functionality to align with users' personality traits can lead to more engaging and relevant user experiences, ultimately improving user satisfaction, engagement, and product success [67, 114].

3 The HEXACO Model

The HEXACO model of personality was developed through a series of lexical studies across multiple European and Asian languages [22]. This model identifies six core dimensions of personality: honesty-humility, emotionality, extraversion, agreeableness, conscientiousness, and openness to experience [23, 92]. Each dimension encompasses a range of traits that reflect varying levels of the respective characteristic. The following are the defining traits associated with each HEXACO's domain-level scale [91].

(1) **Honesty-humility (H):** Individuals who score high on the honesty-humility scale avoid manipulating others for personal gain, resist rule-breaking, and show little interest in wealth or luxury. They do not feel entitled to elevated social status. In contrast, those with low scores tend to flatter others for personal benefit, disregard rules for their own advantage, seek material wealth, and possess a strong sense of self-importance.
(2) **Emotionality (E):** High scorers on the emotionality scale are prone to fear physical dangers, experience anxiety in stressful situations, seek emotional support, and form deep empathetic connections with others. Conversely, low scorers are more fearless, remain calm under pressure, prefer emotional independence, and may appear emotionally detached from others.
(3) **Extraversion (X):** Those with high extraversion scores are self-confident, enjoy social interactions, and exhibit high enthusiasm and energy levels. They thrive in group settings and social gatherings. On the other hand, individuals with low scores may see themselves as less popular, feel awkward in social situations, prefer solitude, and are generally less lively and optimistic.
(4) **Agreeableness (A):** Individuals scoring high in agreeableness are forgiving, lenient in their judgments, cooperative, and capable of controlling their temper. In contrast, those with low scores tend to hold grudges, be critical of others, defend their viewpoints stubbornly, and are quick to anger when feeling mistreated.
(5) **Conscientiousness (C):** High scorers on the conscientiousness scale are organized, disciplined, and strive for accuracy

and perfection in their tasks. They carefully consider their decisions. Those with low scores, however, may be disorganized, avoid challenging tasks, are content with less precise work, and often make impulsive decisions without much deliberation.

(6) **Openness to Experience (O):** Individuals who score high on openness to experience are deeply moved by art and nature, intellectually curious, creative, imaginative, and open to unconventional ideas and people. In contrast, those with low scores may show little interest in artistic or intellectual pursuits, prefer routine and traditional ideas, and are less receptive to novel or unconventional concepts.

3.1 Motivation for the HEXACO Model

The Big Five personality traits framework is one of the most widely used models in personality research [123, 147]. The HEXACO model expands on the Big Five by adding an honesty-humility dimension and redefining agreeableness and emotionality [1]. Many recent studies and meta-analyses have recognized HEXACO as a more comprehensive alternative to the Big Five [19, 21, 145], arguably due to these adjustments. Furthermore, the inconsistent predictive power of the Big Five has been observed in various technological contexts [117], highlighting challenges in its applicability. Although the HEXACO model has also been criticized, Ashton and Lee [20] demonstrated that many of these objections lack empirical support. Therefore, we chose to use this model in our investigation.

4 User Study

We conducted a user study to explore potential relationships between the six HEXACO personality traits and text entry behaviors, specifically in composition and transcription tasks. Due to the lack of previous research in this area, we could not form specific hypotheses linking different personality traits to various aspects of text entry. Therefore, we explore the relationships between all personality traits and all aspects of text entry. However, given the different cognitive processes involved in text composition and transcription (§ 2), we speculated that different traits would correlate with performance differently for the two tasks. Furthermore, we anticipated that results from classroom-based studies might not apply to freewriting.

4.1 Apparatus

The study was conducted on an AMD Ryzen 3 3000 Series HP desktop computer (8GB RAM, AMD Radeon) with a 24" LED touchscreen display and an HP Pavilion 800 wireless keyboard and mouse combo, running Windows 10.

We used an online version of the 100-item HEXACO-PI-R inventory, as recommended by Lee and Ashton [91], which automatically calculated scores for the six broad factor scales based on participant responses (Fig. 1a). Participants were presented with a series of statements and instructed to indicate their level of agreement or disagreement on a 5-point scale (5 = strongly agree, 1 = strongly disagree). To ensure the integrity of the data collected, the form also includes multiple attention-check questions. For transcription tasks, we used a commonly used web application [13]. We developed a similar web application for composition tasks (Fig. 1b). These applications were accessed through the Microsoft Edge v107 browser.

4.2 Participants

Forty participants (N = 40) from a local university and community college took part in the study. Their median scores for honesty-humility, emotionality, extraversion, agreeableness, conscientiousness, and openness to experience among participants fall within the middle 80% range (10th to 90th percentiles) reported in the inventory [91], as shown in Fig. 2. This suggests that the study results are likely generalizable to a broader audience. Section 5.1 provides an overview of the participants' demographics. Each participant was compensated with US $15 for their participation.

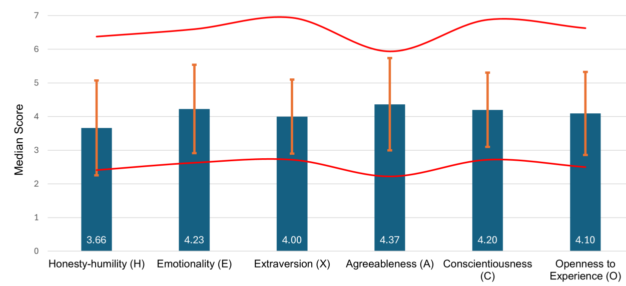


Figure 2: Median scores on the six broad factor scales of the HEXACO model. Error bars represent ±1 standard deviation. The red lines indicate the middle 80% of scores (10th to 90th percentiles) reported in the inventory [91].

4.3 Composition Tasks & Metrics

For the composition task, participants were asked to write an essay, choosing either from ten commonly used topics in US high school writing exercises or selecting a custom topic, though none chose the latter. The topics were carefully selected from the narrative and personal essay category, as research suggests that these topics generate high experiential demand [66], leading to more variation and longer essays [111]. Following recommendations, we also ensured that topics did not require pre-existing knowledge and excluded those that were too personal or could potentially cause emotional distress or trauma [71]. The final ten topics are listed in Appendix A.

For composition tasks, we calculated the average composition time, text length, editing efforts, ponder frequency and time, and readability. Since the error rate cannot be directly calculated for composition tasks due to the absence of a reference text for comparison [97], we focused on measuring the editing efforts. The metrics are discussed below.

(1) **Composition Time:** This metric represents the average total time, in minutes, spent composing an essay, including revising and editing. The timer starts when participants enter the editor and ends when they submit the essay. This metric is comparable to the commonly used task completion time metrics in evaluating interaction techniques [121].

(2) **Text Length:** This metric measures the average number of characters in the composed text, including spaces and symbols.
(3) **Editing Efforts:** This metric calculates the average number of error corrections and editing actions performed by participants, including the use of backspace or delete keys and mouse or keyboard shortcuts to reposition the caret.
(4) **Ponder Frequency (or Count):** This metric represents the total number of times participants paused, presumably to gather their thoughts while composing the essays. A 2.4-second threshold was used to identify a pause as a "ponder." This threshold is based on the combined average novice verification time (1.2 seconds) and preparation time (1.2 seconds) reported and validated in the literature [15]. The ponder counter increments for each instance when participants remain idle for more than 2.4 seconds.
(5) **Ponder Time:** This metric measures the total time spent pondering, expressed in seconds.
(6) **Readability:** The readability of the composed text is calculated using the revised Dale-Chall readability formula, which provides a numeric measure of the comprehension difficulty that readers may encounter when reading a text: $0.1579(\frac{\textit{difficult words}}{\textit{words}} \times 100) + 0.0496(\frac{\textit{words}}{\textit{sentences}})$ [35, 47]. *Difficult words* refers to the total number of words in the composed text that are not on the list of 3,000 words that fourth-grade American students can reliably understand [130]. $Words$ and $sentences$ refer to the total number of words and sentences in the text, respectively. Spelling mistakes were detected and corrected using the SpellCheck library [107], and out-of-vocabulary (OOV) words were excluded from the calculation. If the percentage of difficult words exceeds 5%, then 3.6365 is added to the raw score to obtain the adjusted score [35]. The readability of the composed text is then determined based on the following convention: a score of 6.9 or lower indicates elementary-level readability, between 7.0 and 8.9 indicates intermediate-level, and 9.0 or higher indicates advanced-level readability. We chose the Dale-Chall readability formula as it was identified as the only valid and consistent indicator of text difficulty in a comparative study of eight commonly used readability formulas [26].

4.4 Transcription Tasks & Metrics

In the transcription task, participants copied fifty short English phrases from a widely used corpus [97], popular in text entry research [11] due to its moderate phrase length (M = 28.6 characters) and its high correlation with the frequency of English characters ($\rho = 0.95$).

Since transcription tasks require users only to copy the presented text rather than plan their writing or fully comprehend the content, text composition metrics are not applicable. Instead, we measured commonly used text entry metrics, including words per minute, error rate, and error correction rate, as detailed below.

(1) **Words per Minute (wpm):** This metric represents the average number of words typed in a minute. For calculation purposes, 5 characters, including spaces and symbols, are considered as one word [14]. The formula used is: $wpm = \frac{|T|-1}{S} \times 60 \times \frac{1}{5}$, where $|T|$ denotes the length of the final text entered by the user while S denotes the time in seconds from the first to the last key press. The constants 60 and $\frac{1}{5}$ represent the number of seconds in a minute and the average word length in characters, respectively. The subtraction of 1 accounts for the initial character entry preparation time.
(2) **Error Rate (%):** This is calculated as the average ratio of incorrect characters to the total number of characters in the transcribed text. Accuracy can be derived from the error rate, where accuracy (%) = 100− error rate (%). Both terms are used interchangeably depending on the context of the discussion.
(3) **Error Correction Rate (%):** This is the ratio of the total number of corrective actions to the total number of actions per phrase. Corrective actions in transcription tasks include the use of backspace and delete keys [13].

4.5 Design & Procedure

The study was conducted in a quiet lab, accommodating one participant at a time. Upon arrival, participants were briefed about the research, though the specific hypotheses were not disclosed to avoid introducing bias. After obtaining informed consent and completing a demographics questionnaire, participants were asked to complete the HEXACO questionnaire. They were instructed to take their time and respond honestly, with assurance that their responses would remain anonymous. Participants were also informed that the form included multiple attention-check questions to ensure the integrity of their responses. Personality assessment results were not shared with participants to avoid any potential influence on their behavior during the study.

Following the questionnaire, participants were introduced to the study applications and allowed to practice by writing a few lines and transcribing 1-3 short phrases on a desktop computer (Fig. 1). Participants then performed the transcription tasks and subsequently the composition task, in that specific order. We chose not to counterbalance the composition and transcription tasks based on previous research suggesting that starting with the composition task can cause participants to rush through their writing to move on to the next task [69]. To mitigate this according to the recommendation of Haw et al. [69], the composition task was always presented last, ensuring that participants had enough time to focus on their writing.

In the transcription task, participants transcribed 50 phrases from a corpus selected for its typical phrase lengths and alignment with English character frequencies [97]. Each phrase was displayed individually on the screen. Participants were instructed to read, understand, and transcribe each phrase as quickly and accurately as possible before pressing the "Enter" key to proceed to the next one. After completing all the phrases, a mandatory break of 5-10 minutes was enforced. In total, participants transcribed 2,000 phrases (40 participants × 50 phrases each).

After the break, participants began the composition task, where they could write an essay on one of ten pre-selected topics or select their own topic. The study application provided a text input area for essay composition. We refrained from imposing strict limitations on the length of the essay or the time of composition to preserve the natural flow of the composition. Restrictive guidelines, such as requiring additional text to meet a specified length, could have disrupted participants' writing process. Instead, participants were instructed to write until they felt their essays were complete. To facilitate easier text analysis, the use of abbreviations, contractions, profanities, uncommon foreign words, and emojis was discouraged. The input area automatically matched the display's height to prevent any perceived need to match essay length to the input space. Participants could adjust the input area's size and had to submit their essay by pressing a "Submit" button. In total, participants composed 40 essays (40 participants × 1 essay each).

Before starting each task, participants were asked whether they would prioritize speed, accuracy, or a balance of both while performing the task. The purpose was to compare their stated pre-task priorities with their actual behaviors during the task. After completion of the study, participants provided feedback on the study during a debrief session.

5 Results

The entire study, including instructions and questionnaires, took approximately one hour to complete. We conducted a Spearman rank correlation (ρ) analysis on the study data, as this method does not assume a linear relationship or normal distribution [129]. This approach is particularly relevant given that self-reported personality scores were collected using a 5-point Likert scale, making them ordinal. There is no universally accepted method for interpreting correlation coefficients, and cut-off points can vary between fields. In psychology, Spearman correlation coefficients (ρ) are generally interpreted as negligible ($\rho \approx 0.10$ to 0.29), moderate ($\rho \approx 0.30$ to 0.49), and strong ($\rho \geq 0.50$) [30, 134]. We also performed post hoc power analyses ($1 - \beta$) for statistically significant results, using an α error probability of 0.05 [11]. A statistical power of $1 - \beta < 0.7$ is considered small, $0.7 \leq 1 - \beta < 0.8$ is considered medium, and $1 - \beta \geq 0.8$ is considered large [41, 134].

5.1 Demographics

We conducted a one-way between-subjects ANOVA to examine the effects of participant characteristics on performance metrics. For statistically significant relationships, we performed post hoc power analysis (η^2). Cohen's [41] interpretation defines $\eta^2 = 0.01$ as a small effect, $\eta^2 = 0.06$ as medium, and $\eta^2 \geq 0.14$ as large.

5.1.1 Age & Gender Identity. All participants were young adults between 18 and 35 years old (M = 22.9, SD = 4.4). Following Simpson's [132] classification, we divided them into three age groups: adolescents (under 20 years), young adults (20 to 25 years), and later adulthood (26 to 35 years). Of the participants who disclosed their age (N = 34), 12% were adolescents (N = 4), 65% were young adults (N = 22), and 24% were in later adulthood (N = 8). An ANOVA found no significant effect of age group on the dependent variables in the composition or transcription tasks.

In terms of gender identity, 53% of participants identified as female (N = 21), 45% as male (N = 18), and 3% as non-binary (N = 1). An ANOVA found no significant effect of gender identity on the dependent variables in either task.

5.1.2 Education & Language Proficiency. The educational backgrounds of the participants varied: 30% had a high school diploma (N = 12), 15% had some college credit without a degree (N = 6), 38% had a university degree (N = 15), 15% had a master's degree (N = 6), and 3% had a Ph.D. (N = 1). An ANOVA did not find a significant effect of educational background on the dependent variables in composition or transcription tasks.

Using the 5-point Interagency Language Roundtable (ILR) scale [61], 58% of the participants rated their English proficiency as *Level 5: Native or bilingual proficiency* (N = 23), 33% as *Level 4: Full professional proficiency* (N = 13), 8% as *Level 3: Professional working proficiency* (N = 3), and 3% as *Level 2: Limited working proficiency* (N = 1). An ANOVA also found no significant effect of language proficiency on the dependent variables in either task.

5.1.3 Qwerty Experience. All participants had experience with Qwerty keyboards, although none had formal keyboard training. All had at least five years of experience, with an average of 13.2 years (SD = 5.6). Interestingly, there was no clear pattern between experience and age. Older participants did not always have the most experience. Instead, experience appeared to depend on when they began using keyboards. Among those who responded to both the age and experience questions (N = 22), 64% reported starting to use Qwerty keyboards before age 10 (N = 14), 32% between ages 10 and 20 (N = 7), and one participant at age 21.

Based on years of experience, participants were categorized into three levels: Level 1 (less than 10 years of experience), Level 2 (10 to 15 years), and Level 3 (more than 15 years). Of the participants who shared their experience (N = 32), 13% were at Level 1 (N = 4), 59% at Level 2 (N = 19), and 28% at Level 3 (N = 9). An ANOVA revealed significant effects of experience on text length ($F_{2,29} = 4.18, p < .05, \eta^2 = 0.27$) and readability score ($F_{2,29} = 5.35, p < .05, \eta^2 = 0.22$) in the composition task. A Tukey-Kramer multiple-comparison test identified two distinct groups in both instances: {Level 1, Level 2} and {Level 3}. Participants at Level 3 composed significantly longer text (M = 2,555 characters) with advanced-level readability (M = 11.69) compared to Levels 1 and 2, whose average text length (M ≈ 1,200 characters) and readability scores (M ≈ 8) were similar. No significant effects of experience were identified for other composition metrics or transcription task variables. These findings suggest that participants with more experience tend to compose longer texts with higher readability levels. However, further research is needed to fully understand this relationship (see § 7).

5.2 Composition Results

On average, participants composed 281 words per essay (Min: 76, Max: 1,076, SD = 224), and each essay took approximately 20 to 40 minutes to complete. Writing an essay involved an average of 28 caret repositioning actions (SD = 66) and 342 corrective actions (SD = 383). Ignoring ponder times, the average text entry speed was measured as 24.56 wpm (SD = 9.25), see Appendix B for the corresponding calculation. Given the exploratory nature of this investigation, we analyzed the relationships between all personality traits and performance metrics. A summary of the results is presented in Table 1.

Table 1: Results of the statistical tests on the composition data. Strong relationships are highlighted with a green background, medium-strength relationships with a blue background, and mild relationships with a white background. Statistically non-significant relationships are indicated with an orange background. The table also marks the strength of the results: strong and moderate correlations, effects, or statistically significant results are marked with green and orange ticks, respectively. Small correlations, effects, or statistically non-significant results are marked with an orange cross. "Comp." represents Composition, and "Read." stands for Readability. Since Spearman's correlation is a non-parametric and symmetric measure of monotonic relationships and although this table presents personality traits as predictors and performance metrics as responses, the roles of variables can also be interpreted interchangeably (e.g., performance metrics as predictors and personality traits as responses).

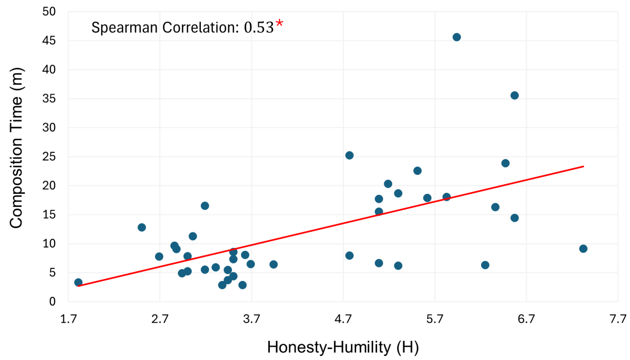
		Comp. Time (m)	Length (chars)	Editing Efforts	Ponder Count	Ponder Time (m)	Read. Score
Honesty-humility (H)	p	< .0005 ✓	< .0001 ✓	< .005 ✓	< .005 ✓	< .01 ✓	< .05 ✓
	ρ	0.53 ✓	0.58 ✓	0.50 ✓	0.50 ✓	0.42 ✓	0.34 ✓
	$1-\beta$	0.96 ✓	0.98 ✓	0.92 ✓	0.91 ✓	0.78 ✓	0.58 ✗
Emotionality (E)	p	< .010 ✓	< .0001 ✓	< .05 ✓	= 0.07 ✗	= 0.16 ✗	= 0.73 ✗
	ρ	0.43 ✓	0.51 ✓	0.36 ✓	0.29 ✗	0.23 ✗	0.06 ✗
	$1-\beta$	0.80 ✓	0.94 ✓	0.63 ✗	– ✗	– ✗	– ✗
Extraversion (X)	p	< .05 ✓	< .05 ✓	< .05 ✓	= 0.19 ✗	= 0.31 ✗	= 0.76 ✗
	ρ	0.32 ✓	0.35 ✓	0.34 ✓	0.03 ✗	0.16 ✗	0.05 ✗
	$1-\beta$	0.53 ✗	0.61 ✗	0.58 ✗	– ✗	– ✗	– ✗
Agreeableness (A)	p	< .0005 ✓	< .0001 ✓	< .005 ✓	< .005 ✓	< .05 ✓	= 0.25 ✗
	ρ	0.56 ✓	0.60 ✓	0.45 ✓	0.47 ✓	0.39 ✓	0.19 ✗
	$1-\beta$	0.97 ✓	0.99 ✓	0.85 ✓	0.88 ✓	0.72 ✓	– ✗
Conscientiousness (C)	p	< .005 ✓	<. 0001 ✓	< .05 ✓	< .05 ✓	< .05 ✓	< .05 ✓
	ρ	0.49 ✓	0.52 ✓	0.38 ✓	0.39 ✓	0.36 ✓	0.33 ✓
	$1-\beta$	0.91 ✓	0.95 ✓	0.69 ✗	0.71 ✓	0.63 ✗	0.55 ✗
Openness to Experience (O)	p	< .005 ✓	< .0001 ✓	< .005 ✓	< .05 ✓	= 0.11 ✗	= 0.11 ✗
	ρ	0.45 ✓	0.59 ✓	0.46 ✓	0.32 ✓	0.26 ✗	0.26 ✗
	$1-\beta$	0.85 ✓	0.99 ✓	0.86 ✓	0.54 ✗	– ✗	– ✗

5.2.1 Honesty-Humility & Composition. A Spearman rank correlation analysis revealed a strong positive correlation between honesty-humility and several composition metrics, including composition time, text length, editing efforts, and ponder time. In addition, a moderate positive correlation was found between the ponder time and readability score. However, despite statistical significance, post hoc power analysis indicated medium and small statistical power for the relationships between honesty-humility and the ponder time and readability score. Therefore, we recommend interpreting these latter two results with caution and encourage further investigation to explore these potential relationships more thoroughly. Fig. 3 presents scatter plots of the statistically significant relationships between honesty-humility and text composition metrics.

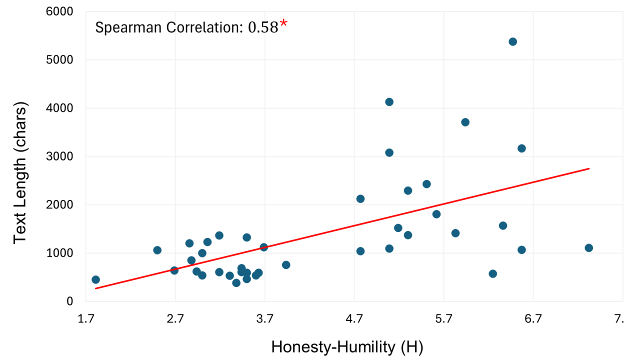
5.2.2 Emotionality & Composition. A Spearman rank correlation analysis revealed a strong positive correlation between emotionality and text length, and a moderate positive correlation with composition time. Both results demonstrated high statistical power in post hoc analysis. Additionally, a moderate positive correlation was found with editing efforts, though this result showed low statistical power, making it indeterminate and likely unreliable, with limited generalizability. No statistically significant correlations were identified between emotionality and ponder frequency, ponder time, or readability. Fig. 4 presents scatter plots of statistically significant relationships between emotionality and the recorded text composition performance metrics.

5.2.3 Extraversion & Composition. A Spearman rank correlation analysis did not identify strong relationships between extraversion and text composition metrics. However, moderate positive correlations with composition time, text length, and editing efforts were observed. Despite statistical significance, post hoc power analysis revealed only small statistical power for these tests. Fig. 5 presents scatter plots of statistically significant relationships between extraversion and the recorded text composition performance metrics.

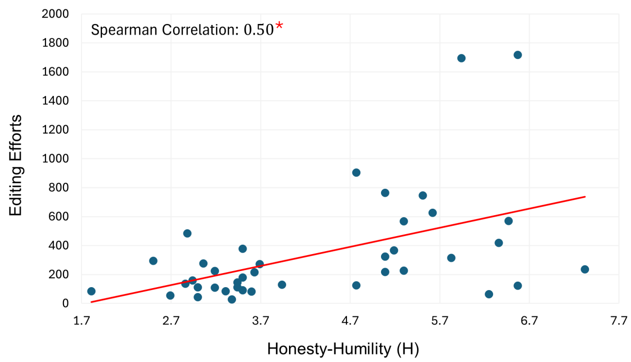
5.2.4 Agreeableness & Composition. A Spearman rank correlation analysis identified a strong positive relationship between agreeableness and both composition time and text length, supported by large power in a post hoc analysis. Agreeableness also exhibited a moderate positive correlation with both editing efforts and ponder frequency, with large power demonstrated in the post hoc analysis for these relationships. Further, a moderate positive correlation was found between agreeableness and ponder time, but this relationship did not yield large power, thus should be interpreted with caution. Fig. 6 presents scatter plots of statistically significant relationships between agreeableness and the relevant performance metrics.



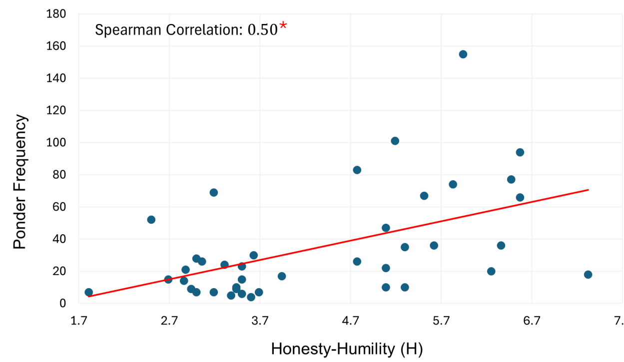
(a) H × Composition Time



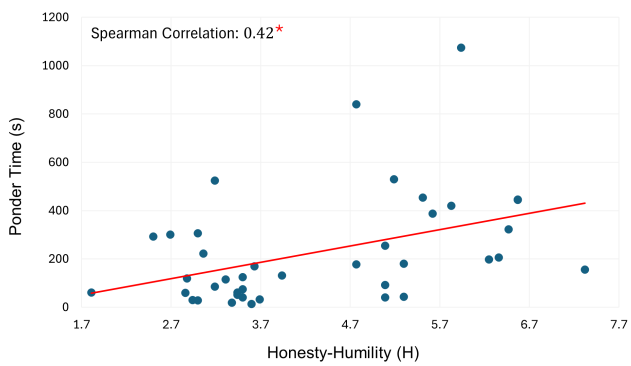
(b) H × Length



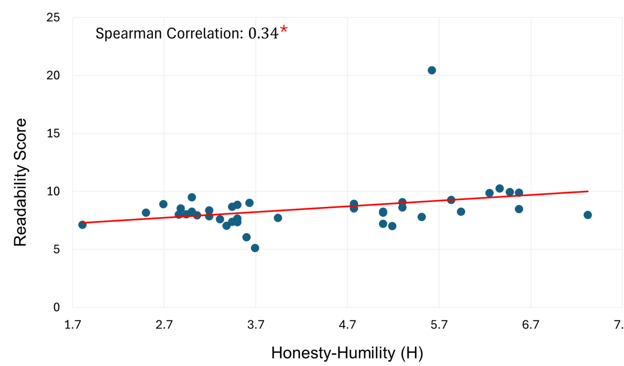
(c) H × Editing Efforts



(d) H × Ponder Frequency



(e) H × Ponder Time

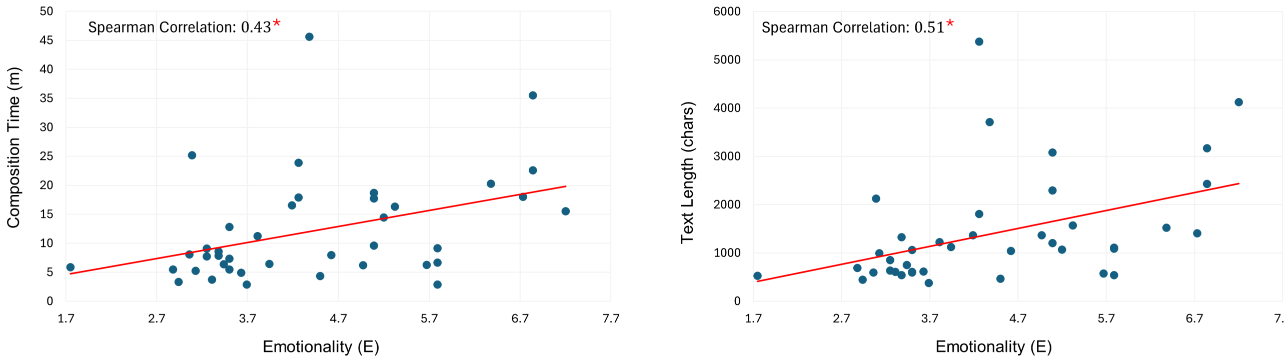


(f) H × Readability

Figure 3: Scatter plots showing statistically significant relationships between honesty-humility and text composition metrics, with trend lines highlighting the correlations. A red asterisk indicates statistical significance.

5.2.5 Conscientiousness & Composition. A Spearman rank correlation analysis revealed a strong positive correlation between conscientiousness and text length, with a large power confirmed in a post hoc power analysis. A moderate positive correlation with composition time was also found, with strong power. In addition, moderate correlations were identified between conscientiousness and editing efforts, ponder frequency, ponder time, and readability. However, the statistical power for these latter relationships ranged from small to medium, suggesting that further investigation might be needed to better understand these potential relationships or their absence. Fig. 7 presents scatter plots of statistically significant relationships between conscientiousness and the subsequent performance metrics.

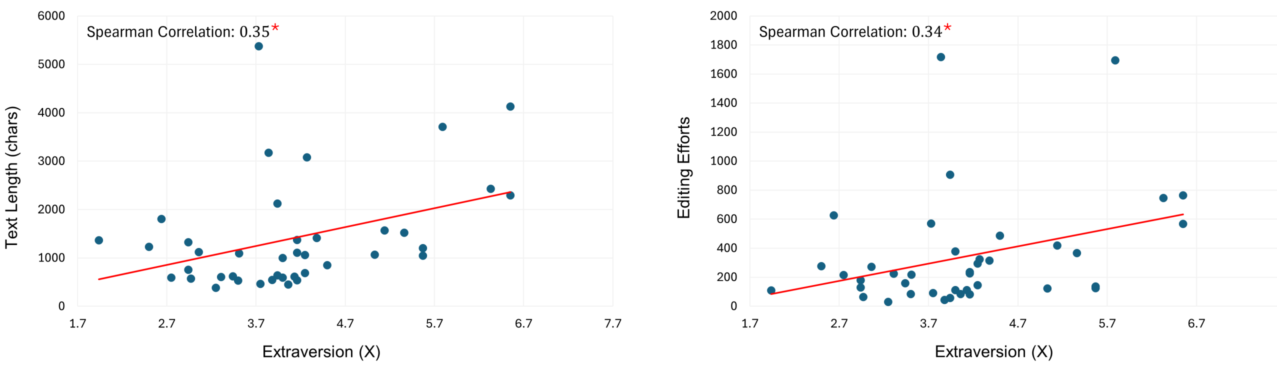
5.2.6 Openness to Experience & Composition. A Spearman rank correlation analysis revealed a strong positive association between openness to experience and text length, with a large statistical



(a) E × Composition Time

(b) E × Length

Figure 4: Scatter plots illustrating statistically significant relationships with large effect sizes between emotionality and text composition metrics, with trend lines highlighting the correlations. A red asterisk indicates statistical significance. The relationship between emotionality and editing efforts was also statistically significant but is not depicted in this figure.



(a) X × Length

(b) X × Editing Efforts

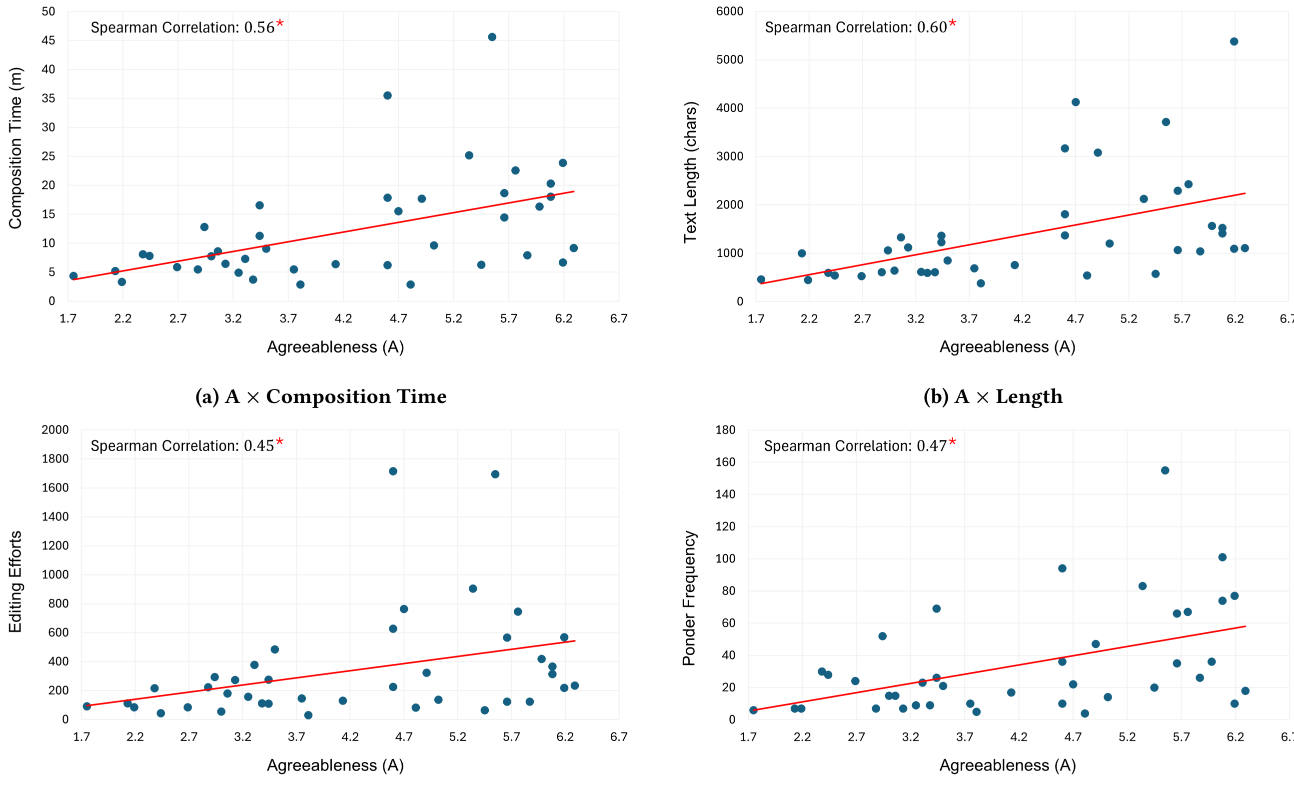
Figure 5: Scatter plots showing two statistically significant relationships between extraversion and text composition metrics, with trend lines highlighting the correlations. A red asterisk indicates statistical significance. The relationship between extraversion and composition time was also statistically significant but is not depicted in this figure.

power confirmed in a post hoc analysis. Moderate positive associations with composition time and editing efforts were also observed, where both exhibited strong statistical power. Furthermore, a moderate link was identified between openness to experience and frequency of ponder. However, the statistical power for this relationship was low, which warranted further investigation to gain a clearer understanding of the results. Fig. 8 presents scatter plots of statistically significant relationships between openness to experience and the relevant composition performance metrics.

5.2.7 Intended vs. Actual Composition Priorities. A Spearman rank correlation analysis found no statistically significant relationship between the preferences stated by participants and their actual entry speed ($\rho = -0.11$, $p = .51$) or accuracy ($\rho = 0.10$, $p = .56$). This suggests that participants may either lack conscious awareness of their actual composition behaviors or adjust their intended approach while performing the task. However, as we did not collect post-study feedback on whether participants followed their stated priorities during the study, the underlying reasons for this discrepancy remain uncertain.

5.3 Multiple Linear Regression

We conducted a multiple linear regression analysis using a backward selection model to explore the relationships between composition performance metrics (outcomes) and all personality traits (predictors). This approach quantifies the strength and direction of these relationships and assesses the feasibility of predicting composition performance based on personality traits. The backward selection model examines the relationship between performance and traits by starting with all predictors included in the model. It then systematically removes the least significant predictors, based on a p-value threshold of 0.05, and continues this process until only statistically significant predictors remain in the model. Systematically removing non-significant predictors during this process helps



(a) A × Composition Time

(b) A × Length

(c) A × Editing Efforts

(d) A × Ponder Frequency

Figure 6: Scatter plots showing statistically significant relationships with large effect sizes between agreeableness and text composition metrics, with trend lines highlighting the correlations. A red asterisk indicates statistical significance. The relationship between agreeableness and ponder time was also statistically significant but is not depicted in this figure.

minimize overfitting and improves the model's generalizability. Table 2 presents the overall fit statistics of the final model for each dependent variable.

We applied the same approach to examine the relationships between personality traits (outcomes) and composition performance metrics (predictors) to evaluate the feasibility of predicting personality traits based on composition behaviors. Table 3 presents the overall fit statistics for the final model corresponding to each dependent variable.

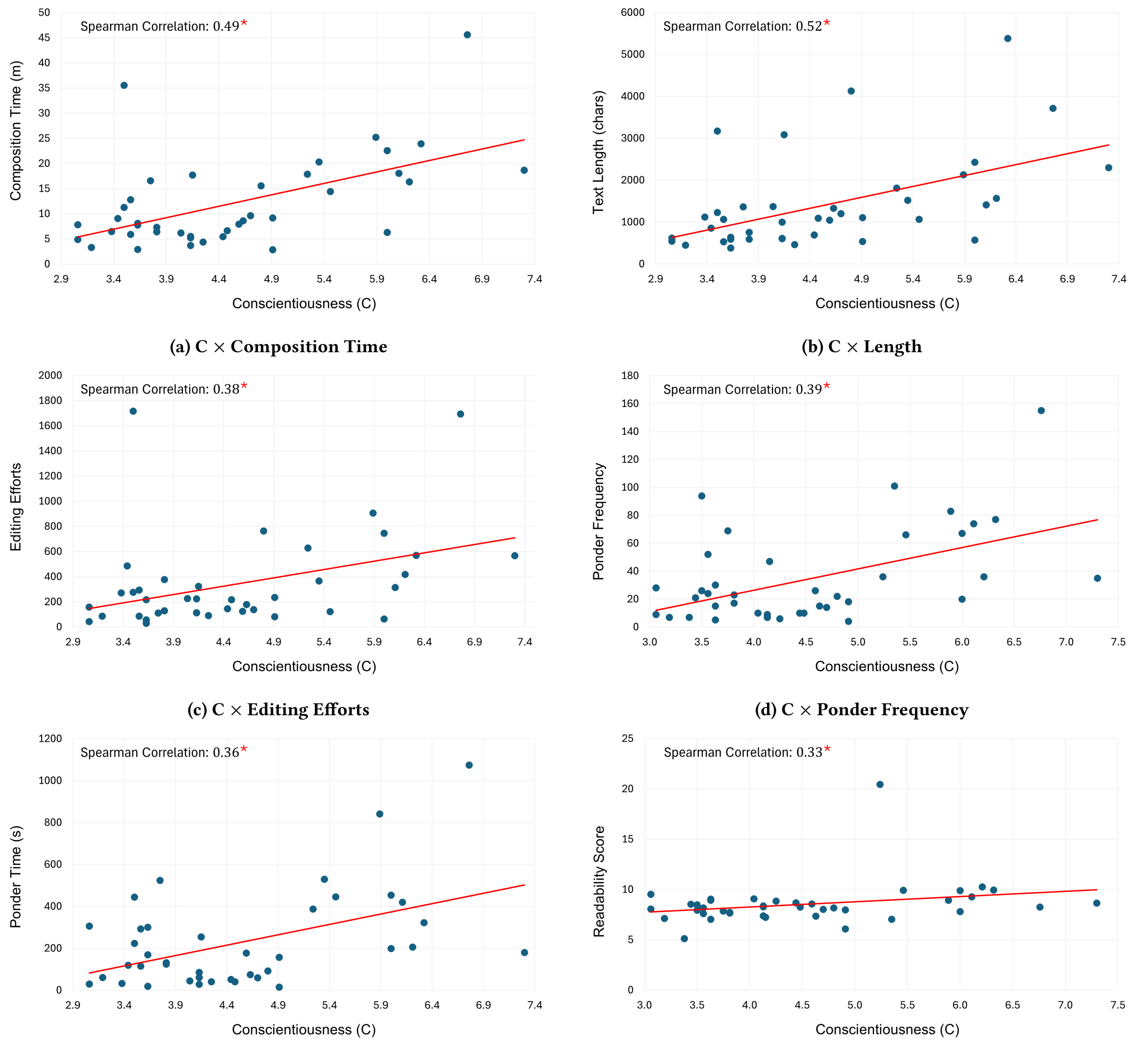
5.4 Discussion: Composition

The results suggest that personality traits may serve as predictors of users' text composition behaviors and, conversely, that text composition patterns could potentially reflect underlying personality traits. In our study, honesty-humility and agreeableness emerged as the strongest predictors of composition behaviors, with both traits correlating with all the measured metrics. Honesty-humility exhibited strong positive correlations with composition time, text length, editing efforts, and ponder frequency, along with a moderate correlation with ponder time. This suggests that individuals high in honesty-humility not only spend more time composing, leading to longer outputs, but also devote more effort to revising and improving the quality of their work. A moderate correlation was also found between honesty-humility and text readability, though the small post hoc power warrants further investigation.

Similarly, agreeableness demonstrated strong positive correlations with composition time and text length, and moderate correlations with editing efforts and ponder frequency. This suggests that individuals high in agreeableness likely spend more time, produce longer texts, and make more revisions. Table 4 presents the predictors of composition performance, classified as substantial, moderate, and mild.

Openness to experience was identified as a moderate predictor of editing efforts and ponder frequency. These findings indirectly support previous research that associates high openness with increased creativity in writing [52, 81, 82, 144]. If spending more time and effort in the composition process can be seen as a marker of creativity, this result aligns with those studies.

Interestingly, extraversion did not emerge as a strong predictor of writing behaviors, which contrasts with previous research linking extraversion to writing performance [56, 57, 99, 120, 146]. This supports our hypothesis that findings from classroom settings may not be directly transferable to freewriting, as academic writing is



(a) C × Composition Time **(b) C × Length**

(c) C × Editing Efforts **(d) C × Ponder Frequency**

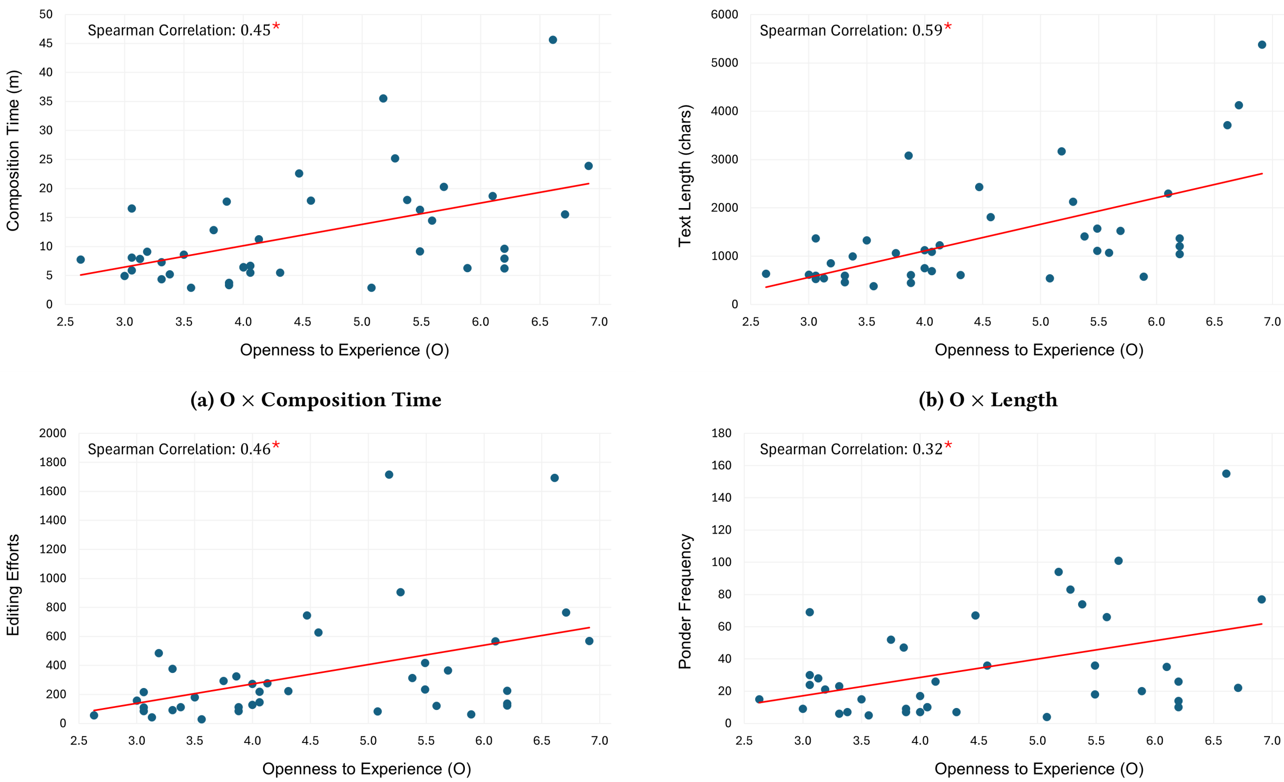
(e) C × Ponder Time **(f) C × Readability**

Figure 7: Scatter plots showing statistically significant relationships between conscientiousness and text composition metrics, with trend lines highlighting the correlations. A red asterisk indicates statistical significance.

often influenced by institutional guidelines and the objective of meeting academic expectations.

The findings also suggest that effort-related metrics, such as editing effort, ponder count, and ponder time, are harder to predict than basic composition metrics such as composition time and text length. While all six personality traits showed moderate to strong correlations with composition time and text length, only honesty-humility, agreeableness, and conscientiousness demonstrated consistent correlations with effort-related metrics (Table 1).

Readability proved to be the most difficult metric to predict. Only honesty-humility and agreeableness showed moderate correlations with the Dale-Chall readability score, but these results had low statistical power and should not be generalized without further study. It is important to note that readability formulas measure comprehension difficulty rather than text quality [35, 47]. Although prior studies have linked readability to perceived text quality [119], quality is inherently subjective and context-dependent, suggesting that this area warrants further exploration.



(a) O × Composition Time

(b) O × Length

(c) O × Editing Efforts

(d) O × Ponder Frequency

Figure 8: Scatter plots showing statistically significant relationships between openness to experience and text composition metrics, with trend lines highlighting the correlations. A red asterisk indicates statistical significance.

Another notable finding is the disconnect between users' perceptions of their writing behavior and their actual performance. Before the study, participants indicated whether they intended to prioritize speed or accuracy, but post hoc analysis did not reveal a significant relationship between these stated goals and actual performance. Interestingly, previous research has similarly shown that readers often form inaccurate perceptions of a writer's behavior and personality based solely on the text they produce [95]. However, as mentioned earlier, because we did not collect post-study feedback to verify whether participants followed their stated priorities, the precise reasons behind this discrepancy remain unclear.

A multiple linear regression analysis indicated that models that use various combinations of personality traits have the potential to predict composition behaviors (Table 2). Interestingly, a single personality trait often proved sufficient as a predictor, although incorporating additional traits generally enhanced the model's overall effectiveness. Likewise, combinations of composition performance metrics showed promise in predicting personality traits, with single metrics often being good predictors (Table 3). Adding additional metrics generally improved the model's fit, presumably by offering greater explanatory power and capturing more nuanced relationships with the outcome variable. By initially including all available predictors, the backward selection approach maximized the model's potential fit. The adjusted R^2 values, which account for the number of predictors in the model, ranged between 0.1 and 0.4 for all statistically significant models. These values are considered acceptable for studying human behavior due to the inherent complexity and variability in such phenomena [104, 115].

5.5 Transcription Results

The average text entry speed in the study was 51.25 words per minute (wpm) (SD = 18.63), with an average error rate of 0.87% (SD = 1.18). On average, 5.65% of all actions were corrective (SD = 3.38). Given the exploratory nature of this investigation, we analyzed the relationships between all personality traits and performance metrics. A summary of the results is presented in Table 5.

5.5.1 Honesty-humility & Transcription. A Spearman rank correlation analysis identified a moderate positive correlation between honesty-humility and entry speed. However, despite statistical significance, a post hoc power analysis revealed low statistical power. Fig. 9 presents a scatter plot of the relationship between honesty-humility and entry speed.

5.5.2 Emotionality & Transcription. A Spearman rank correlation analysis revealed a moderate positive correlation between emotionality and entry speed, as well as a moderate negative correlation

Table 2: Overall fit statistics of the final models predicting composition performance (outcomes) based on personality traits (predictors). R^2 represents the proportion of variance in the dependent variable explained by the model, adjusted R^2 accounts for the number of predictors in the model, and the t-value indicates the number of standard errors a coefficient is away from zero.

Dependent Variable	Model	Predictor	R^2	Adjusted R^2	Standard Error	t	p
Composition Time	1	O, X, E, C, H, A	.394	.284	7.73	−1.88	< .010
	2	X, E, C, H, A	.394	.305	7.61	−1.90	< .005
	3	X, C, H, A	.393	.324	7.51	−2.06	< .010
	4	X, C, H	.387	.335	7.44	−1.20	< .001
	5	C, H	.375	.341	7.41	−1.82	< .001
	6	H	.334	.316	7.55	−1.05	< .001
Text Length	1	O, X, E, C, H, A	.426	.322	920.3	−2.15	< .005
	2	O, X, C, H, A	.426	.342	906.7	−2.26	< .005
	3	O, X, H, A	.425	.359	894.7	−2.34	< .001
	4	O, H, A	.415	.366	889.7	−2.26	< .001
	5	O, H	.406	.374	884.3	−2.26	< .001
	6	O	.368	.351	900.4	−1.98	< .001
Editing Effort	1	O, X, E, C, H, A	.320	.196	343.4	−1.83	< .050
	2	O, X, E, H, A	.320	.219	338.3	−2.03	< .050
	3	O, X, H, A	.319	.241	333.5	−2.11	< .010
	4	X, H, A	.310	.253	331.0	−2.03	< .005
	5	X, H	.276	.237	334.5	−1.94	< .005
	6	H	.236	.216	338.0	−1.31	< .005
Ponder Count	1	O, X, E, C, H, A	.309	.184	30.14	−1.57	< .050
	2	O, X, E, C, H	.309	.208	29.70	−1.67	< .050
	3	X, E, C, H	.309	.230	29.28	−1.69	< .050
	4	X, C, H	.304	.246	28.96	−1.85	< .005
	5	C, H	.302	.264	28.62	−1.89	< .005
	6	H	.258	.239	29.11	−1.16	< .001
Ponder Time	1	O, E, C, H	.266	.182	207.39	−1.08	< .050
	2	E, C, H	.263	.201	204.95	−1.14	< .050
	3	C, H	.240	.199	205.19	−1.64	< .010
	4	C	.227	.207	204.19	−1.60	< .005
Readability Score	1	X, C, H	.193	.126	2.04	4.80	< .050
	2	X, C	.169	.124	2.05	4.91	< .050

with error correction rate. However, neither of these relationships reached statistical significance. Fig. 10 illustrates the relationships between emotionality and these two performance metrics.

5.5.3 Extraversion & Transcription. A moderate positive correlation between extraversion and accuracy rate was identified through Spearman rank correlation analysis, though it did not reach statistical significance. Fig. 11a presents scatter plots of the relationship between extraversion and accuracy rate.

5.5.4 Agreeableness & Transcription. A Spearman rank correlation analysis showed a moderate positive correlation between agreeableness and entry speed. Despite statistical significance, a post hoc power analysis revealed low statistical power. Fig. 11b illustrates the relationship between agreeableness and entry speed.

5.5.5 Conscientiousness & Transcription. No notable correlations were found between conscientiousness and any of the performance metrics.

5.5.6 Openness to Experience & Transcription. A Spearman rank correlation analysis identified a statistically significant strong positive correlation between openness to experience and entry speed, with post hoc analysis confirming high statistical power. Fig. 12 shows scatter plots of this relationship. No significant correlations were found between openness and other metrics.

5.5.7 Intended vs. Actual Transcription Priorities. Similarly to the composition task findings, a Spearman rank correlation analysis revealed no statistically significant relationship between participants' stated priorities and actual performance (speed: $\rho = -0.09$, $p = .58$; precision: $\rho = -0.10$, $p = .53$). This suggests participants may either lack conscious awareness of their transcription behaviors or adjust their approach during the task. Since we did not collect post-study feedback on whether participants adhered to their stated priorities, the underlying cause remains uncertain and warrants further investigation.

Table 3: Overall fit statistics of the final models predicting personality traits (outcomes) based on composition task performance metrics (predictors): composition time (CT), length (L), editing efforts (EE), ponder count (PC), ponder time (PT), and readability score (R). R^2, adjusted R^2, and t-value are as defined in Table 2.

Dependent Variable	Model	Predictor	R^2	Adjusted R^2	Standard Error	t	p
Honesty-humility (H)	1	R, PC, L, EE, PT, CT	.447	.347	1.14	2.22	$< .005$
	2	R, L, EE, PT, CT	.441	.359	1.13	2.36	$< .001$
	3	R, EE, PT, CT	.437	.372	1.12	2.36	$< .001$
	4	R, PT, CT	.409	.360	1.13	2.68	$< .001$
	5	R, CT	.377	.344	1.14	2.90	$< .001$
	6	CT	.334	.316	1.17	10.53	$< .001$
Emotionality (E)	1	PC, L, EE, PT, CT	.292	.164	1.20	8.51	$< .032$
	2	PC, EE, PT, CT	.292	.188	1.18	8.69	$< .050$
	3	EE, PT, CT	.292	.211	1.17	9.65	$< .010$
	4	PT, CT	.290	.230	1.15	11.55	$< .005$
Extraversion (X)	1	R, PT, CT	.211	.145	1.02	6.35	$< .050$
	2	PT, CT	.178	.134	1.02	12.78	$< .050$
	3	CT	.129	.106	1.04	13.00	$< .050$
Agreeableness (A)	1	R, PC, L, EE, PT, CT	.353	.236	1.20	5.87	$< .050$
	2	R, L, EE, PT, CT	.353	.258	1.18	5.95	$< .010$
	3	L, EE, PT, CT	.350	.275	1.17	6.04	$< .005$
	4	EE, PT, CT	.342	.287	1.16	2.55	$< .005$
	5	EE, CT	.301	.263	1.18	12.78	$< .005$
	6	CT	.252	.233	1.20	13.00	$< .001$
Conscientiousness (C)	1	R, PC, L, EE, PT, CT	.427	.323	0.91	4.62	$< .005$
	2	R, PC, L, EE, CT	.427	.343	0.89	4.86	$< .005$
	3	R, PC, EE, CT	.422	.356	0.89	5.00	$< .001$
	4	PC, EE, CT	.413	.364	0.88	10.95	$< .001$
	5	EE, CT	.368	.334	0.90	13.80	$< .001$
Openness to Experience (O)	1	R, PC, L, EE, PT, CT	.381	.269	1.05	4.22	$< .050$
	2	R, PC, L, EE, PT	.381	.289	1.04	4.54	$< .010$
	3	R, PC, L, PT	.380	.309	1.03	4.64	$< .050$
	4	PC, L, PT	.374	.321	1.02	13.23	$< .005$
	5	PC, L	.371	.337	1.00	13.62	$< .001$
	6	L	.368	.351	0.99	14.14	$< .001$

Table 4: Positive correlations between the six broad HEXACO factor scales and various text composition performance metrics, highlighting different aspects of the composition process.

		Substantial	**Moderate**	**Mild**
Duration	*Composition Time*	H · A	E · C · O	X
Length	*Text Length*	H · E · A · C · O	X	X
Effort	*Editing Efforts*	H	A · O	E · X · C
	Ponder Frequency	H	A	C · O
	Ponder Time	–	–	H · A · C
Quality	*Readability*	–	–	H · C

5.6 Multiple Linear Regression

We conducted a multiple linear regression analysis using a backward selection model to examine the relationships between transcription performance metrics (outcomes) and personality traits (predictors), following the approach outlined in Section 4. Table 6 summarizes the overall fit statistics of the final model for the sole statistically significant dependent variable, words per minute (wpm).

We also investigated the relationships between personality traits (outcomes) and transcription performance metrics (predictors) to assess the feasibility of predicting personality traits based on text

Table 5: Results of the statistical tests on the transcription data. Strong relationships are highlighted with a green background and mild relationships with a white background. Statistically non-significant relationships are indicated with an orange background. The table also marks the strength of the results: strong and moderate correlations, effects, or statistically significant results are marked with green and orange ticks, respectively. Small correlations, effects, or statistically non-significant results are marked with an orange cross. Although this table presents personality traits as predictors and performance metrics as responses, Spearman's correlation, being a non-parametric and symmetric measure of monotonic relationships, also allows the roles of variables to be interpreted interchangeably (e.g., performance metrics as predictors and personality traits as responses).

		Speed (wpm)		Accuracy (ER)		Correction Rate	
Honesty-humility (H)	p	$< .05$	✓	$= 0.47$	✗	$= .29$	✗
	ρ	0.36	✓	-0.12	✗	-0.17	✗
	$1-\beta$	0.64	✗	–	✗	–	✗
Emotionality (E)	p	$= .06$	✗	$= .88$	✗	$= .06$	✗
	ρ	0.30	✓	-0.03	✗	-0.30	✓
	$1-\beta$	–	✗	–	✗	–	✗
Extraversion (X)	p	$= .56$	✗	$= .052$	✗	$= .10$	✗
	ρ	0.10	✗	0.31	✓	0.26	✗
	$1-\beta$	–	✗	–	✗	–	✗
Agreeableness (A)	p	$< .05$	✓	$= .60$	✗	$= .15$	✗
	ρ	0.32	✓	0.09	✗	-0.24	✗
	$1-\beta$	0.53	✗	–	✗	–	✗
Conscientiousness (C)	p	$= .21$	✗	$= .80$	✗	$= .85$	✗
	ρ	0.20	✗	0.04	✗	0.03	✗
	$1-\beta$	–	✗	–	✗	–	✗
Openness to Experience (O)	p	$< .001$	✓	$= .46$	✗	$= .43$	✗
	ρ	0.51	✓	0.12	✗	-0.13	✗
	$1-\beta$	0.93	✓	–	✗	–	✗

Table 6: Overall fit statistics of the final models predicting transcription wpm (outcomes) based on personality traits (predictors). The models incorporating the other metrics failed to effectively predict the outcomes ($p > .05$). R^2, adjusted R^2, and t-value are as defined in Table 2.

Dependent Variable	Model	Predictor	R^2	Adjusted R^2	Standard Error	t	p
Words per Minute (wpm)	1	O, X, E, C, H, A	.432	.329	15.27	2.09	$< .005$
	2	O, E, C, H, A	.430	.347	15.06	2.11	$< .005$
	3	O, E, C, H	.422	.356	14.96	2.37	$< .001$
	4	O, E, C	.395	.345	15.08	2.16	$< .001$
	5	O, C	.371	.337	15.17	1.90	$< .001$
	6	O	.329	.311	15.46	1.28	$< .001$

transcription behaviors. Table 7 presents the overall fit statistics for the final model for statistically significant dependent variables.

5.7 Discussion: Transcription

The results confirm our assumption that different personality traits correlate with transcription performance compared to those for composition. The transcription findings are consistent with previous studies that identified positive relationships between openness to experience and writing performance [52, 81, 82, 144]. However, *unlike composition*, no single personality trait emerged as a strong predictor of all aspects of transcription performance. This may be due to the performance-driven nature of transcription tasks, where participants strive to be "as fast and as accurate as possible" when copying text [12]. In contrast, freestyle writing involves creativity, skill, and experience, which may be more closely associated with other personality traits. We encourage further work in psychology and personality research to explore this distinction.

The results also suggest that predicting transcription performance based on personality traits is more challenging than predicting composition performance. Aside from openness to experience, no other traits were both strongly and statistically significantly

Table 7: Overall fit statistics of the final models predicting personality traits (outcomes) based on transcription task performance metrics (predictors): words per minute (WPM), error rate (ER), and correction rate (CR). Some models failed to effectively predict the remaining outcomes ($p > .05$). R^2, adjusted R^2, and t-value are as defined in Table 2.

Dependent Variable	Model	Predictor	R^2	Adjusted R^2	Standard Error	t	p
Honesty-humility (H)	1	CR, WPM	.168	.123	1.32	3.63	< .050
	2	WPM	.160	.138	1.31	4.53	< .050
Agreeableness (A)	1	CR, WPM, ER	.208	.142	1.27	3.94	< .050
	2	WPM, ER	.149	.103	1.30	3.59	< .050
	3	WPM	.120	.097	1.30	1.11	< .050
Openness to Experience (O)	1	CR, WPM, ER	.439	.392	0.96	3.72	< .001
	2	WPM, ER	.417	.386	0.97	3.70	< .001

Table 8: Correlations between the six broad HEXACO factor scales and the three text transcription performance metrics. Negative correlations are highlighted in red.

		Substantial	Moderate	Mild
Speed	*Words per Minute*	O	H · A	E
Accuracy	*Error Rate*	–	–	X
Effort	*Error Correction Rate*	–	–	E

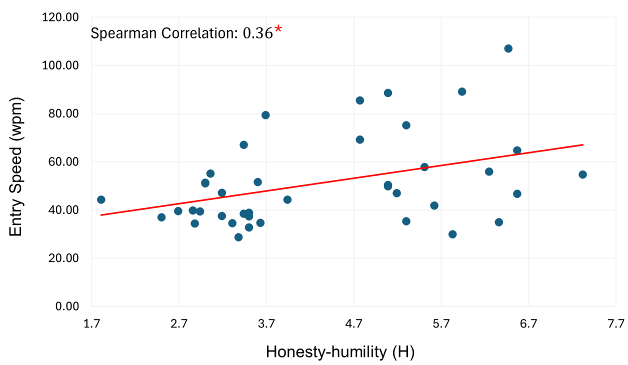


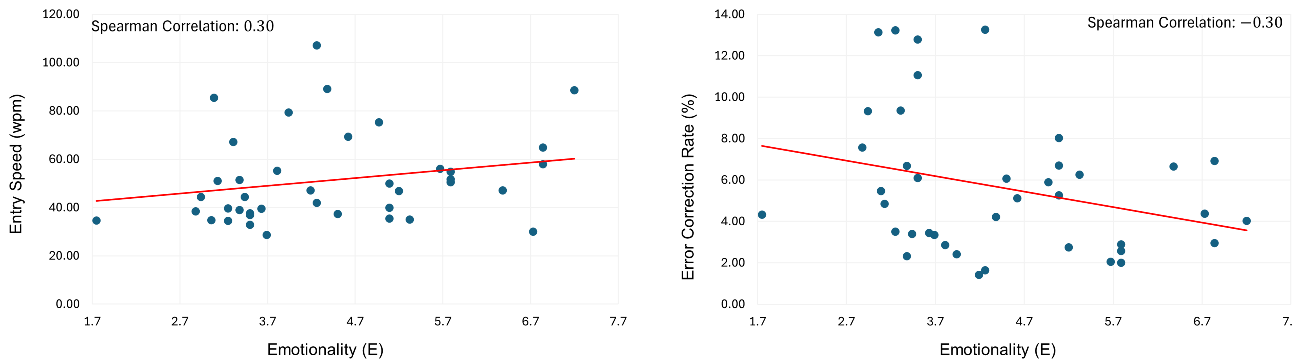
Figure 9: Scatter plot of the relationship between honesty-humility and entry speed, with a trend line highlighting the correlation. A red asterisk indicates statistical significance.

correlated with transcription performance. Furthermore, error correction and accuracy proved to be more difficult to predict than speed. In our study, only two traits (extraversion and emotionality) were moderately correlated with error rate and error correction rate, but these correlations were not statistically significant (see Table 8). This may be due to the mechanical nature of transcription tasks. Unlike composition, which involves a goal-oriented approach requiring planning, re-planning, and accessing long-term memory, transcription is a sequence of fast, repetitive keystrokes that may be less influenced by personality traits. However, more data is needed to fully investigate this. Both correlations approached statistical significance ($p = .05$ and $.06$), and additional data could help determine whether these relationships are significant. We recommend further research on this topic. It would also be interesting to explore whether personality traits have more pronounced relationships with texting behaviors and performance, as texting involves short English phrases similar to transcription, yet users must also plan their responses before entering, much like composition.

Similarly to composition, the results showed no correlation between the participants' stated prioritization of speed or accuracy and their actual performance in the study. This suggests that participants may either lack awareness of their actual transcription behaviors or adjust their intended approach during the task. However, unlike composition, where speed is secondary, it is a primary measure of transcription performance. Therefore, these findings should be interpreted cautiously, as the comparison was made with the study performance of the participants rather than their typical daily text entry behavior.

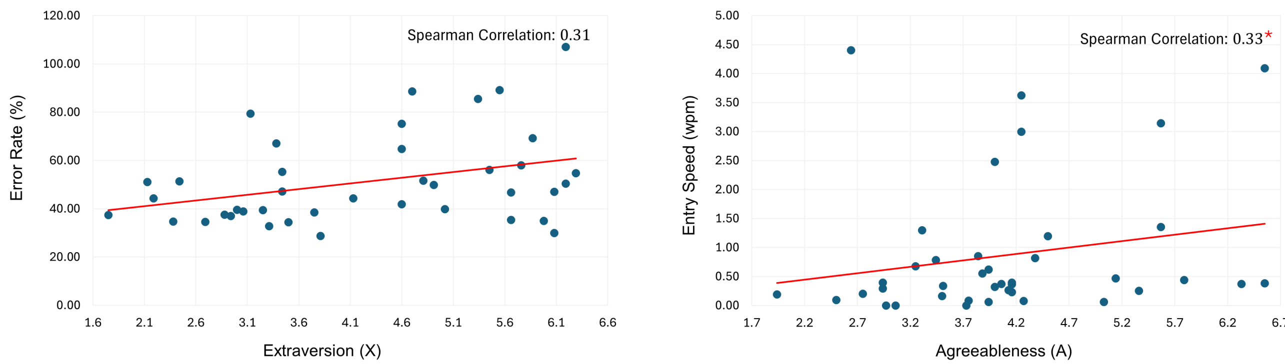
A multiple linear regression analysis failed to find statistically significant models capable of predicting most of the transcription performance metrics evaluated in this study. However, several significant models were found for entry speed (Table 6). The results indicate that models incorporating various combinations of personality traits have the potential to predict transcription speed. In this case, a single personality trait was sufficient as a predictor, though adding additional traits generally enhanced the fit, presumably by providing greater explanatory power and capturing more subtle relationships with the outcome variable.

Similarly, we did not identify statistically significant predictors for all personality traits based on transcription behaviors. However, honesty-humility, agreeableness, and openness to experience emerged as traits that could potentially be predicted using transcription metrics (Table 7). For honesty-humility and agreeableness, single predictors provided a good fit, with additional metrics typically improving the models' fit. In contrast, no single predictor was sufficient for openness to experience, where a combination of metrics was necessary for a statistically significant and effective model. In all significant models, adjusted R^2 values ranged from



(a) E × Entry Speed **(b) E × Correction Rate**

Figure 10: Scatter plots showing statistically significant relationships between emotionality and text transcription metrics, with trend lines highlighting the correlations. A red asterisk indicates statistical significance.



(a) X × Error Rate **(b) A × Entry Speed**

Figure 11: Scatter plots showing statistically significant relationships between extraversion and error rate, and agreeableness and entry speed, with trend lines illustrating the correlations. A red asterisk denotes statistical significance.

0.1 to 0.4, which are considered acceptable for studying human behavior, given its inherent complexity and variability [104, 115].

The differences between transcription and composition results suggest that both the prediction of performance based on personality and the determination of personality based on performance are more reliable in extended text entry tasks like composition.

6 Practical Implications

Personalization in human-computer interaction (HCI) typically relies on past user behavior, preferences, and the context of interaction [142]. Although effective when ample data are available, this approach often struggles to address deeper intrinsic user needs, particularly in situations with limited data or when adapting to the evolving requirements of users [114, 142]. To address these limitations, researchers propose incorporating personality traits into personalization strategies to enhance user experiences [67, 114].

Personality traits provide insights that transcend context- and device-specific behaviors, enabling systems to better align with individual preferences and needs [142]. As discussed in Section 2.5, adapting interfaces and interactions based on personality traits has shown positive results across a variety of domains, including desktop and mobile e-learning platforms, recommender systems, chatbots, personal assistants, video games, and generative AI. Systems designed with this approach often adjust design elements, such as fonts, colors, and icons, as well as information presentation formats and system responses, to better resonate with users.

Völkel et al. [142] identified several promising but underexplored domains in which personality-based personalization could offer significant benefits. For example, tailoring communication styles in interpersonal communication and networking to align with personality traits can enhance interaction quality. In recommender systems, personality traits can help deliver relevant content to users, particularly when past behavioral data is limited. Similarly, personality-based adaptations could enhance autocorrect and predictive systems in text entry by tailoring suggestions and corrections to individual preferences (§ 9). Persuasive systems could similarly benefit from personality-based adaptations, employing tailored strategies to motivate users to achieve specific goals or

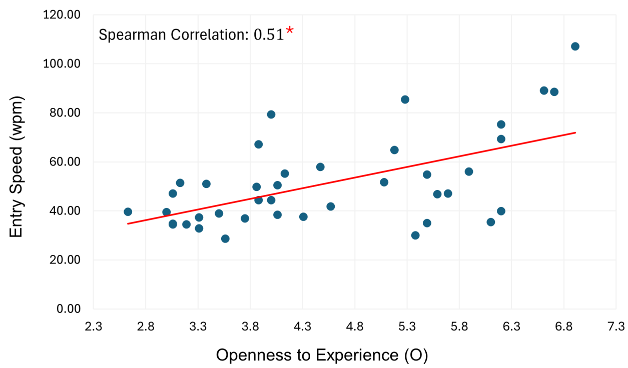


Figure 12: Scatter plot of the relationship between openness to experience and entry speed, with a trend line highlighting the correlation. A red asterisk indicates statistical significance.

adopt healthy behaviors, such as exercising. In automotive user interfaces, aligning explanations of autonomous vehicle actions with passengers' personality traits could build trust and improve user experience. Applying this approach could also build trust between users and text entry autocorrect systems (§ 9). In addition, personality traits could be leveraged to develop empathic systems, such as intelligent robots, that create a sense of deep understanding and emotional connection by personalizing their interactions to reflect individual personality profiles.

However, as predicting users' personality traits remains a challenging and tedious task [63], a straightforward and reliable method for doing so could significantly enhance interactive systems by enabling deeply personalized and engaging experiences, laying the foundation for future adaptive systems. With ongoing technological progress, potential applications of personality-based personalization are likely to extend well beyond the aforementioned examples.

7 Limitations

One limitation of this study is the limited diversity among participants, as the majority were young adults recruited from local community colleges and universities. Therefore, the findings may not be fully generalizable to broader age groups. Future research with a more diverse sample that includes participants across a wider age range is necessary to investigate potential age-related impacts on composition and transcription performance.

Although participants varied in their Qwerty experience, we did not evaluate their text entry speed separately, as traditional speed tests are similar to the transcription tasks used in this study [54]. Instead, we collected years of self-reported experience with Qwerty keyboards. Still, this metric may not fully capture text entry proficiency, as factors such as usage frequency and text entry behaviors could also influence performance [51]. Our results showed a significant effect of experience on composition length and readability scores, with more experienced participants composing longer texts and achieving higher readability. In particular, those who began using Qwerty keyboards earlier typically had more experience, suggesting that early exposure may play a key role. Factors influencing early keyboard use, such as socioeconomic status [76, 93] and parents' education [74], may also play a role, but these were beyond the scope of this work. Understanding and measuring the full impact of Qwerty experience on composition and transcription performance is a complex and resource-intensive task that warrants further investigation.

Due to the exploratory nature of the work, this study focused on monotonic relationships[2] between personality traits and performance metrics. We acknowledge that numerous human characteristics, including age and education, likely contribute to composition and transcription performance. However, fully understanding these multivariate relationships requires larger sample sizes and comprehensive analyses, challenges that are difficult to address in controlled lab studies. In addition, personality itself may encompass some of these variables, as research suggests that personality evolves with age [39, 135, 137], education [31, 75], as well as personal and technological experiences [28, 53]. Further exploration is needed to unravel these complex relationships and their impact on composition and transcription behaviors.

7.1 Privacy & Security

A challenge in detecting personality traits from text entry episodes is the need for continuous monitoring of the entered text, raising potential security and privacy concerns. However, many widely used systems, such as grammar checkers, translators, screen readers, and cloud storage clients, already access user-typed data. These systems typically protect user data through encryption for secure transmission and storage [84] and by limiting data collection to only what is essential for their functionality [49]. Some tools also process data locally on user devices to minimize the risk of breaches [84]. While such measures address many concerns, the topic of data privacy and security is beyond the scope of this work.

7.2 Predicting Personality Traits

The results showed correlations between personality traits and text entry performance, suggesting the theoretical possibility of predicting personality traits based on text entry behaviors. While an extensive body of work links personality traits to writing patterns (§ 2.1), relatively little research has focused on predicting personality traits from text entry behaviors. Although prior studies have attempted to predict personality traits from existing text [3, 83], these approaches have focused on analyzing prewritten content rather than exploring real-time text processing. Therefore, a validation study is necessary to determine more definitively whether personality can be reliably predicted in real-time as users type, particularly in real-world, in-the-wild scenarios.

For Spearman correlation analysis, we interpret a correlation coefficient (ρ) above 0.50 as strong, following recommendations from studies in psychology [30] and social sciences [134]. However, the threshold for interpreting the correlation strength is somewhat arbitrary and varies between disciplines. For instance, in some fields, a coefficient above 0.70 is typically regarded as strong [129]. Hence, it is generally advised to consider the context of the specific

[2] A monotonic relationship describes a consistent connection between two variables, where an increase in one variable corresponds to a consistent increase or decrease in the other, even if not at a constant rate.

research question when interpreting correlations [129]. Similarly, in multiple linear regression analysis, we considered a coefficient of determination (R^2) above 0.10 as acceptable, again based on social science conventions [104, 115]. However, in other fields, such as finance, an R^2 above 0.70 is often considered indicative of a strong explanatory relationship [58]. Given that ideal thresholds for interpreting correlation coefficients or measures of explanatory power have not been explicitly defined in the context of personality traits, the exact impact of these relationships remains uncertain. This gap in the literature presents a valuable opportunity for statisticians to explore.

8 Conclusion

This study explored the relationships between the six HEXACO personality traits and text entry behaviors in both composition and transcription tasks. The results provide evidence that personality traits influence text entry performance, although their impact differs between the two task types.

In composition tasks, honesty-humility and agreeableness arose as the strongest predictors of composition behaviors. These traits were significantly correlated with composition time, text length, and editing efforts, suggesting that individuals high in these traits tend to invest more time and effort into composing longer texts and revising their work. However, personality traits such as extraversion, typically associated with writing performance in classroom studies, did not show significant strong correlations with composition in this study. This difference may reflect the unique nature of freeform writing, which blends creativity, skill, and experience, making it less performance-driven than academic writing. These findings suggest that personality influences the more creative and reflective aspects of composition. Further investigation is needed to fully understand the relationships between personality traits and creative writing behaviors.

In transcription tasks, while openness, honesty-humility, and agreeableness significantly influenced performance, no single trait emerged as a strong predictor across all metrics, highlighting the repetitive and mechanical nature of the task. Unlike composition, transcription is more performance-oriented, with participants focusing on being "as fast and accurate as possible." This contrasts with composition, which involves more complex cognitive engagement. The findings also suggest that error correction and accuracy in transcription are harder to predict based on personality traits, probably because of the less cognitively demanding nature of the task.

The results revealed a disconnect between participants' stated performance priorities and their actual behaviors in both tasks. Participants who indicated a preference for either speed or accuracy did not show significant alignment with these goals during their actual performance. This discrepancy could arise from participants' lack of awareness regarding their text entry behaviors or adjustments made to their intended approach during the task. However, the precise cause cannot be determined without further investigation.

A multiple linear regression analysis identified several statistically significant models for predicting composition and transcription performance based on personality traits, as well as personality traits based on composition and transcription behaviors. In many cases, a single personality trait served as an effective predictor, although incorporating additional traits generally enhanced the model's accuracy. The results also suggested that combinations of composition performance metrics were better predictors of personality traits than transcription metrics, indicating that personality determinations are more reliable with extended text entry episodes.

The study did not find statistically significant correlations between age, gender, education, or language proficiency and text entry performance. However, it remains uncertain whether a more diverse sample might have revealed significant effects on these variables.

In general, this study highlights the nuanced relationship between personality traits and text entry behaviors. Although traits like honesty-humility, agreeableness, and openness to experience influence text entry performance, their effects vary depending on the task, whether it is with the creative demands of composition or the mechanical requirements of transcription. Future research should further explore these relationships, particularly in more naturalistic settings, to better understand how personality influences interaction with text-based technologies.

9 Future Work

In future work, we plan to extend this study to mobile text entry behaviors. As previously discussed, texting involves short English phrases similar to transcription but requires users to plan their responses before entering text, much like composition. Therefore, we hypothesize that some of the relationships identified in composition tasks might generalize to texting. We plan to explore this possibility in the future.

We will also explore practical applications of our findings, particularly the possibilities discussed in Section 6, as well as adapting text entry system behaviors for individual users. Connections between users' personality traits and various text entry behaviors have been suggested in the literature. Arif and Stuerzlinger [16] speculated that personality traits might influence error correction behaviors, while Kneifel et al. [86] suggested that users' tolerance for incorrect autocorrections could be influenced by personality traits. However, while substantial research exists linking personality traits to writing habits (§ 2.2), specific links with text entry behaviors remain unexplored. We aim to investigate these connections and, based on our findings, explore ways to customize grammar checkers, autocorrect systems, and predictive systems to better align with users' personalities. This could include but is not limited to, adjusting the frequency of visual feedback on potential spelling, grammatical, or stylistic issues, tailoring the types of corrections or edits recommended by the system, customizing next-word predictions, and fine-tuning the intensity of autocorrection and completion (e.g., setting predictive keyboards to weak or strong modes).

In addition, we plan to conduct a longitudinal study with a more diverse and larger sample to investigate the impact of sample characteristics on correlation coefficients and measures of explanatory power, to better understand the relationships identified in this work. Furthermore, some of the applications mentioned above should be validated in real-world settings, which will also require longitudinal studies spanning months or even years to evaluate their effectiveness and adaptability. Such extended evaluations will provide deeper insights into how these solutions can enhance the overall user experience.

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A Essay Topics

The freewriting topics presented in the composition task in order of frequency, along with the percentage of participants who chose each topic.

(1) *A trip you will never forget* (20%)
(2) *Your best friend and how you met* (20%)
(3) *Your favorite vacation with your family* (15%)
(4) *Your first day at a new school* (13%)
(5) *A story from a trip* (13%)
(6) *The best birthday party you have ever had* (5%)
(7) *The best present you have ever received* (5%)
(8) *Learning a life lesson* (5%)
(9) *A time you made friends in an unusual circumstance* (3%)
(10) *Discussing the phenomena of moral wiggle room* (3%)

B Composition Words per Minute

We did not use words per minute (wpm) as a primary evaluation metric for composition tasks because the traditional wpm calculation would suffer from pondering pauses, where users stop to collect their thoughts while composing (§ 4.3). However, we recorded both the traditional wpm and the following variant designed for composition tasks.

- **Typing words per minute (t-wpm)** measures the average number of words typed per minute, excluding the time spent pausing or contemplating [69]. This metric isolates active text entry speed by focusing only on periods of continuous text entry. To compute t-wpm, the composed text is split into chunks wherever a pause exceeds the 2.4-second threshold (§ 4.3). The standard wpm formula (§ 4.4) is applied to the concatenated fragments, with an adjustment of 1 to exclude characters immediately after each pause: $t\text{-wpm} = \sum_{i=1}^{n} \left(\frac{|T_i|-1}{S_i}\right) \times 60 \times \frac{1}{5}$, where n is the total number of fragments based on the count of ponders, S_i is the time in seconds from the first to the last keystroke for the fragment i-th and $|T_i|$ is the length of that fragment.

Participants achieved an average of 24.56 wpm (SD = 9.45) using the traditional wpm metric and 33.52 wpm (SD = 9.25) with the t-wpm metric during composition tasks. Compared to transcription tasks, t-wpm revealed a 42% slower entry speed, which indicates the possibility that participants generally type more slowly when composing. A Spearman rank correlation analysis identified negligible correlations ($|\rho| < 0.30$) between the six personality traits and both wpm metrics, with no statistically significant results ($p > 0.05$).