Using machine-learning approach to predict Big-five personality traits based on subconscious behaviors

by

Juhwan Lim

B.B.A., Korea Aerospace University, 2017
M.S., Korea Advanced Institute of Science and Technology, 2019

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Hospitality Management
College of Health and Human Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2024

Abstract

Hiring the right people is the first step for hospitality organizations to enhance service quality and customer satisfaction by obtaining competitive advantages. To find the right people, numerous hospitality companies pay attention to job candidates' personality traits to evaluate the fit between the companies and job candidates during job interviews. However, evaluations of personality traits can be biased and misunderstood as interviewees often disguise their personalities to create desired impressions. Previous studies in psychology have suggested that people's unique characteristics can be inferred by their subconscious communication types, that is, verbal, para-verbal, and non-verbal behaviors. Nevertheless, it is yet to be tested how three subconscious behaviors are associated with personality traits, thus influencing hiring decisions made by interviewers.

Thus, the primary purpose of this study is to investigate the relationships between interviewees' three communication types, Big-five personality traits, and interviewers' hiring decisions in the job interview context. Moreover, Big-five personality traits are measured by three types of Big-five personality traits assessments: interviewer-reported, self-reported, and machine learning-inferred Big-five personality traits, to capture various aspects of personality traits assessment.

To test the proposed hypotheses, 10 mock-up interviewers and 106 mock-up interviewees were recruited from Prolific and one of the universities in mid-west areas of US, using four screening conditions: (1) 18 years or older, (2) currently living in the United States, (3) seeking supervisory job opportunities in the hospitality industry, and (4) having LinkedIn personal page, for mock-up interviews. Four machine learning-based techniques were employed to measure interviewees' verbal, para-verbal, and non-verbal behaviors. Confirmatory factor analysis was

performed to verify the validity and reliability of interviewer-reported and self-reported Big-five personality traits. Regression analyses were employed to test the proposed hypotheses.

Regarding the relationships between three communication types, interviewer-reported Big-five personality traits, and hiring decisions, verbal behaviors had significant effects on extraversion (β = .364, p < .01), openness (β = .227, p < .01), and agreeableness (β = .169, p < .01) traits, while para-verbal behaviors were significantly associated with openness (β = .108, p < .01) and consciousness (β = .090, p < .01) traits. Non-verbal behaviors had significant impacts on openness (β = .079, p < .05), agreeableness (β = .083, p < .01), and conscientiousness (β = .104, p < .01) traits. Among five dimensions of interviewer-reported Big-five personality traits, neuroticism (β = -.406, p < .01), extraversion (β = .270, p < .01), agreeableness (β = .327, p < .01) were significantly associated with hiring decisions.

In terms of the associations between three communication types, self-reported Big-five personality traits, and hiring decisions. both para-verbal behaviors (β = -.096, p < .01) and non-verbal behaviors (β = .045, p < .05) were significantly related to an openness trait. Extraversion (β = .288, p < .05) and conscientiousness (β = .486, p < .01) traits, among five dimensions of self-reported Big-five personality traits, were found to be significant in explaining hiring decisions.

When it comes to the effects of three communication types on machine learning-inferred Big-five personality traits, verbal (β = .650, p < .05) and non-verbal (β = .322, p < .05) behaviors were significantly related to an extraversion trait. Among five dimensions of machine learning-inferred Big-five personality traits, neuroticism (β = -.072, p < .05), extraversion (β = .063, p < .05), openness (β = .082, p < .05) traits had significant effects on interviewers' hiring decisions.

Finally, regarding the relationships between interviewees' three communication types and hiring decisions, verbal ($\beta = .304$, $p < .01$) and non-verbal ($\beta = .104$, $p < .05$) were significantly associated with hiring decisions.

Based on the results, this study's theoretical and practical contributions, and limitations with recommendations for future research are discussed.

Keywords: Job interviews, Communication types, Big five personality traits, Machine learning, Hiring decisions, Signaling theory.

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Major Professor
Jichul Jang, Ph.D.

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To test the proposed hypotheses, 10 mock-up interviewers and 106 mock-up interviewees were recruited from Prolific and one of the universities in mid-west areas of US, using four screening conditions: (1) 18 years or older, (2) currently living in the United States, (3) seeking supervisory job opportunities in the hospitality industry, and (4) having LinkedIn personal page, for mock-up interviews. Four machine learning-based techniques were employed to measure interviewees' verbal, para-verbal, and non-verbal behaviors. Confirmatory factor analysis was

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When it comes to the effects of three communication types on machine learning-inferred Big-five personality traits, verbal (β = .650, p < .05) and non-verbal (β = .322, p < .05) behaviors were significantly related to an extraversion trait. Among five dimensions of machine learning-inferred Big-five personality traits, neuroticism (β = -.072, p < .05), extraversion (β = .063, p < .05), openness (β = .082, p < .05) traits had significant effects on interviewers' hiring decisions.

Finally, regarding the relationships between interviewees' three communication types and hiring decisions, verbal (β = .304, p < .01) and non-verbal (β = .104, p < .05) were significantly associated with hiring decisions.

Based on the results, this study's theoretical and practical contributions, and limitations with recommendations for future research are discussed.

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Acknowledgements

I came to Kansas State University in the middle of COVID-19. The first two semesters were online. My doctoral study could not be achieved without the support and commitment of my parents. Their unlimited love and dedication have motivated me to continue my doctoral study.

My deep acknowledgment goes to Dr. Jichul Jang, my major professor. His guidance, knowledge, insight, wisdom, and commitment led to my successful Ph.D. journey. His motivation encourages me to challenge myself to experience various activities, in addition to enhancing my academic performance. I have never regretted that I worked with Dr. Jang for my doctoral study and future academic journey.

I would like to thank my dissertation committee members who supported me in developing and finishing my doctoral dissertation. Dr. Kevin Roberts, Dr. Bongsug Chae, Dr. Jin Lee, and Dr. Cen Wu provided my invaluable comments and insight that helped me enhance the quality of my dissertation. Not only during the dissertation proposal and defense presentation, but also whenever I had questions and needed their help, they were always happy to answer the questions and help me. Since they came from different departments, I was able to learn various perspectives and aspects in terms of research.

I would also like to thank Dr. Yue Teng Vaughan and Ms. Ericka Bauer. They always welcomed me whenever I said hello and had a chat with me, helping me forget about loneliness as an international student who left my family and friends in my homeland. Finally, I thank the staff, other colleagues, and other students in our department and college. Even though I cannot name them all, they put the little pieces of my academic journey and life at Kansas State University.

Chapter 1 - Introduction

As labor shortages and turnover significantly influences the quality of service and customer satisfaction, finding the right people with the right experience and skills has been a severe and ongoing challenges for many hospitality businesses (Song et al., 2022; Yang & Lee, 2023). While hospitality employers can evaluate job candidates on their skills and experiences, many hospitality firms are increasingly adopting personality measures to determine whether a candidate is a good fit with a company's culture (Carless, 2005; Kim et al., 2019). As hospitality employees' communication skills and sympathetic attitudes are the key to satisfying customers' diverse needs, hospitality employers are now paying a lot more attention to employees' personalities (Doan et al., 2021). For instance, Hyatt Hotels & Resorts actively uses plyometrics, an artificial intelligence AI-based personality assessment system, that generates behavioral interview questions based on the results of job candidates' personality assessments. This system helps employers find the fit between job positions and job candidates and hire the best-fitting talent. (Hyatt Corporation, 2024). Empirical evidence has also found that job candidates' personality traits have been identified as the critical success factors of job performance and organizational commitment in the hospitality industry (Bellou et al., 2018; Kim et al., 2009; Köşker et al., 2019; O'Neill & Xiao, 2010; Shiwen & Ahn, 2023).

Researchers have widely adopted the Big-five personality framework with its five primary dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism (McCrae & John, 1992). For example, in the hospitality industry, a meta-analysis study conducted by Doan et al. (2021) demonstrated that hospitality employees' Big-five personality traits have significant relationships with various outcomes, such as organizational commitment, job satisfaction, emotional exhaustion, and organizational citizenship behaviors. The meta-analysis study emphasizes the importance of personality traits by analyzing 105 prior studies in the hospitality context. Among the five dimensions of Big-five personality traits, Doan et al. (2021) found that employees' agreeableness, extraversion, neuroticism, and conscientiousness traits strongly predict the relevant outcomes mentioned above. Thus, since numerous dimensions of Big-five personality traits have been found to be associated with individual and organizational performance, it is critical for hospitality employers to find and select the right people based on their personality traits displayed during the recruitment process (Kwok et al., 2011).

While interviewers may perceive and recognize job candidates' personality traits, their evaluations are based on subjective intuition and therefore might be possibly biased (Connelly & Ones, 2010). As humans, interviewers may misunderstand the interviewees' personality traits due to their subjective perceptions or miss critical signals about the interviewees' personality traits during job interviews (Levashina et al., 2014). Moreover, job candidates can consciously embellish the truth and disguise their personalities to create desired impressions, thus putting employers at a greater risk of hiring the wrong people (Ho et al., 2020). Instead of trying to recognize personality traits as they appear, using possible predictors of personality traits might be helpful to achieve genuine personality identification. One of the possible predictors of human personality can be facilitated by analyzing people's subconscious behaviors using machine learning-based approaches. These approaches, such as face recognition and voice recognition analytics, allow researchers to capture and quantify human subconscious behaviors in real time and with a high reliability based on pre-trained algorithms and natural language processing models (Hickman et al., 2022; Hildebrand et al., 2020). By adopting these novel methodologies, the current study argues that the subconscious behaviors measured by machine learning-based approaches can predict people's personality traits. This study makes connections between the novel methodological opportunities and theories regarding personality traits, as previous studies have suggested a link between people's subconscious behaviors and unique characteristics, such as attitudes and beliefs (Kernberg, 2016; Lewicki & Hill, 1987). Because subconscious behaviors are activated by their underlying psychological processes that create consistent patterns in each human over time (DeGroot & Motowidlo, 1999; Guidi et al., 2019; Winkielman & Berridge, 2004), subconscious behaviors are likely to have associations with personality trait through focalized patterns of thoughts, emotions, and attitudinal system peculiar to the individual. To better understand subconscious behaviors, three communication types, that is, verbal, para-verbal, and non-verbal behaviors, have been conceptualized and suggested in psychology and general management disciplines (Feine et al., 2019; Hollandsworth Jr et al., 1979; Wilhelmy et al., 2016). However, it is yet to be tested whether these three subconscious communication types (i.e., verbal, para-verbal, and non-verbal behaviors) may also play an integral role in predicting the Big-five personality traits, and the judgment based on three types of communication may influence the hiring decisions during interviews.

While understanding job candidates' personality traits is critical for employers to find and recruit the right people, there are several personality assessments for recognizing job candidates' personality traits. Prior studies regarding personality traits commonly used two types of personality assessment: 1) other (e.g., interviewer)-reported Big-five personality traits and 2) interviewees' self-reported Big-five personality traits (Barrick et al., 2000; Connelly & Ones, 2010; Hall et al., 2018; McCrae, 1982; Mount et al., 1994; Van Iddekinge et al., 2005; Oh et al., 2011). Although personality ratings from interviewer-reported and self-reported Big-five personality traits are considerably correlated, they have a fundamental difference as self-perspectives and other-perspectives are not basically same (Hogan, 1991). For instance, personality traits that are innate and private (e.g., emotional stability and openness to experience) are not readily recognized by others, thus creating a discrepancy between self-reported and other-reported ratings regarding emotional stability and openness to experience (Connolly et al., 2007). Moreover, personality ratings between interviewer-reported and self-reported Big-five personality traits can be different because of human biases and situational factors (Oh et al., 2010). This difference is more obvious in the job interview context, where interviewers evaluate the Big-five personality traits of the job candidates who they had barely met before the interview and then during the short time of the interview (Mount et al., 1994). Thus, this paper argues that understanding any differences and/or similarities between personality ratings from interviewer-reported and self-reported Big-five personality traits related to the three communication types and hiring decisions is crucial to fully understanding job candidates' Big-five personality traits and making the right hiring decisions.

Due to the advancement of information technology and AI, employers actively use job candidates' professional social media, such as LinkedIn, to understand job candidates' personality traits (Tay et al., 2020). By looking at candidates' pictures and/or reading their postings, candidates' personality traits can be inferred (Roulin & Stronach, 2022). While it may take a long time to look at all pictures and postings, the recent development in machine learning techniques, such as IBM Watson personality insight and Receptiviti API, enables researchers and employers to effectively infer job candidates' Big-five personality traits (Kong & Ding, 2024; Koutsoumpis et al., 2022). Recent personality studies have confirmed the reliability and validity of the three types of Big-five personality assessments (i.e., interviewer-reported, self-reported, and machine learning-inferred) in predicting relevant outcomes, such as job performance or academic performance (Connelly & Ones, 2010; Fan et al., 2023; Hickman et al., 2022; Klinger

& Siangchokyoo, 2024; Mount et al., 1994; Oh et al., 2011). These studies provide the fundamental psychometric properties of the three types of Big-five personality assessments and lead me to empirically investigate and compare the relationships between three communication types, three types of Big-five personality traits assessments, and hiring decisions, which may be helpful in fully understanding job candidates' Big-five personality traits and making better hiring decisions.

The primary goal of the proposed study in addressing this theoretically and practically relevant research issue will be to extend the line of research to examine the relationships between interviewee's communication types, Big-five personality traits, and interviewers' hiring decisions by using signaling theory as an overarching theoretical framework. Signaling theory suggests that people use signaling cues to infer facts or characteristics that are difficult to observe (Spence, 1973). Hence, I argue that Big-five personality traits could be predicted by the interviewees' verbal, para-verbal, and non-verbal behaviors as a signaling set of people's personalities (Wilhelmy et al., 2016) using machine learning algorithms. More specifically, job candidates' Big-five personality traits are measured by three different personality assessments, that is, interviewer-reported, self-reported, and machine learning-inferred. Analyzing interviewees' communication types to identify their personalities with machine learning techniques can help hospitality hiring managers reduce human unconscious biases during recruitment decisions and elevate the quality of new hires. Based on signaling theory, I claim that the significant relationships among interviewees' three communication types, three types of Big-five personality traits assessments, and hiring decisions would be found and compared to fully understand interviewees' personality traits and to make the right hiring decisions.

Statement of Problem

The COVID pandemic has enormously affected hospitality businesses by creating a massive labor shortage and huge numbers of laid-off employees despite the recovery in labor demand, thus impairing service quality and customer satisfaction. In 2022, the hospitality industry showed an 82% employee turnover rates, compared to the average turnover rate of 47% across the industries in the United States (U.S. Bureau of Labor Statistics, 2023). Moreover, recent statistics showed that although hospitality companies had 1.6 million job openings, they were able to hire only 1.18 million employees, generating a 420,000 hiring gap in April 2023 (U.S. Bureau of Labor Statistics, 2023). This ongoing challenge leads hospitality companies to hire the right people to enhance the quality of service and reduce turnover rates to sustain their businesses (McCartney et al., 2022). To find the right people, employers evaluate job candidates based on various factors, such as skills, knowledge, GPA, leadership, work experiences, motivation, and so forth (Kwok et al., 2011; Raza & Carpenter, 1987). A meta-analysis conducted by Huffcutt et al. (2001) showed that employers most frequently considered employees' personality and social skills, followed by mental capability and job knowledge during the hiring process. The importance of employees' personality traits should be emphasized more in the hospitality context because hospitality employees' soft skills and attitudes toward customers are the main drivers that enhance customer satisfaction and organizational outcomes (Doan et al., 2021).

Despite the significance of personality traits, several research gaps prompted me to conduct this study, especially in the hospitality and job interview contexts. First, while hospitality researchers have arguably investigated the role of employees' personality traits to explain various consequences (e.g., customer relationships, team relationships, organizational benefits, and individual benefits), limited empirical hospitality studies have investigated the role of personality traits in predicting hiring decisions. Addressing this gap is important because the relationships between Big-five personality traits and particular consequences can vary due to the multidimensional nature of human personality and the circumstances of specific consequences where five personality traits are manifested (Klinger & Siangchokyoo, 2024; Oh et al., 2011). For example, while agreeableness has the largest effect on hospitality employees' service orientation, it has a negligible impact in explaining the tendency to work (Köşker et al., 2019). Similarly, employees' openness has no significant relationship with their job burnout (Kim et al., 2007); however, it is significantly associated with job flow experience (Kim et al., 2019). Theoretically, only one study by Kwok et al. (2011) suggested that hospitality interviewees' personality traits would influence employers' hiring decisions and scant hospitality research empirically investigates the relationships between Big-five personality traits and hiring decisions. Since a job interview is the very first opportunity to understand future employees' personality traits for organizations, including hospitality companies (Martin & Groves, 2002; Mejia & Torres, 2018), how interviewees' personality traits are associated with interviewees' hiring decisions and how the personality traits can be understood during job interviews should be studied in the hospitality context.

Second, numerous previous studies outside the hospitality context have documented the effects of interviewees' personality traits (commonly Big-five personality traits) on interview outcomes, such as interviewees' performance and hiring decisions made by interviewees (Barrick et al., 2000; Cortina et al., 2000; Levashina et al., 2014; Roth et al., 2005; Salgado & Moscoso, 2002). However, prior studies rarely explored possible predictors that signal interviewees' personality traits. This is possibly because human personality traits are considered a foundation system of human attitudes and behaviors (Allport & Allport, 1921; Gustavsson et al., 2003). Prior studies have commonly investigated the relationships between personality traits and relevant consequences (e.g., fit and attractiveness) rather than searching possible predictors of personality traits and their relationships with personality traits (Barrick et al., 2000; Cortina et al., 2000; Levashina et al., 2014; Roth et al., 2005; Salgado & Moscoso, 2002).

In reality, though, interviewees can intentionally disguise their personality traits to create desired impressions for interviewers (Ho et al., 2020). Moreover, interviewers' misunderstanding of interviewees' personality traits can also happen due to subjective perceptions and information loss (Connelly & Ones, 2010; Levashina et al., 2014). Thus, simply looking at interviewees' behaviors and trying to recognize their personality traits may lead to misunderstanding and wrong hiring decisions. Accordingly, possible predictors for personality traits need to be investigated to more deeply understand personality traits with limited conscious intervention and bias. Several studies in psychology have adopted the concept of subconscious communication types (i.e., verbal, para-verbal, and non-verbal behaviors) to comprehend the interviewees' behaviors and their effects on hiring decisions (DeGroot & Gooty, 2009; DeGroot & Motowidlo, 1999; Feiler & Powell, 2016; Wilhelmy et al., 2016). Yet, it has not been tested whether these three subconscious communication types are associated with Big-five personality traits. Thus, it would be valuable to examine the relationships between three subconscious communication types as predictors and Big-five personality traits to demonstrate a possible way to identify interviewees' personality traits without the intervention of interviewees' disguising behaviors during job interviews.

Third, more specifically, while it is assumed that these three communication types would have significant relationships with Big-five personality traits and hiring decisions, interviewees' personality traits can be shown and measured in several ways (interviewer-reported, self-reported, and machine learning-inferred, in this study). Interviewers commonly refer to interviewer-reported personality ratings to evaluate and record job candidates' personality traits (Connelly & Ones, 2010; Mount et al., 1994). However, since interviewers' perceptions might be different from interviewees' self-perceptions regarding their personality traits, this discrepancy may hinder interviewers from genuinely and fully understanding the personality traits and provide a higher probability of hiring the wrong people (Hogan, 1991; Oh et al., 2011). Thus, using both interviewer-reported and self-reported ratings of Big-five personality traits, prior studies in psychology have documented the reliability and validity of two personality assessments in explaining relevant outcomes, such as job performance or academic performance (Connelly & Ones, 2010; Fan et al., 2023; Hickman et al., 2022; Klinger & Siangchokyoo, 2024; Mount et al., 1994; Oh et al., 2011). However, empirical studies investigating and comparing the relationships of interviewer-reported and self-reported Big-five personality traits with the three communication types and hiring decisions are still lacking. More recently, with the advancement of information technology, employers have increasingly used job candidates' professional social media, such as LinkedIn, for personality identification purposes (Tay et al., 2020). Accordingly, recent research has confirmed the psychometric properties of Big-five personality traits, inferred from social media using machine learning algorithms, in predicting various outcomes, such as academic performance (Fan et al., 2023; Hickman et al., 2022). Since machine learning-inferred Big-five personality traits use novel sources of personality identification and methodological approach, I expect that there would be new findings to discover, compared to interviewer-report and self-reported ratings. Nevertheless, similar to self-reported Big-five personality traits, there is little attention to empirical approaches to examine the associations of machine learning-inferred Big-five personality traits with three the communication types and hiring decisions and compare any significant dimensions of Big-five personality traits with interviewer-reported and self-reported ratings. These two neglected spots are much more critical in the hospitality context, even though employees' personality traits are one of the most critical factors for service quality and customer satisfaction.

Last but not least, from the methodological perspective, previous studies' approaches to measure interviewees' communication types have room for improvement by using machine learning-based analysis, such as face and voice recognition techniques, to reduce human bias. For example, most studies measured interviewees' non-verbal behaviors, such as body posture, smile, personal appearance, or facial expression, by asking human coders to manually count the behaviors or rate the behavioral intensiveness with Likert scales (DeGroot & Gooty, 2009; DeGroot & Motowidlo, 1999; Cuddy et al., 2015; Stevens & Kristof, 1995; Feiler & Powell, 2016; Fox & Spector, 2000; Peeters & Lievens, 2006). However, human manual identification of others' behaviors can be possibly incomplete and/or biased based on subjective intuition (Connelly & Ones, 2010; DePaulo, 1992). To address this issue, a few recent psychology studies have adopted machine learning-based behavior analysis and confirmed the reliability and the validity of these machine learning-based approaches (Hickman et al., 2019; Hickman et al., 2022; Hildebrand et al., 2020). Thus, it would be valuable to identify and measure the interviewees' three communication types by adopting the machine learning-based approach and further examine their associations with personality traits and hiring decisions based on the theoretical framework. Moreover, to predict the Big-five personality traits implicit in LinkedIn profile pages when measuring the consistency of Big-five personality traits, this study uses data mining techniques and machine learning-based prediction models. For instance, using textual data and self-reported Big-five personality traits, several prediction models, such as least absolute shrinkage and selection operator (LASSO) regression, ridge regression, and elastic net regression, can be developed and trained (Fan et al., 2023). The trained prediction models will generate the predicted values using textual data from LinkedIn profile pages, which will be machine learning-inferred Big-five personality traits. The data mining techniques and machine learning-based prediction models will be beneficial for me to effectively and efficiently infer the Big-five personality traits from LinkedIn pages in real-time with high reliability.

Purpose of the Study

The purpose of this study is to investigate the relationships between three communication types, three types of Big-five personality traits, and hiring decisions in the job interview context. Three types of Big-five personality traits assessments include interviewer-reported, self-reported, and machine learning-inferred Big-five personality traits. For the relationship between interviewees' communication types and three types of Big-five personality traits assessments, the effects of interviewees' communication types (i.e., verbal, para-verbal, and non-verbal behaviors) on five dimensions (i.e., neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness) of three types of Big-five personality traits assessments (i.e., interviewer-reported, self-reported, and machine learning-inferred) are examined. In order to investigate the role of communication types and personality traits in evaluating interviewees, interviewees' communication types (i.e., verbal, para-verbal, and non-verbal behaviors) and five dimensions (i.e., neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness) of three types of Big-five personality traits assessments (i.e., interviewer-reported, self-reported, and machine learning-inferred) are included as independent variables and interviewers' hiring decisions are included as a dependent variable. The specific objectives of the present study are:

1. To examine the effects of interviewees' three communication types (i.e., verbal, para-verbal, and non-verbal behaviors) on five dimensions of interviewer-reported Big-five personality traits.
2. To examine the effects of interviewees' three communication types on five dimensions of self-reported Big-five personality traits.
3. To examine the effects of interviewees' three communication types on five dimensions of machine learning-inferred Big-five personality traits.
4. To examine the effects of interviewees' three communication types on hiring decisions made by interviewers.
5. To examine the effects of five dimensions of interviewer-reported Big-five personality traits on hiring decisions made by interviewers.
6. To examine the effects of five dimensions of self-reported Big-five personality traits on hiring decisions made by interviewers.
7. To examine the effects of five dimensions of machine learning-inferred Big-five personality traits on hiring decisions made by interviewers.

Significance of the Study

Finding and hiring the right people is critical for hospitality businesses to obtain competitive advantages (Barrick et al., 2000; O'Neill & Xiao, 2010). After the pandemic, the labor shortage and high turnover rates forced hospitality companies to make hiring decisions more accurate than ever (Yang & Lee, 2023). Many hospitality employers are increasingly paying more attention to personality traits to find better job candidates, as employees' attitudes and communication skills are the main drivers of enhancing service quality and customer satisfaction (Doan et al., 2021; Kim et al., 2019). Given the importance of personality traits in the hospitality industry, this study primarily aims to investigate how to understand job candidates' Big-five personality traits during the selection process and to make better hiring decisions. By addressing these proposed research objectives, this research demonstrates its significance by providing the following theoretical and practical implications.

First, the current study provides empirical evidence of how the dimensions of the job candidates' Big-five personality traits are related to hiring decisions in the recruitment context. While numerous hospitality studies arguably have investigated the effects of employees' Big-five personality traits on their relevant consequences, such as job satisfaction (Doan et al., 2021; Leung & Law, 2010; Silva, 2006; Tracey et al., 2007), the relationships between job candidates' Big-five personality traits and hiring decisions have not been addressed. Therefore, investigating the significant dimensions of Big-five personality traits on particular consequences is important as their significance would vary depending on the characteristics of specific consequences (Klinger & Siangchokyoo, 2024; Oh et al., 2011). Thus, by empirically confirming the influential dimensions of Big-five personality traits on hiring decisions, this study expands our knowledge of Big-five personality traits in job interviews and interviewees' selection in the hospitality industry.

Second, this study also adopts the concept of three communication types (i.e., verbal, para-verbal, and non-verbal behaviors) to understand the interviewees' Big-five personality traits and predict the hiring decisions. Prior studies in psychology have suggested three communication types to apprehend interviewees' behaviors (DeGroot & Motowidlo, 1999; Feiler

& Powell, 2016; Wilhelmy et al., 2016). By extending this theoretical foundation, the current study empirically investigates the relationships of interviewees’ three communication types on Big-five personality traits and hiring decisions. These three communication types are identified and measured by using machine learning algorithms. This approach is beneficial as machine learning algorithms capture subconscious behaviors with less human bias and intervention (Hickman et al., 2022). The current study provides empirical contributions to the literature by demonstrating how these three communication types are related to Big-five personality traits and hiring decisions.

Third, this research uses the three types of Big-five personality trait assessments (i.e., interviewer-reported, self-reported, and machine learning-inferred) in measuring the targets’ (interviewees) Big-five personality traits and examines their effects on hiring decisions. Since each Big-five personality trait assessment has a unique and distinctive measurement system, understanding the possible discrepancies is significant for fully recognizing the target’s Big-five personality traits (Connolly et al., 2007; Oh et al., 2011; Roulin & Stronach, 2022). Previous studies have confirmed the validity and reliability of the three types of Big-five personality traits in predicting relevant consequences, such as academic outcomes (Connelly & Ones, 2010; Fan et al., 2023; Hickman et al., 2022; Mount et al., 1994). By expanding this research stream to an empirical approach, this study investigates and compares significant relationships between the three types of Big-five personality traits assessments’ dimensions and hiring decisions. The results of this study provide empirical evidence of how certain Big-five personality traits assessments can be used to identify the particular dimensions of the Big-five personality traits to make better hiring decisions.

The current study also offers practical implications to practitioners and HR managers in the hospitality field by showing relationships among interviewees' three communication types, Big-five personality traits, and hiring decisions. For example, while this study finds an extraversion trait as the most influential personality trait in predicting hiring decisions, an extraversion trait can be mainly explained by interviewees' verbal behaviors. Thus, HR managers may want to train interviewers in a way that they need to pay attention to interviewees' language usage to understand their extraversion traits. However, no organization or job positions only seek job candidates with greater extroversion. Thus, this study also provides empirical information that might be helpful for recognizing interviewees' particular personality traits by selecting the effective Big-five personality traits assessment of their personality traits.

Definitions of Terms

Communication Types: Communication types refer to the ways in which speakers deliver and transmit information to audiences during conversations, consisting of verbal, para-verbal, and non-verbal behaviors (Feine et al., 2019; Mehrabian, 1969; Wilhelmy et al., 2016).

Verbal Behaviors: Verbal behaviors mean people's innate cognitive structure, which generates their linguistic expressions (Chomsky, 1965; Hollandsworth Jr. et al., 1979).

Para-verbal Behaviors: Para-verbal behaviors are defined as how people convey information to audiences during conversation through acoustic features, such as pitch and loudness (Gumperz, 1992; Hildebrand et al., 2020).

Non-verbal Behaviors: Non-verbal behaviors refer to the visually perceptible movements and positions of human bodies, such as eye contact, limb, facial expressions, or posture during conversations (Forbes & Jackson, 1980; Mehrabian, 1969).

Big-five Personality Traits: While personality traits refer to people's neuropsychic system generating adaptive and expressive behaviors, Big-five personality traits explain people's personality traits based on five dimensions: Neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness (Allport, 1961; Cattell, 1946; Goldberg, 1999; McCrae & Costa Jr., 1985).

Neuroticism: As one of the dimensions of Big-five personality traits, neuroticism refers to a trait related to being depressed, embarrassed, insecure, and irritable (Goldberg, 1999). People who have a higher level of neuroticism are more likely to show an unbalanced emotional mood (Barrick & Mount, 1991).

Extraversion: Extraversion means a personality trait associated with being sociable, assertive, and talkative; thus, a person having a greater level of extraversion tends to be more readily familiar with others and take on leadership positions (Roccas et al., 2002).

Openness to experience: Openness to experience, as one of the Big-five personality traits, is a trait regarding being imaginative, curious, and board-mindedness (Goldberg, 1999). A person with a lower level of openness to experience is more likely to be conventional and down-to-earth (Roccas et al., 2002).

Agreeableness: Agreeableness is one of the Big-five personality traits which is associated with being flexible, cooperative, trustworthy, and tolerant (McCrae & Costa Jr., 1985). People who are highly agreeable are more likely to be empathic and work with others who need help (Roccas et al., 2002).

Conscientiousness: Conscientiousness refers to a personality trait related to carefulness, diligence, having responsibilities, and being achievement-oriented (Barrick & Mount, 1991).

People with a higher level of conscientiousness tend to demonstrate a strong worker ethic and pay more attention to details (Goldberg, 1999).

Interviewer-reported Big-five Personality Traits: Interviewer-reported Big-five personality traits refer to targets' (i.e., interviewees) Big-five personality traits evaluated by interviewers rather than targets themselves (McCrae, 1982).

Machine Learning-inferred Big-five Personality Traits: Machine learning-inferred Big-five personality traits mean the target's (i.e., interviewees) personality traits are measured and inferred by several machine learning techniques (Fan et al., 2023) from secondary dataset (i.e., LinkedIn pages).

Hiring Decisions: In the recruitment process, hiring decisions refer to decisions whether to hire a job candidate or not based on their evaluations of the job candidate as a final decision during the recruitment process (Cable & Judge, 1997).

Chapter 2 - Literature Review

This chapter provides a review of the existing literature on three types of communication: 1) Verbal behaviors, 2) Para-verbal behaviors, and 3) non-verbal behaviors as independent variables, Big-five personality traits: a) neuroticism, b) extraversion, c) openness to experience, d) agreeableness, and e) conscientiousness as a mediator, surface acting and consistency scores as moderators, and hiring decisions as a dependent variable. Based on the conceptualization of the constructs and two theories (i.e., signaling theory and cue consistency theory), research hypotheses are proposed.

Communication Types

Speaker's communication types influence the audience's reactive attitudes and behaviors as each communication type conveys information and thoughts in different ways (Mehrabian, 1969; Pennycook, 1985). While there might be several ways of communicating and information transmission during job interviews, prior studies in psychology and business management have documented three communication types: verbal, para-verbal, and non-verbal behaviors (Feine et al., 2019; Hickman et al., 2022; Hollandsworth Jr et al., 1979; Wilhelmy et al., 2016). In the following section, three communication types and the role of three communication types in the job interview context are introduced.

Verbal Behaviors

Verbal behaviors were first defined by Skinner (1957) in his book Verbal Behavior as a "behavior reinforced through the mediation of other persons" (Skinner, 1957, p. 2). By definition, verbal behaviors are differentiated from non-verbal behavior, as non-verbal behaviors are assumed to be reinforced by direct contact with the tangible and physical environment (Sundberg & Michael, 2001).

There are four primary verbal operants, the elements of language usage: mand, tact, intraverbal, and echoic (Oah & Dickinson, 1989; Skinner, 1957). The mand implies what is said or written is determined by what a speaker requests and wants (Michael, 1982). For instance, when a speaker wants to have cookies, the speaker uses the mand operant to say, “Can I have some cookies?” The tack involves the actions of naming, labeling, or describing in the environment (Michael, 1982). Saying “apple” when pointing out an apple is operated by the tack operant. The intraverbal operant means what is being said by others and reciprocal interactions in conversation (Goldsmith et al., 2007). For example, saying “a cat” to the question “What is your favorite animal?” is regarding the intraverbal operant. Echoic involves a speaker’s ability to repeat or copy what others say (Michael, 1982). By understanding those elementary verbal operants, verbal behaviors can be effectively analyzed (Goldsmith et al., 2007; Skinner, 1957).

However, some scholars argued that Skinner’s definition of verbal behaviors over-emphasized behaviorism, which mainly focuses on observable and external influence (e.g., what others say) and over-simplified the complexity of mental and cognitive processes that occur when humans use language (Palmer, 2006; Watrin & Darwich, 2012). While other scholars have not provided a single precise definition of verbal behaviors, Chomsky (1965) emphasized the cognitive and mental structure that generates linguistic expressions regarding verbal behaviors. Similarly, the innate process and conveyed meanings generated by the innate process have been highlighted by psychology scholars (Bruner & Allport, 1940; Hollandsworth Jr et al., 1979; Lakey et al., 2008).

In the job interview context, previous studies conceptualized verbal behaviors to understand and measure what interviewees say during interviews (Hollandsworth Jr et al., 1978; Schneider, 1981; Stevens & Kristof, 1995). Interestingly, many studies investigated interviewees' verbal behaviors in terms of impression management tactics (Ellis et al., 2002; Kristof-Brown et al., 2002; Peeters & Lievens, 2006; Stevens & Kristof, 1995). This is because interviewees commonly utilize their verbal behaviors to create a desired impression for interviewers when answering interview questions (Jones et al., 1968). Prior studies regarding interviewees' impression management commonly operationalized verbal behaviors based on the following dimensions: 1) assertive (Ellis et al., 2002), 2) defensive (Ellis et al., 2002; Levashina et al., 2014; McFarland et al., 2005; Peeters & Lievens, 2006), 3) ingratiation (Ellis et al., 2002), 4) other-focused (i.e., praising of another person; Kristof-Brown et al., 2002; Levashina et al., 2014; McFarland et al., 2005; Peeters & Lievens, 2006; Stevens & Kristof, 1995), and 5) self-promotion (Ellis et al., 2002; Kristof-Brown et al., 2002; Levashina et al., 2014; McFarland et al., 2005; Peeters & Lievens, 2006; Stevens & Kristof, 1995). The primary finding of the prior studies is that, as an effective impression management tactic, interviewees' verbal behaviors containing self-promotion are strongly associated with interview outcomes, such as evaluation, ratings, and person-job fit (Kristof-Brown et al., 2002; Levashina et al., 2014; Peeters & Lievens, 2006; Stevens & Kristof, 1995).

Other studies regarding interviewees' verbal behaviors tend to focus on the content of interviewees' conversations rather than intentional verbal tactics (Cuddy et al., 2015; Hollandsworth Jr. et al., 1979). For example, Hollandsworth Jr. et al. (1978) employed four dimensions of verbal behaviors: 1) focused responses (i.e., concise and clear verbal statements), 2) overt coping statements (e.g., verbal statements that correct any verbal mistakes), 3) fluency of speech, and 4) appropriateness of content and showed that evaluations on four dimensions of verbal behaviors significantly increase by having social skill training. Similarly, Hollandsworth Jr. et al. (1979) reported that appropriateness of content and fluency of speech strongly influence employment decisions, while composure, as one of the dimensions of non-verbal behaviors, is another critical factor in employment decisions. Cuddy et al. (2015) measured interviewees' verbal content by evaluating how interviewees' speeches were structured, straightforward, intelligent, and qualified, as a potential mediator between pose (high vs. low pose) and job interview performance. They found that verbal content does not mediate the relationship between pose and interview performance, while non-verbal presence (e.g., being enthusiastic or confident) moderated the relationship, implying the independence of verbal and non-verbal behaviors.

In the hospitality context, a few studies investigated the role of verbal behaviors in the recruitment process, including job interviews (Durrani & Rajagopal, 2016; Lolli, 2013; Su et al., 2015). Lolli (2013) surveyed the importance of various interpersonal communication skills that employers seek during the selection process. Interpersonal communication skills consist of four categories: listening skills, body language, verbal language, and conduct. In specific, there were five sub-categories for verbal language: appropriate tone of voice, appropriate choice of words, being articulate, being concise, and asking appropriate questions to assess understanding. The survey results showed that using an appropriate tone of voice and being articulate are considered the most and least important verbal language skills, respectively. Su et al. (2015) investigated the effects of job-related knowledge and cognitive abilities on hiring decisions during job interviews across four verbal impression management tactics. For instance, while verbal behaviors were categorized into assertive and defensive verbal tactics, mock-up interviewees were asked to use pre-developed scripts regarding either self-focused or other-focused tactics under the assertive verbal tactics. Under the defensive verbal tactics, scripts regarding either excuse (i.e., reducing their personal responsibility for a negative concern) or justification tactics (i.e., accepting their personal responsibility for a negative concern) were used by mock-up interviewees. The results showed that the effect of job-related knowledge on hiring decisions was stronger for interviewees who used self-focused tactics than other-focused tactics. The effect of cognitive abilities on hiring decisions was greater for interviewees who utilized excuse rather than justification tactics. More recently, Durrani and Rajagopal (2016) qualitatively studied ethical interviewing practices in view of interviewees. By conducting interviews with hospitality employees, they found that job applicants perceive interviewers' verbal behaviors, such as friendliness and questions limited to the applicant's skill/knowledge, as indicators of ethical hiring practices.

While previous studies regarding verbal behaviors in the job interview context have widely documented the effect of verbal behaviors on interview outcomes, there remains room for investigating mediators, such as personality traits or fit, to explain why verbal behaviors influence interview outcomes. Moreover, little attention has been paid to innate psychological properties in verbal behaviors when measuring verbal behaviors. Consideration of psychological properties (e.g., their own language patterns) can help understand interviewees' unique characteristics, such as personality (Pennebaker & Lay, 2002).

Para-verbal Behaviors

Para-verbal behaviors refer to people's acoustic features in their speeches (Trager, 1958). The term "para" originates from prosody, emphasizing vocal characteristics of para-verbal behaviors (Gumperz, 1992). While scholars generally categorized communicative dimensions into verbal and non-verbal behaviors, Mehrabian (1972) argued that humans' articulative or vocal phenomena should be differentiated from verbal and non-verbal behaviors. According to Trager (1958), human utterance can allow researchers to identify various human features, such as emotions, health state, gender, and age, through the physiological and physical peculiarities of their voices (Pennycook, 1985). By demonstrating that people show different reactions to vocal features, scholars have recognized the differentiation of para-verbal behaviors (Addington, 1968; DeGroot & Gooty, 2009; Feiler & Powell, 2016; Gumperz, 1992). For instance, Feiler and Powell (2016) showed that interviewees' pause frequency and time and speech rate during conversations are associated with interviewers' perceptions of anxiety.

Trager (1958) conceptualized the two principal components of para-verbal behaviors: 1) vocalizations and 2) voice qualities. Vocalizations means the non-linguistic vocal sounds and/or noises that do not belong to linguistic relevance of speech, including a) vocal characterizes, b) vocal qualifiers of intensity, and c) vocal segregates (James, 2017). Vocal characterizes include such things as laughing and crying, vocal qualifiers of intensity include pitch height and extent, and vocal segregates present segmental sounds, such as "uh" or "mhm" (Duncan Jr., 1969). Voice qualities refer to modifiable characteristics of voice and/or noise, such as acceleration or speech, resonance, and articulation control (Trager, 1958).

Few studies using para-verbal behaviors have been conducted in the job interview context (DeGroot & Gooty, 2009; DeGroot & Motowidlo, 1999; Feiler & Powell, 2016). Assuming vocal cues as unique personal characteristics that people cannot easily disguise (Nighswonger & Martin Jr., 1981), DeGroot and Motowidlo (1999) analyzed the relationships between para-verbal behaviors and job performance of managers from utility and news publishing companies.

While they measure interviewees' para-verbal behaviors based on pitch, pitch variability, speech rate, pauses, and amplitude variability, it was found that all vocal cues are correlated with supervisory evaluations of job performance, mediated by personal affective reaction (e.g., trust and credibility to interviewees). Later, DeGroot and Gooty (2009), using the same vocal cue dimensions, investigated whether interviewees' para-verbal behaviors generate personality attributions perceived by interviewers, thus influencing interview ratings. As a result, extraversion attributions significantly mediate the relationship between interviewees' vocal cues and interview ratings, implying that interviewers infer interviewees' extraversion personality through their para-verbal behaviors (DeGroot & Gooty, 2009). More recently, Feiler and Powell (2016) explored interviewees' anxious behaviors using their para-verbal behaviors. They found that interviewees' ratings of anxiety are associated with pause frequency and time and speech rate, while interviewers' ratings of anxiety are correlated with speech rate (Feiler and Powell, 2016). The results imply that more anxious interviewees tend to speak slowly with more and longer pauses during job interviews.

Based on the literature review on para-verbal behaviors in the interview context, only a few empirical studies were identified compared to studies using verbal behaviors. This may be because of methodological difficulties in defining and measuring vocal characteristics (Hildebrand et al., 2020; Scherer, 1986). Moreover, although DeGroot and Gooty (2009) explained the relationships between interviewees' para-verbal behaviors and personality attributions perceived by interviewers, the findings could be extended to the relationship between para-verbal behaviors and self-reporting personality traits to make more generalizable knowledge.

Non-verbal Behaviors

Non-verbal behaviors mean the visually perceptible movements and positions of human bodies, such as eye contact, limb, facial expressions, or posture (Forbes & Jackson, 1980; Mehrabian, 1969). Visual cues that render non-verbal behaviors differentiated from verbal and para-verbal behaviors can be made by three different ways: 1) kinesics, 2) proxemics, and 3) artifacts (Feine et al., 2019; Leathers, 1976). Kinesics includes such things as eye, head, hands, feet, or body movements (Baesler & Burgoon, 1987). Proxemics is the concept of space and distance, which determines the directness and/or closeness of interaction between communicators (Leathers, 1976; Mehrabian, 1969). Artifacts are related to the aspects of the environment and personal appearance, such as clothing or accessories (Baesler & Burgoon, 1987). These components of non-verbal behaviors trigger various attribution sources (e.g., competence, sociability, or composure), thus influencing persuasion and credibility in communication (Burgoon et al., 1990). For example, interviewees are dressed in formal attire (i.e., artifacts), keep an appropriate distance from interviewers (i.e., proxemics), and try to make eye contact with interviewers (i.e., kinesics) to make credible impressions.

The pioneering empirical study regarding non-verbal behaviors in the job interview context was conducted by Keenan and Wedderburn (1975). They investigated the relationship between interviewers' non-verbal indicators of approval (i.e., smile, positive head nods, and eye contact) and interviewees' favorable perceptions of interviewers and found that all three behaviors are significantly associated with interviewees' favorable perceptions. Similarly, Young and Beier (1977) used the same non-verbal behaviors of interviewees and showed that the best combination of non-verbal behaviors to get a higher chance of a job is using all three non-verbal behaviors (i.e., smile, head nods, and eye contact). In 1980, Forbes and Jackson (1980) made the foundational non-verbal behaviors by providing ten categories of interviewees' non-verbal behaviors that might influence interviewers' evaluation: leg position, arm position, body position, eye contact, facial expression, body movement, hand movement, head movement, feet movement, and leg movement. The result showed that interviewees who made more eye contact, smiling (facial expression), and shaking or nodding their heads received more job offers (Forbes & Jackson, 1980). Later, many empirical studies have extended the role of non-verbal behaviors in the job interview context (Burnett & Motowidlo, 1998; DeGroot & Motowidlo, 1999; Feiler & Powell, 2016; Martín-Raugh et al., 2023). For example, Burnett and Motowidlo (1998) included interviewees' physical attractiveness as one of the non-verbal behaviors and showed that physical attractiveness significantly influences interview ratings as well as eye contact. Feiler and Powell (2016) analyzed 17 non-verbal behaviors in terms of interviewees' expressions of anxiety, and it was found that interviewees who feel more anxious tend to move their hands, heads, and bodies and bite their lips more. More recently, by summarizing 70 years of research regarding non-verbal behaviors in the job interview context, Martín-Raugh et al. (2023) conducted a meta-analysis on 63 studies and showed that physical attractiveness, eye contact, and head movement have the strongest associations with interview performance.

In the hospitality industry, a small number of studies considered non-verbal behaviors in the selection process, including job interviews (Durrani & Rajagopal, 2016; Lolli, 2013). Lolli (2013) investigated various communication skills, such as listening skills, body language, verbal language, and conduct, that employers seek during the selection process. Especially, there were four sub-categories for body language (i.e., non-verbal behaviors in the current study): maintaining eye contact, using respectful rather than threatening/defensive gestures, using open and inviting gestures, and maintaining poise. The results showed that employers perceive maintaining eye contact and using open and inviting gestures as the most and least crucial non-verbal language skills. From the interviewees' perspective, Durrani and Rajagopal (2016) found that interviewers' non-verbal behaviors (e.g., shaking hands and eye contact) can indicate the company's ethical hiring practices, emphasizing interviewers' suitable non-verbal behaviors during the hiring process.

Through the literature review on non-verbal behaviors in the job interview context, several inconsistent results were identified. For example, while physical attractiveness, smiles, eye contact, and hand and body movements had significantly positive effects on interview performance ratings (DeGroot & Motowidlo, 1999), the same behaviors were not significantly influential on interview performance (Burnett & Motowidlo, 1998; Goldberg, S., & Rosenthal, 1986). This inconsistency may come from incomplete human identification of non-verbal behaviors while raters manually count the non-verbal behaviors (DePaulo, 1992), implying the need for more objective approaches to measure non-verbal behaviors. Moreover, some of the results might be tricky to interpret. For instance, even though hand and head movements have positive effects on interview performance, it does not necessarily mean interviewees should continuously move their hands and heads. More concrete interpretations can be made by considering more straightforward measures, such as facial expressions and emotions (Keltner, 1996).

Automated Coding Regarding Verbal, Para-verbal, and Non-verbal Behaviors

When identifying and measuring three communication types (i.e., verbal, para-verbal, and non-verbal behaviors), prior studies have commonly adopted manual identification of the three communication types (Burnett & Motowidlo, 1998; DeGroot & Gooty, 2009; Feiler &

Powell, 2016; Goldberg & Rosenthal, 1986; McFarland et al., 2005). For example, in Feiler and Powell's (2016) study, 16 non-verbal behaviors (e.g., hand gestures and head nodding) were manually coded by human coders while watching recordings. However, this approach may provide inaccurate and less reliable coding results, possibly due to human's limited cognitive resources and bias (DePaulo, 1992). Thanks to the recent advancement of technology, some studies have utilized computer-aid techniques to measure three communication types. These studies mainly fall into two research streams: (1) prediction (Chen et al., 2016; Hickman et al., 2021; Naim et al., 2016; Nguyen et al., 2014) and (2) validation (Fan et al., 2023; Hickman et al., 2019; Hickman et al., 2022). Please note that some studies apparently indicate that they consider verbal, para-verbal, or non-verbal behaviors. For example, Nguyen et al. (2014) used the term "audio features" to describe interviewees' speaking behaviors, categorized as para-verbal behaviors by the author of the current study.

Prior studies in the prediction category have developed models that predict interviewees' personality traits or interview outcomes based on the combination of three communication types. Nguyen et al. (2014) aimed to predict hiring decisions using interviewees' para-verbal and non-verbal behaviors. Para-verbal behaviors were measured by several acoustic features (e.g., speaking time, pauses, and pitch) using a speech feature extraction coder made by MIT Media Lab, and non-verbal behaviors were measured by head nodding and visual region using a customized coder. Comparing prediction models based on ordinary least squares (OLS), ridge regression, and random forest algorithm, they found that the random forest model without dimensionality reduction significantly predicts hiring decisions better than other models. Chen et al. (2016) measured interviewees' verbal, para-verbal, and non-verbal behaviors from 36 interview recordings employing several computer-aid techniques. For instance, Linguistic

Inquiry and Word Count (LIWC) was used to measure verbal behaviors by calculating the frequency of the psycholinguistic words, emotions, and function words. Face recognition engine (i.e., Visage SDK's FaceTrack) automatically identified interviewees' head posture, eye gazes, and facial emotions. They built prediction models based on support vector machine (SVM) and ride regression and showed that the combination of verbal and para-verbal better-predicted interview ratings (F-1 = 0.44) than non-verbal behaviors (F-1 = 0.45). Naim et al. (2016) also adopted LIWC software to calibrate verbal behaviors based on 23-word categories (e.g., articles, verbs, and adjectives). When capturing para-verbal behaviors, PRATT (speech analysis software) was performed to calculate 25 acoustic features (e.g., jitter and shimmer). Prediction models, including support vector regression (SVR) and lasso regression, showed that interview performance was better predicted by the combination of verbal and para-verbal behaviors rather than verbal, para-verbal, and non-verbal behaviors. More recently, Hickman et al. (2021) developed predictive models to explain the relationship between verbal behaviors and Big-five personality traits. From 441 interview recordings, LIWC software calculated the frequency of 75 textual themes (e.g., health, informal, and leisure). The elastic net regression found several significant words for each personality trait. For instance, the words regarding common adjectives, discrepancy, health, and home were significantly related to an agreeable trait (Please see Table 3 for details of their study).

While prior studies regarding prediction have contributed to the usage of three communication types to predict personality traits and interview outcomes, concerns about the validity and reliability of using three communication types have been raised. Thus, several recent studies have investigated the validity and reliability of using three communication types (Fan et al., 2023; Hickman et al., 2019; Hickman et al., 2022). Hickman et al. (2019) compared interviewee self-reported personality scores, other-reported personality scores, and language-based personality assessment scores to investigate the validity and reliability of text-based personality assessments. Rather than building their own personality assessment prediction model, they used IBM Watson Personality Insights, which is a personality prediction model made by IBM based on Twitter textual data and users' self-reported personality scores. The language-based personality assessment (possibly verbal behavior in the current study's context) showed low convergent and discriminant validities with self-reported and other-reported personality scores. The result may imply that developing a customized prediction model and including more behaviors could be more valuable and accurate in predicting personality traits. Thus, Hickman et al. (2022) aimed to generate more generalizable implications by including verbal, para-verbal, and non-verbal behaviors from 289 interview recordings. Each behavior was measured by textual, acoustic, and facial features by LIWC, openSMILE (voice recognition technique), and openFace (face recognition technique). They trained models based on elastic net regression using self-reported and other-reported personality assessments to investigate whether each prediction model would generate more valid and reliable outcomes (i.e., in their models, three communication types were used as independent variables to predict both self-reported and other-reported personality assessment). The result showed that automated assessment on three communication types presented stronger evidence of validity when trained on other-reported rather than self-reported assessments. More recently, Fan et al. (2023) validated the machine learning-inferred personality scores using textual data (possibly verbal behaviors in the current study's context) from conversation data. By extracting 512 textual features from the conversation data and running lasso regression, the results showed that machine learning-inferred personality scores had acceptable reliability and factorial validity compared to self-reported personality scores.

As prior studies have validated the usage of automated assessments on three communication types, it would be valuable to investigate the statistical associations between three communication types, Big-five personality traits, and hiring decisions, in the job interview context. It might be helpful for employers to make better decisions by understanding the relationships between those three variables. Moreover, more interpretable and feasible implications can be made from the findings of prior studies. For example, prior studies used a vast number of features (e.g., 512 textual features and 19 facial action units) to build prediction models and validate the models (Fan et al., 2023; Hickman et al., 2022). While an enormous number of features (e.g., independent variables) might be helpful in developing better-performing prediction models, it is hard to interpret the results by humans (i.e., the curse of dimensionality). Thus, considering an interpretable and controllable number of variables based on a theoretical framework would be valuable for better hiring decisions.

Big-five Personality Traits

Personality traits are defined as “a generalized and focalized neuropsychic system (peculiar to the individual), with the capacity to render many stimuli functionally equivalent, and to initiate and guide consistent (equivalent) forms of adaptive and expressive behavior’’ (Allport, 1961; p. 295). Since personality traits determine how people perceive and react to things, tasks, and other people, personality traits are the most essential concept to understand and describe individuals (Allport & Allport, 1921; Gustavsson et al., 2003). In terms of understanding personality traits, the most challenging task for personality theorists was how to describe and measure personality traits (Allport, 1966; Goldberg, 1993; McCrae & John, 1992). To address this issue, called the lexical hypothesis, scholars contributed to establishing the Big-five personality trait theory by compiling trait terms and validating instruments (Allport, 1966; Cattell, 1946; McCrae & Costa Jr., 1985; Eysenck, 1990). Finally, Goldberg (1999) developed a personality trait inventory, including Big-five personality traits, by refining the specific lexical markers for each personality trait and empirically validating the stability of the Big-five personality traits model. While several personality trait assessments exist, such as the Eysenck Personality Questionnaire, Minnesota Multiphasic Personality Inventory, or Myers-Briggs Type Indicator, the Big-five personality trait model has been widely adopted due to its greater cross-cultural applicability, simplicity, and predictive validity (Barrick & Mount, 1991; Larson et al., 2002).

The Big-five personality traits model, as its name suggests, consists of five different dimensions of personality traits: 1) neuroticism, 2) extraversion, 3) openness to experience, 4) agreeableness, and 5) conscientiousness. Neuroticism (or emotionality or emotional stability) refers to traits related to being depressed, embarrassed, insecure, and irritable, and a person who has a higher level of neuroticism tends to show an unbalanced emotional mood (Barrick & Mount, 1991). Extraversion means characteristics associated with being sociable, assertive, and talkative (Roccas et al., 2002). Openness to experience is associated with imaginative, curious, and board-mindedness (Goldberg, 1999). People with a lower level of openness to experience tend to be conventional and down-to-earth (Roccas et al., 2002). Agreeableness is a trait explained by being flexible, cooperative, trustworthy, and tolerant (McCrae & Costa Jr., 1985). Finally, conscientiousness indicates traits such as carefulness, diligence, having responsibilities, and being achievement-oriented (Barrick & Mount, 1991).

Prior studies regarding Big-five personality traits have largely investigated the effects of Big-five personality traits on various consequences in the organizational management context, possibly to find effective ways to manage employees for organizational success (Barrick & Mount, 1991; Blickle et al., 2010; Chiaburu et al., 2011; Parra et al., 2022; Yang & Hwang, 2014). For instance, since the recent notorious effect of the COVID pandemic forced employees to work remotely, thus possibly damaging their mental health, Parra et al. (2022) investigated which Big-five personality trait is associated with remote work exhaustion. They found that employees with high levels of neuroticism tend to feel more remote work exhaustion. In contrast, employees with high levels of agreeableness and conscientiousness are less likely to feel remote work exhaustion. Specifically, in the job interview context, several meta-analyses found that interviewees' conscientiousness and extraversion traits have greater levels of correlations with interview performance, while other traits are still associated with interview performance (Barrick et al., 2000; Cortina et al., 2000; Levashina et al., 2014; Roth et al., 2005; Salgado & Moscoso, 2002). While prior studies regarding Big-five personality traits have largely investigated the effects of personality traits on various consequences in the organizational context, some studies in psychology have explored the antecedents of Big-five personality traits (Costa Jr et al., 2001; Jang et al., 1998; McCrae & Costa Jr, 1997; Riemann et al., 1997; Schmitt et al., 2008; Thalmayer et al., 2019), implying that personality traits may change depending on chronicle and situational factors and can be predicted by contextualized factors. For example, Schmitt et al. (2008) examined the effects of gender, culture, and socioeconomic factors on Big-five personality traits. The results showed that women tend to have higher levels of neuroticism, extraversion, agreeableness, and conscientiousness than men across most nations. Moreover, several socioeconomic factors, such as a healthy life, equal access to knowledge and education, and economic wealth, play the nation-level predictors of gender differences in Big-five personality traits. Table 2.1 summarizes the details of prior studies regarding Big-five personality traits in various research contexts.

Various hospitality studies have also arguably investigated the effects of employees' personality traits on diverse individual and organizational consequences, given that hospitality employees' communication skills and sympathetic attitudes are the key to satisfying customers' diverse needs and enhancing the quality of services (Doan et al., 2021; Leung & Law, 2010). For example, Silva (2006) found that non-managerial hotel employees who have greater scores on extraversion, conscientiousness, and emotional stability (neuroticism) tend to show more organizational commitments. One interesting study conducted by Tracey et al. (2007) compared the relative importance of ability and personality in predicting the job performance of restaurant employees by arguing "hire for attitude *and* skill" (Tracey et al., 2007, p. 314) despite the importance of personality traits in the hospitality industry. They showed that both general mental ability (representing ability) and conscientiousness (representing personality) significantly predict job performance. However, general mental ability predicted job performance better for new employees; on the other hand, conscientiousness performed better prediction on job performance for experienced employees. Most recently, Doan et al. (2021) conducted a meta-analysis using 105 studies from hospitality and other industries regarding employees' personality traits. They showed that agreeableness, extraversion, neuroticism, and conscientiousness traits have the strongest relationships with organizational commitment, job satisfaction, emotional exhaustion, and organizational citizenship behaviors, respectively. Nevertheless, no empirical hospitality study investigates the role of (Big-five) personality traits in the job interview context, except for one study that argues that interviewees' personality traits would affect recruiters' expectations, thus influencing hiring decisions (Kwok et al., 2011). The details of prior hospitality studies regarding Big-five personality traits are summarized in Table 2.1.

Table 2.1 Prior Studies Regarding Big-Five Personality Traits

Sources	Independent variable	Moderator	Mediator	Dependent variable	Context	Findings
McCrae and Costa Jr (1997)	· Culture			· BFP*	· Psychology	· Personality trait structure is basically universal across various culture.
Riemann et al. (1997)	· Genetic factors · Environmental factors			· BFP*	· Psychology	· Genetics substantially influence all BBF dimensions. · No difference in the effect of genetics for self-reported and peer-reported personality scores. · The influence of environmental factors is similar to that of genetics.
Jang et al. (1998)	· Genetic factors · Environmental factors · Cultural factors			· BFP*	· Psychology	· Both genetic and environmental factors' effects on BBF are fundamentally the same in form and magnitude in Germany and Canada.
Costa Jr et al. (2001)	· Gender · Culture			· BFP*	· Psychology	· Women have higher levels of neuroticism, agreeableness, and openness.

						· Gender differences are the most pronounced in European and American countries.
Kim et al. (2007)	· BFP*			· Burnout	· Hospitality	· Extraversion, agreeableness, and conscientiousness negatively influence burnout. · Neuroticism positively influences burnout.
Saroglou and Muñoz-García (2008)	· Religiousness			· BFP*	· Psychology	· Differences in individual religion and spirituality reflect differences in personality traits. · Extraversion and neuroticism are less relevant for individual differences in religion. · Spiritual and religious people tend to be conscientious.
Schmitt et al. (2008)	· Gender · Culture · Socioeconomic factors			· BFP*	· Psychology	· Women have higher levels of neuroticism, extraversion, agreeableness, and conscientiousness than men across most nations.

						· Higher levels of socioeconomic factors are the primary nation-level predictors of gender differences in personality traits.
Kim et al. (2009)	· BFP*			· Burnout · Engagement	· Hospitality	· Neuroticism is the most influential trait on burnout. · Conscientiousness and neuroticism are the most critical traits on engagement.
Blickle et al. (2010)	· BFP*		· Political skills	· Job performance	· Sale business	· A positive effect of extraversion on sale performance is fortified for individuals high on political skills.
O'Neill and Xiao (2010)	· BFP* · Occupational characteristics			· Emotional exhaustion	· Hospitality	· Extraversion and neuroticism are negatively and positively associated with emotional exhaustion, respectively.
Chiaburu et al. (2011)	· BFP*			· Task performance · OCB**	· Organization	· Openness and agreeableness have stronger relationships with OCB and task performance than other traits.
Soto et al. (2011)	· Age			·	· Psychology	· Agreeable and conscientiousness traits have curvilinear and non-monotonic trends on age. · Extraversion shows a negative trend on age.

Yang and Hwang (2014)	· BFP*			· Job performance · Job satisfaction	· Organization	· Agreeableness has the greatest effect on job performance followed by extraversion. · Only extraversion has a significant effect on job satisfaction.
Bellou et al. (2018)	· BFP*	· Self-esteem		· Employer attractiveness	· Hospitality	· Extraversion is related to development opportunities. · Conscientiousness is associated with development opportunities, attractive working environment, and recognition. · Openness is related to being curious, adventurous, and innovative.
Köşker et al. (2019)	· BFP*			· Service orientation · Tendency to work	· Hospitality	· Agreeableness has the strongest effect on service orientation followed by extraversion and openness. · Openness has the largest effect on tendency to work.
Thalmayer et al. (2019)	· Ethics-relevant valeus			· BFP*	· Psychology	· Individualism and mature values influence openness. · Unmitigated self-interest and collectivism are negatively and positively associated with

						conscientiousness and agreeableness, respectively.
Kim et al. (2019)	· BFP*		· Job flow experience	· Consumer-oriented behavior	· Hospitality	· Openness, conscientiousness, and extraversion have positive effects on job flow experience. · Agreeableness and neuroticism have negative effects on job flow experience.
Presenza et al. (2020)	· BFP* · Internal/external locus of control			· Efficiency · Innovation	· Tourism	· Only conscientiousness trait is associated with efficiency.
Parra et al. (2022)	· BFP*			· Remote work exhaustion	· Remote work	· Neuroticism positively influences remote work exhaustion. · Agreeableness and conscientiousness negatively affect remote work exhaustion.
Shiwen and Ahn (2023)	· BFP*	· Service type		· Job performance	· Restaurant	· Agreeableness and conscientiousness are positively associated with job outcomes. · Employees in full-service restaurant are more affected by personality traits.

Notes. *BFP: Big-five personality traits, **OCB: Organizational citizenship behavior

Interviewer-reported Big-five Personality Traits

Other-reported Big-five personality traits refer to targets' Big-five personality traits evaluated by others rather than targets themselves (McCrae, 1982). Others can be spouses, friends, acquaintances, and strangers of targets (Connelly & Ones, 2010). In the selection process, including job interviews, employers or interviewers can be others who rate interviewees' (i.e., target) personality traits, and thus, interviewer-reported Big-five personality traits can be defined in the job interview context (Mount et al., 1994). In terms of evaluating personality traits, self-perspectives and others' perspectives have a fundamental difference (Hogan, 1991). That is, personality traits based on self-perspectives are more related to less observable structures and processes of individuals that shape their ideas and behaviors. On the other hand, personality traits from others' perspectives are more associated with the target's public or social reputation (Oh et al., 2011). Due to this difference, self-reported and other-reported Big-five personality traits are not necessarily the same, while they are meaningfully related and explain unique variance regarding targets' personality traits (Connelly & Ones, 2010). Similar to (self-reported) Big-five personality traits, while other-reported personality traits can be rated by several personality assessments , prior studies using other-reported personality traits also commonly adopted Big-five personality traits due to their validity and popularity and used the same five dimensions of personality traits, that is, neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness (Connolly et al., 2007; McCrae et al., 1998).

Countless prior studies have adopted self-reported Big-five personality traits to predict relevant outcomes because self-reported ratings can be more easily obtained and show positive validity in predicting various outcomes (Judge et al., 1999; Oh et al., 2011; Roberts et al., 2007). Moreover, it is plausible that personality traits assessed by a target might be the most accurate ones, especially for some personality traits that are not easily understood and recognized by others (Connelly & Ones, 2010; Spain et al., 2007). Nevertheless, there are reasons that researchers paid attention to other-reported ratings of personality traits. Individuals can distort or fake their personality traits when measuring self-reported ratings (Viswesvaran & Ones, 1999). This faking or distortion can be made by a target intentionally or unintentionally, damaging the validity of self-reported ratings of personality traits either way (Paulhus & Reid, 1991; Sackett, 2011). However, other-reported personality traits are not always better performing than self-reported personality traits for some reason. First, others may have limited frequency and/or duration of observing targets, so others may not fully understand the targets' personality traits (Mount et al., 1994). These factors further hinder others from understanding targets' personality traits that are more private and internal, such as emotional stability and openness to experience (Connolly et al., 2007). Second, others can provide biased responses regarding personality traits depending on situational and contextual factors (Oh et al., 2010). For instance, others may evaluate the target's personality traits in a more beneficial way simply because the target showed better performance, even though the better performance might come from other situational and contextual factors, not personality traits. Due to these possible drawbacks of other-reported personality traits, some researchers still have a favorable stance on self-reported personality traits (Ones et al., 2007; Tett & Christiansen, 2007).

Prior studies using other-reported Big-five personality traits can lie into one of the two research streams: 1) assessing the accuracy of other-reported ratings measuring targets' Big-five personality traits (Barrick et al., 2000; Connelly & Ones, 2010; Funder, 1995; Hall et al., 2018; McCrae, 1982; Mount et al., 1994; Van Iddekinge et al., 2005; Oh et al., 2011) and 2) examining incremental validity of other-reported Big-five personality traits over other ratings, commonly self-reported ratings (Barrick et al., 2000; Connelly & Ones, 2010; Klinger & Siangchokyoo, 2024; Mount et al., 1994; Oh et al., 2011). In terms of the accuracy of other-reported ratings of targets' Big-five personality traits, prior studies have reached a substantial agreement that other-reported and self-reported ratings are highly correlated (Hall et al., 2018; McCrae, 1982; Van Iddekinge et al., 2005). For example, Connolly et al. (2007) conducted a meta-analysis on 36 prior studies and showed that the mean correlation coefficients between self-reported and other-reported ratings were .46 for agreeableness, .56 for conscientiousness, .51 for emotional stability, .62 for extraversion, and .59 for openness to experience traits, implying the great accuracy of other-reported ratings for targets' Big-five personality traits. However, the level of agreement can vary depending on the level of acquaintanceship with targets and/or the nature of personality traits (Connelly & Ones, 2010; Connolly et al., 2007). It is common that others who have more intimacy, such as close friends or family members, more accurately measure targets' personality traits and others who have less intimacy, such as co-workers or strangers (Connelly & Ones, 2010). The nature of each personality trait also affects the level of agreement (Barrick et al., 2000; Funder, 1995). For instance, an extraversion trait related to actively talking and behaving increases the visibility of the trait and thus enhances the agreement between others and self-reported. On the other hand, a neuroticism (i.e., emotional stability) trait more related to internal thoughts and feelings is less visible and recognizable by others, and thus reduces the agreement between other-reported and self-reported.

Common findings regarding the incremental validity of other-reported Big-five personality traits are that other-reported ratings (e.g., interviewers, friends, and family members) provide incremental validity over self-reported ratings in predicting relevant outcomes, such as job performance or academic performance (Connelly & Ones, 2010; Klinger & Siangchokyoo, 2024; Mount et al., 1994). A possible reason for the incremental validity of other-reported Big-five personality traits ratings over self-reported ratings is the self-perception bias of targets in understanding their personality traits, which may occur due to self-esteem, social desirability, or lack of self-awareness (Connelly & Ones, 2010). The findings are consistent in the job interview context, showing that interviewer-reported ratings have significant incremental validity over self-reported ratings in explaining applicant suitability (Barrick et al., 2000). However, Barrick et al. (2000) also pointed out interviewers were not able to assess interviewees' personality traits likely to lead to high performance, such as conscientiousness and emotional stability traits. Thus, despite the incremental validity of other-reported ratings over self-reported ratings, prior studies suggested the utilization of multiple rating sources (e.g., including other- and self-reported) to make more generalizable results and fully understand targets' personality traits in various circumstances and contexts (Connelly & Ones, 2010; Klinger & Siangchokyoo, 2024; Oh et al., 2011). The details of prior studies regarding other-reported ratings on Big-five personality traits are summarized in Table 2.2.

Table 2.2 Prior Studies Regarding Other-reported Personality Traits

Sources	Independent variable	Moderator	Mediator	Dependent variable	Context	Findings
McCrae (1982)	· The source of information (Self vs. spouse)			· NEO-PI and Eysenck Personality Inventory (EPI)	· General	· Substantial agreement between self-reports and ratings · The agreement was not due to shared artifacts or transient states evidenced by the convergent and discriminant validity · Personality traits are real and measurable regularities in human behavior and experience
Mount et al. (1994)	· Self-reported, supervisor-reported, coworker-reported, and customer-reported personality traits			· Supervisor-reported and coworker-reported performance ratings	· Job performance	· Conscientiousness and extraversion by supervisors, coworkers, and customers were significantly correlated with performance ratings for sales representatives · Observer-reported ratings accounted for significant variance in performance ratings beyond self-reported ratings for conscientiousness, extraversion, agreeableness, and openness to experience

						· The magnitude of the validities varied by rating sources, and that self-reported ratings were generally higher than observer-reported ratings · The agreement between different rating sources was relatively low, suggesting that observers have different views of the sales representatives' personality than they do of themselves
McCrae et al. (1998)	· The source of information (Self vs. spouse)	· Acquiescence, Extreme responding, positive/negative presentation, inconsistency, age, education, vocabulary, years married,		· NEO-PI-R (Big-five personality traits)	· General	· Self-reports and spouse ratings of personality traits show moderate agreement, but also significant discrepancies · Moderators do not explain the variation in agreement. · A qualitative analysis of interviews revealed 16 reasons for disagreement, such as different interpretation of items and different roles considered

		martial adjustment, and similarity				
Barrick et al. (2000)	· 1) The source of information (self-reported, interviewer-reported, friend-reported, and stranger-reported) and 2) 2. Self-reported, interviewer-reported, friend-reported, and stranger-reported ratings	· 1) Design of the interview (structure and question)		· 1) Big-five personality traits and 2) Interviewer ratings of applicants' suitability	· Job interview	· Interviewer-reported ratings correlate higher with self-reported ratings than stranger-reported ratings, but lower than friend-reported ratings · Interviewer-reported ratings of Conscientiousness and Emotional Stability were not significantly correlated with self-reported-ratings · Interviewer-reported ratings showed a significant incremental contribution to explain interviewer ratings of applicant suitability, over self-reported ratings · The design of the interview (structure and question) did not show significant moderating effects
Spain et al. (2000)	· Neuroticism and extraversion traits			· Emotional experience (internal and	· General	· Self-reported ratings were more accurate than other-reported in

				private) and behaviors (external and observable)		predicting emotional experience, especially positive emotions · Self-reported ratings also outperformed other-reported in predicting extraversion-related behaviors, but neuroticism-related behaviors
Blackman (2002)	· The structure of interviews (structured vs. unstructured)		· Coded behaviors (e.g., the length of interviews and the number of follow-up questions)	· Self-reported and interviewer-reported agreement and peer-reported and interviewer-reported agreement in California Q-set personality test	· Job interview	· Self-reported and interviewer-reported agreement and peer-reported and interviewer-reported agreement were significantly greater in the unstructured interview method · The percentage of time that the applicant spent talking during the interview mediated the effect of the interview structure on personality judgment · The content of the questions is less important than the interview format
McCrae and Terracciano (2005)	· Gender, age, and education, cultural	·	·	· Self-reported and observer-reported	· General	· Women's scores were higher than men on all five factors NEO PI

	values of targets and raters			ratings on NEO PI (Big-five personality traits)		· Conscientiousness increases and Extraversion and Openness decrease with age in self-reported ratings, while Neuroticism and Agreeableness show different patterns in observer-reported ratings · Openness to Experience and Competence (in Conscientiousness) increase with higher education
Van Iddekinge et al (2005)	· Interview type (designed to measure agreeableness, conscientiousness, and emotional stability; NEO) and response instructions to interviewees (honestly vs. applicant-like)			· Interviewer-reported and self-reported ratings on NEO	· Job interview	· Interviewer-reported ratings were moderately related to self-reported ratings of the NEO · Applicant-like condition had a negative effect on the construct-related validity of both interviewer-reported and self-reported ratings · Self-reported ratings were more susceptible to response inflation (i.e., manipulating the content of responses) than interviewer-reported ratings

Connolly et al. (2007)	· Meta-analysis on Big-five personality traits				· Workplace	· Self-observer correlations for the Big Five personality dimensions are high, ranging from .46 for agreeableness to .62 for extraversion, indicating a substantial construct overlap between the two sources of ratings · The self-observer convergence is not moderated by the personality dimension rated, but is moderated by the level of acquaintanceship between the raters and the ratee, with higher convergence for close relatives than for strangers
Connelly and Ones (2010)	· Meta-analysis on Big-five personality traits				· General	· Other-reported ratings were consistent and agreed with self-reported ratings based on interrater reliability, self–other correlations, and behavioral predictions · Traits that were more visible and less evaluative (e.g., Extraversion) were more accurately rated than traits that were less visible and more evaluative (e.g., Agreeableness)

						· Other-raters who had more interpersonal intimacy (e.g., spouses, friends) were more accurate than other-raters who had less intimacy (e.g., strangers, coworkers) · Accuracy was influenced by both the extent to which traits were expressed to others (relevance and availability) and the extent to which others perceived the traits correctly (detection and utilization) · Other-reported ratings had higher and incremental validity over self-reported ratings, especially for traits that were less visible or more evaluative, for predicting academic and job performance.
Oh et al. (2011)	· Meta-analysis on Big-five personality traits				· Job performance	· Observer-reported ratings of personality traits had higher operational validity than self-reported ratings of the same traits in predicting overall job performance

						· Observer-reported ratings of personality traits accounted for significant incremental validity over self-reported of the same traits in predicting overall job performance · Observer-reported ratings of personality traits are more robust across performance criteria
Nederström and Salmela-Aro (2014)	· Pearson's correlations between Jackson's Personality Research Form self-report and expert-reported ratings	· The trait being judged, evaluativeness of the trait, the social desirability, the gender, and the age of the target		· Pearson's correlations between Jackson's Personality Research Form self-report and expert-reported ratings	· Job interview	· The level of agreement varied depending on the trait being judged, the gender of the applicant, and the social desirability of the trait · The most visible and non-evaluative traits, such as Dominance and Exhibition, had the highest agreement · The most covert and evaluative traits, such as Dependence and Guilt Feelings, had the lowest agreement · The age of the applicant had a positive moderating effect on the agreement for Anxiety, meaning that older applicants were more accurately judged on this trait

						· The social desirability of the applicant had a negative moderating effect on the agreement for Dominance and Dependence, meaning that applicants who tried to present themselves in a favorable way were less accurately judged on these traits
Powell and Bourdage (2016)	· Training condition (detection of cues, utilization of cues, combined detection and utilization, and no training)			· The accuracy of personality ratings by correlating self-reported and expert-reported ratings on the Big Five personality traits	· Job interview	· The utilization of cues training improved the accuracy of personality ratings compared to the detection of cues training and the no training condition · The combined training did not have an additional benefit over the utilization training alone
Hall et al. (2018)	· Meta-analysis on Big-five personality traits				· Job interview	· Trait and profile accuracies were only weakly correlated, and that trait accuracies had more in common with

						distinctive profile accuracy than with normative profile accuracy
Kim et al. (2019)	· Meta-analysis on Big-five personality traits				· General	· Self-reported ratings' means were generally not different from informant-reported ratings' means, suggesting high elevation accuracy of personality ratings · Self-enhancement was more likely for traits that were less visible and more evaluative, and for informants who were strangers rather than acquaintances ·
McCredie and Kurtz (2020)	· Self-reported, parent-reported, and peer-reported ratings of Big five-factor personality trait	· Major		· Cumulative GPA upon graduation	· Academic performance	· Conscientiousness from self-reported, parents-reported, and peers-reported ratings were all significantly correlated with cumulative GPA upon graduation, with peer ratings being the strongest predictor · Openness to experience from self-reported and parents-reported ratings were significantly correlated with GPA for students majoring in Social Sciences, but not for other majors.

Klinger and Siangchokyoo (2024)	· Observer-reported ratings on targets' personality traits	· Observer personality characteristics		· Supervisor-reported job performance of the targets	· Job performance	· Observer-reported ratings explained more variance in targets' supervisor-rated job performance than self-reported ratings, and also captured incremental variance over self-reported ratings · Observer's conscientiousness and openness traits enhanced the predictive validity of observer-reported ratings of personality for job performance, while observer's agreeableness, extraversion, and emotional stability traits had mixed effects · Observer-reported ratings capture both higher relative and incremental predictive validity over self-reported ratings in predicting job performance

Machine learning-inferred Big-five Personality Traits

Machine learning-inferred Big-five personality traits mean the target's personality traits are measured and inferred by several machine learning techniques (Fan et al., 2023; Hickman et al., 2022). Machine learning refers to various computational algorithms that train statistical models based on input and output data, which are designed to predict and infer outcomes from other datasets using the trained models (Alpaydin, 2020). In terms of personality traits, inputs can be the target's behaviors, languages, writings, and so forth, while outputs can be self-and/or other-reported ratings of Big-five personality traits (Fernandez et al., 2021; Hickman et al., 2019). Although studies regarding Big-five personality traits have a long history, researchers have paid attention to the application of machine learning to infer Big-five personality traits recently due to technical limitations before the breakthrough of machine learning techniques in social science (Koutsoumpis et al., 2022). Machine learning-inferred Big-five personality traits are differentiated from self-reported and other-reported (e.g., interviewer-reported) Big-five personality traits in primarily three ways: technologies, data type, and algorithms (Fan et al., 2023). While the most common and traditional way of assessing personality traits is a survey, machine learning-inferred Big-five personality traits can be obtained from various technological platforms, such as Facebook, LinkedIn, or video interviews (Hickman et al., 2022; Roulin & Stronach, 2022; Tay et al., 2020). Accordingly, the type of data can vary, such as textual data or video data, while personality traits ratings are measured by the Likert scale in the survey. The most distinctive thing regarding machine learning-inferred Big-five personality traits might be algorithms that are designed to predict Big-five personality traits (Tippins et al., 2021). While the application of the survey is entirely restricted to the samples that conduct the survey, machine learning-inferred Big-five personality traits can be obtained from other samples once researchers develop well-trained models and algorithms (Hoppe et al., 2018). While some researchers build their own models and algorithms for machine learning-inferred Big-five personality traits (Fan et al., 2023; Hickman et al., 2022), other researchers utilize commercial software or algorithms made by institutions or companies, such as Receptiviti or Crystal Knows, to preserve reliability and save economic resources for developing own algorithms (Kong & Ding, 2024; Rhea et al., 2022).

The machine learning approach to measuring Big-five personality traits has several benefits over the traditional survey method. First, machine learning approaches are efficient in measuring Big-five personality traits (Bleidorn & Hopwood, 2019). While researchers using the survey method are required to recruit survey participants and the participants spend the amount of time to fill out the survey, researchers can measure targets' Big-five personality traits once they have trained algorithms that can be applied to various types of data (Fan et al., 2023). This benefit can provide researchers not only a timewise advantage but also a moneywise aid, if researchers want to collect and analyze data available online (e.g., social media or online reviews). Moreover, machine learning algorithms can be used to measure targets' Big-five personality traits in a natural setting. Survey participants need to read and complete survey items, which may lead to any bias by perceiving others' (e.g., researchers or employers) perspectives (Buijsrogge et al., 2016; Connelly & Ones, 2010). However, machine learning algorithms measure targets' Big-five personality traits by capturing targets' behaviors or writings when targets don't even know machine learning techniques are measuring their personality traits (Fan et al., 2023). Despite the benefits of using machine learning approaches to measure personality traits, researchers point out any potential concerns regarding privacy issues and legal ramifications, such as collecting social media postings or recording targets' behaviors (Shet et al., 2021; Zhang et al., 2021). Thus, it is important for researchers to ask for consent from participants to avoid these issues.

As the most distinctive characteristic compared to studies using survey method alone, prior studies using machine learning-inferred Big-five personality traits have adopted novel datasets (i.e., textual data and video data) and investigated the reliability and validity of machine learning-inferred Big-five personality traits. Studies utilizing textual data commonly collected their dataset from LinkedIn.com, the most widely used professional platform (Fernandez et al., 2021; Hickman et al., 2019; Koutsoumpis et al., 2022; Roulin & Stronach, 2022). Previous studies using textual data have shown inconsistent results of using machine learning-inferred Big-five personality traits. For example, Hickman et al. (2019) measured machine learning-inferred Big-five personality traits using IBM Watson Personality Insights on textual data in interview transcription. They showed that machine learning-inferred Big-five personality traits have low convergence with self-reported ratings for an openness trait and with self-reported and other-reported ratings for an agreeableness trait. For extraversion and conscientiousness traits, no valid evidence was found. Similarly, Roulin and Stronach (2022) used Receptiviti software on textual data on LinkedIn pages and found that machine learning-inferred Big-five personality traits have low convergent validity and criterion-related validity with self-reported and other-reported Big-five personality traits. Conversely, Fernandez et al. (2021) found 33 signals of machine learning-inferred Big-five personality traits in LinkedIn pages and confirmed they are significantly correlated with self-reported Big-five personality traits. Most recently, Fan et al. (2023) developed their own machine learning algorithm using a natural language processing technique called universal sentence encoder, where inputs were 512 textual features from AI chatbot conversation and outputs were self-reported Big-five personality traits as ground truth.

The results showed that machine learning-inferred Big-five personality traits have an acceptable reliability level and good convergent validity but poor discriminant validity and low criterion-related validity with self-reported ratings. Moreover, machine learning-inferred Big-five personality traits had incremental validity over self-reported ratings when predicting participants' academic performance. One interesting study conducted by Hickman et al. (2022) also built their own machine learning model where interviewees' verbal, para-verbal, and non-verbal behaviors were inputs and self-reported and interviewer-reported ratings were output. It was found that machine learning-inferred Big-five personality traits showed stronger validity when trained with interviewer-reported ratings than with self-reported ratings. Moreover, machine learning-inferred Big-five personality traits trained with interviewer-reported ratings showed incremental validity over self-reported ratings in predicting targets' academic outcomes. The details of prior studies regarding machine learning-inferred Big-five personality traits are summarized in Table 2.3.

Table 2.3 Prior Studies Regarding Machine Learning-inferred Personality Traits

Sources	Context	Technique for inference	Method	Main variables	Findings
Hickman et al. (2019)	· Video interview	· IBM Watson Personality Insights on textual data in interview transcription	· Heterotrait-monomethod (HTMM) correlations	· Self-reported ratings · Observer-reported ratings · Machine learning-inferred ratings	· The language-based assessment scores showed low convergence with self-reported ratings for openness, and with self-reported and observer-reported ratings for agreeableness · No validity evidence was found for extraversion and conscientiousness · The language-based assessment scores did not outperform zero-acquaintance ratings in converging with self-reported ratings, except for agreeableness and openness
Fernandez et al. (2021)	· LinkedIn	· Automatic coding for signals of personality traits in LinkedIn page	· Correlation and regression	· Numerous signals of each personality traits in LinkedIn page · Self-reported ratings	· 33 indicators of personality trait in LinkedIn page were identified and most of them were correlated with self-reported ratings · Extraversion was the most observable trait on LinkedIn
Hickman et al. (2022)	· Video interview	· Elastic net regression to select and weight the behavioral predictors for	· Correlation and	· Self-reported ratings	· AVI-PAs trained on interviewer-reported ratings exhibited stronger evidence of validity than those trained on self-reported

		each personality trait by predicting the self-reported and interviewer-reported ratings based on interviewees' verbal, paraverbal, and nonverbal behaviors	regression	· Interviewer-reported ratings · Self-reported academic performance · Interviewee's verbal behaviors for AVI-Pas · Interviewee's para-verbal behaviors for AVI-PAs · Interviewee's non-verbal behaviors for AVI-Pas	ratings rather than interviewer-reported ratings · AVI-PAs predicted academic outcomes such as GPA and standardized test scores, incrementally beyond self-reported and interviewer-reported ratings · The interviewer-reported models also showed better construct discrimination than the self-reported models, meaning that they were more able to distinguish between different traits · The interviewer-reported models had more consistent and stronger relations with academic outcomes than the self-report models, demonstrating their predictive validity
Koutsoumpis et al. (2022)	· Text-based personality assessment	· Meta analysis on studies using LIWC (not machine learning)		· 52 linguistic categories measured by the Linguistic Inquiry and	· Self-reported personality traits are significantly correlated with linguistic categories, but the effect sizes are relatively small

				Word Count (LIWC) · Five dimensions of personality traits	· Observer-reported personality traits are significantly correlated with linguistic categories, with the effect sizes being small-to-medium · 20 linguistic categories (out of 260; 5 Personality Traits × 52 LIWC Categories) correlated both with self-reported and observer-reported personality traits
Roulin and Stronach (2022)	· LinkedIn	· Receptiviti software on textual data in LinkedIn pages	· Correlation	· Self-reported ratings of personality traits, cognitive ability ratings, and organizational citizenship behaviors · Rater-reported (recruited from Prolific) ratings of personality traits, cognitive	· LinkedIn-based assessments of personality, cognitive ability, and OCB had low inter-rater reliability, low convergent validity, and low criterion-related validity for most traits and outcomes with self-reported and rater-reported (except some weak evidence for honesty- humility) · Automated assessments of personality were more consistent with rater-reported ratings than self-reported ratings

				ability ratings, and organizational citizenship behaviors · Automated assessments of personality	
Fan et al. (2023)	· AI Chatbot	· Natural language processing (NLP) technique called Universal Sentence Encoder (USE) to analyze the text data and extract various textual features that may reflect personality traits	· Correlation and regression	· Self-reported ratings · Machine learning-inferred ratings · Objective college performance · Peer-reported college adjustment	· Machine-inferred personality scores had overall acceptable reliability at both the domain and facet levels of personality traits · Machine-inferred personality scores yielded a comparable factor structure to self-reported ratings · Machine-inferred personality scores displayed good convergent validity but relatively poor discriminant validity and showed low criterion-related validity. · Machine-inferred personality scores showed incremental validity over self-reported ratings in predicting academic performance and college adjustment

Hiring Decisions

Hiring decisions refer to employers' decisions whether to hire a job candidate or not based on their evaluations of the job candidate as a final decision during the recruitment process (Cable & Judge, 1997). Hiring decisions on job candidates are influenced by various factors, such as interviewees' demographics, attractiveness, knowledge, experiences, and skills (Raza & Carpenter, 1987; Schmidt & Hunter, 1998). These factors characterizing job candidates give interviewers fundamental information in evaluating person-organization (P-O) fit between job candidates and the organization (Cable & Judge, 1997). Given that individuals are more likely to be attracted to others with similar characteristics, interviewees who show higher P-O fit tend to stimulate interviewers' recommendation to hire, thus receiving more job offers (Bowen et al., 1991; Cable & Judge, 1997). Although types and strengths of influential factors on hiring decisions might differ depending on specific organization and industry, interviewers generally assess interviewees' personality traits, social skills, mental capacities, and knowledge and skills (Huffcutt et al., 2001).

In the hospitality industry, Martin and Groves (2002) conducted a qualitative study with 85 hospitality human resource professionals or managers to find out behavioral factors that are looked for during behavioral interviews. The results revealed that personality, attitudes, enthusiasm, dependability, and customer orientation are the top five factors that hotel managers consider in hiring employees. Restaurant employers rated ride in appearance, attitudes, abilities to do the job, friendliness, and dependability as the top five factors in terms of hiring. More recently, Kwok et al. (2012) analyzed characteristics of hospitality senior students and actual job offer information and showed that interviewees' job experience, P-O fit, leadership, career preparedness, professionalism, and interview behaviors significantly affect hiring decisions, while intellectual skills, academic performance, extra-curricular activities, and job pursuit intention do not significantly influence hiring decisions. The results emphasize the role of interviewees' personality and job experiences in the hospitality context in terms of recruitment.

Outside of the hospitality context, more recent studies have investigated the influential factors on interview outcomes, including hiring decisions and interview performance. Robie et al. (2020) analyzed the effects of interviewees' impression management tactics on interview performance ratings, as impression management tactics may overamplify or devaluate interviewers' evaluations. By distinguishing honest and deceptive impression management tactics, the authors investigate potential desired and undesired images created by two tactics. Interestingly, they also considered the non-linear effects of two tactics and interview evaluations. The results showed that a deceptive tactic has a linear and negative effect on interview evaluations; however, an honest tactic shows a non-linear positive effect on interview evaluation, emphasizing the negative influence of the too-much-of-a-good-thing effect (Pierce & Aguinis, 2013). In terms of personality traits, Wehner et al. (2022) explored Big-five personality traits choices made by recruiters depending on different tasks. In general, while all dimensions of Big-five personality traits are influential on the hiring probability, conscientiousness and agreeableness traits have the strongest positive effect on hiring decisions. Moreover, recruiters prefer conscientious and openness traits for analytical tasks, while openness, extraversion, and agreeableness traits are preferred by recruiters for interactive tasks. Regarding non-verbal behaviors, one of the three communication types, Martín-Raugh et al. (2023) conducted a meta-analysis on 63 studies that examined the effects of various dimensions of non-verbal behaviors on interview performance. The results showed that interviewees' professional appearance, eye contact, and head movement have the greatest effects on interview performance. The authors emphasized the significant role of non-verbal behaviors, because non-verbal behaviors are not largely influenced by structures, modality, or duration of interviews as moderators.

Overarching Theories

Signaling Theory

Signaling theory was introduced by Spence (1973) in the field of economics to explain how employers make hiring decisions for job candidates under uncertain situations using signals from the job candidates, such as academic credentials and job experience. Signaling theory holds three key concepts: signaler, signals, and receivers (Connelly et al., 2011). Under the uncertainty where receivers do not have enough information about signalers (i.e., information asymmetry), receivers gain and interpret signals from the signalers to infer any relevant information about the signalers. Another key concept is costly signals, implying that an effective signal should be costly to obtain (e.g., educational credentials) so that a signal can archive its value as a differentiator from others (Spence, 1973). The primarily significant implication of signaling theory is concerned with the reduction of information asymmetry between two different parties (Spence, 1973). Since information asymmetry always exists among numerous parties (e.g., businesses, consumers, or stakeholders), signaling theory has served as a fundamental framework for studies in various disciplines, such as marketing, financial, organizational behavior, consumer behavior, and so forth (Connelly et al., 2011; Karasek III & Bryant, 2012). For example, Boulding and Kirmani (1993) examined the effects of product warranties, as a signal of product quality, and consumers' perceptions of product quality and purchase intentions. They found that manufacturers can effectively signal their product quality by offering longer and/or more comprehensive product warranties.

Signaling theory also provides a valuable framework for recruitment studies, especially in the job interview context, given that recruitment is the process where interviewers and interviewees endeavor to alleviate information asymmetry with each other and communicate better (Cable & Judge, 1997). Thus, a job interview is described as a signaling game because interviewees and interviewers continuously send and interpret signals to infer relevant information (Bangerter et al., 2012; Rynes et al., 1991). From the job candidates' perspective, the recruitment process, including interviews, is an opportunity to obtain and interpret a wide range of signals to infer unobservable organizational characteristics (Rynes et al., 1991). Chapman et al. (2005) conducted a meta-analysis to investigate influential signals on applicant attraction to organizations and job choices considering various signals, such as 1) job and organizational characteristics (e.g., benefits and company image), 2) recruiter characteristics (e.g., friendliness), 3) perceptions of the recruitment process (e.g., interpersonal treatment), 4) perceived fit (P-J and P-O fit), 5) perceived alternatives (i.e., another job), and 6) hiring expectancies. The results showed that job and organizational characteristics, recruiter characteristics, perceived recruitment process, perceived fits, and hiring expectancies play significant signals in affecting applicant attraction outcomes.

Similarly, the recruitment process is a valuable time for employers to evaluate job candidates and select the right candidates by utilizing numerous signals from the candidates (Cuddy et al., 2015). A meta-analysis conducted by Huffcutt et al. (2001) identified several interviewees' psychological constructs used in 47 interview studies: 1) mental capability (e.g., intelligence), 2) knowledge and skills, 3) personality tendencies (including Big-five personality traits), 4) applied social skills (e.g., communication skills), 5) interest and preferences, 6) organizational fit, and 7) physical attributes. They found that interviewees' personality and applied social skills are the most influential signals on interview ratings, followed by mental capability and knowledge and skills. Later, Huffcutt et al. (2011) conceptualized applicant behaviors that may influence interview performance and interviewer ratings: 1) general attributes (e.g., personality, education, and experiences), 2) qualifications (e.g., knowledge, skills, and motivation), 3) interviewee state (e.g., self-efficacy and anxiety), 4) interviewer-interviewee dynamics (e.g., social interaction), 5) supplemental preparation (e.g., interview training). Thus, previous studies have documented that job candidates and employers utilize numerous signals to alleviate information asymmetry and make better decisions for each other (Cable & Judge, 1997; Chapman et al., 2005; Huffcutt et al., 2011; Rynes et al., 1991).

Hypotheses Development

Communication Types, Big-five Personality Traits, and Hiring Decisions

This dissertation advances recruitment research by investigating the effects of communication types on Big-five personality traits and hiring decisions in the job interview context. Especially, this study operationalizes interviewees' communication types into three behaviors: verbal, para-verbal, and non-verbal behaviors (Feine et al., 2019; Hollandsworth Jr et al., 1979; Wilhelmy et al., 2016). Drawing upon signaling theory that posits people interchange and interpret signals from each other to infer any unobservable characteristics, which impacts their perceptions and evaluations of each other (Spence, 1973), the present study argues that interviewees' three communication types would significantly signal their personality traits and thus influencing interviewers' hiring decisions.

First of all, I argue that interviewees' verbal behaviors during the interview signal their interviewer-reported Big-five personality traits and further have significant effects on interviewers’ hiring decisions. During job interviews, the information of interviewees’ answers could be one of the main resources for interviewers to create perceptions and evaluations of the interviewees (Levashina et al., 2014). As verbal behaviors are defined as people’s innate cognitive structure, which generates their linguistic expressions (Chomsky, 1965; Hollandsworth Jr. et al., 1979), it is expected that interviewers’ verbal behaviors can be captured by their linguistic expressions in their answers.

Signaling theory suggests that interviewers utilize unique signaling features of interviewees to infer interviewees’ characteristics and evaluate fit with the company (Connelly et al., 2011). In this regard, interviewees’ verbal behaviors may convey their unique signals because language patterns in verbal communication largely depend on their distinctive underlying psychological properties and personalities (Tausczik & Pennebaker, 2010). For example, if a speaker says more positive emotional words, such as “happy,” a counterpart would be more likely to find them having a greater level of agreeable personality. On the other hand, if a speaker uses more negative emotional words (e.g., “no” or “terrible”), then the receiver may think the speaker has a lower level of agreeable personality. Thus, in view of signaling theory, interviewees’ verbal behaviors may play a unique signal to interviewers to predict interviewees’ personality traits. Accordingly, I hypothesize that interviewers may assess interviewees' personality traits by interpreting their verbal cues captured by psychological language patterns in dialogue.

In the hospitality context, since hospitality employees directly communicate with their customers and their language patterns influence the quality of communication (Wang et al., 2015), interviewers may pay attention to interviewees’ verbal behaviors. Moreover, supervisors’ interpersonal verbal and communication skills with their subordinates determine how the subordinates trust and engage their supervisors (Lolli, 2013). Accordingly, interviewers may actively utilize interviewees' verbal behaviors in evaluating their supervisory competence when it comes to hiring supervisory positions. Therefore, it is expected that interviewees' verbal behaviors would affect the hiring decisions made by interviewers. Taken together, I hypothesized that:

H1: Interviewees' verbal behaviors would be significantly associated with interviewer-reported Big-five personality traits.

H1a: Interviewees' verbal behaviors would be significantly associated with a neuroticism trait of interviewer-reported Big-five personality traits.

H1b: Interviewees' verbal behaviors would be significantly associated with an extraversion trait of interviewer-reported Big-five personality traits.

H1c: Interviewees' verbal behaviors would be significantly associated with an openness trait of interviewer-reported Big-five personality traits.

H1d: Interviewees' verbal behaviors would be significantly associated with an agreeableness trait of interviewer-reported Big-five personality traits.

H1e: Interviewees' verbal behaviors would be significantly associated with a conscientiousness trait of interviewer-reported Big-five personality traits.

H2: Interviewees' verbal behaviors would be significantly associated with interviewers' hiring decisions.

While it is hypothesized that interviewees' verbal behaviors would be significantly associated with interviewer-reported Big-five personality traits, I argue that interviewees' verbal behaviors would also be related to self-reported and machine learning-inferred Big-five personality traits. As language patterns in interviewees' verbal behaviors highly depend on their innate psychological properties and personalities (Tausczik & Pennebaker, 2010), it is expected that verbal behaviors would have significant relationships with self-perceptions on their Big-five personalities assessed by self-reported survey and inherent in their LinkedIn pages. From the signaling theory's perspective, signalers (i.e., interviewees) make efforts to show unique signals (i.e., verbal behaviors based on innate psychological properties) in order to effectively differentiate themselves from others (i.e., other interviewees; Connelly et al., 2011; Spence, 1973). For instance, in the job interview context, interviewees who talk about numerous creative problem-solving experiences during job interviews are more likely to identify themselves as a person who has a greater level of an openness trait as one of their strengths. Accordingly, to signal the strength, they would give higher ratings on an openness trait when conducting self-reported surveys. Similarly, job candidates utilize their professional social media, such as LinkedIn, to emphasize their strengths and show their abilities (Kong & Ding, 2024; Tay et al., 2020). For example, job candidates who believe they have a higher level of openness trait may want to write more words related to an openness trait (e.g., "novel" or "innovate") on their LinkedIn postings, to emphasize their strengths. Taken together, I expect that interviewees' verbal behaviors would have significant relationships with self-reported and machine learning-inferred (from LinkedIn) Big-five personality traits:

H3: Interviewees' verbal behaviors would be significantly associated with self-reported Big-five personality traits.

H3a: Interviewees' verbal behaviors would be significantly associated with a neuroticism trait of self-reported Big-five personality traits.

H3b: Interviewees' verbal behaviors would be significantly associated with an extraversion trait of self-reported Big-five personality traits.

H3c: Interviewees' verbal behaviors would be significantly associated with an openness trait of self-reported Big-five personality traits.

H3d: Interviewees' verbal behaviors would be significantly associated with an agreeableness trait of self-reported Big-five personality traits.

H3e: Interviewees' verbal behaviors would be significantly associated with a conscientiousness trait of self-reported Big-five personality traits.

H4: Interviewees' verbal behaviors would be significantly associated with machine learning-inferred Big-five personality traits.

H4a: Interviewees' verbal behaviors would be significantly associated with a neuroticism trait of machine learning-inferred Big-five personality traits.

H4b: Interviewees' verbal behaviors would be significantly associated with an extraversion trait of machine learning-inferred Big-five personality traits.

H4c: Interviewees' verbal behaviors would be significantly associated with an openness trait of machine learning-inferred Big-five personality traits.

H4d: Interviewees' verbal behaviors would be significantly associated with an agreeableness trait of machine learning-inferred Big-five personality traits.

H4e: Interviewees' verbal behaviors would be significantly associated with a conscientiousness trait of machine learning-inferred Big-five personality traits.

Second, I claim that interviewees' para-verbal behaviors would signal their personality traits, thus influencing interviewers' hiring decisions. Para-verbal behaviors refer to how interviewees convey their answers to interviewers through acoustic features, such as pitch and loudness (Gumperz, 1992; Hildebrand et al., 2020). During conversations, people receive information through speakers' voices. Previous studies say that human voices facilitated by acoustic features can be used to identify numerous human physiological and physical features, such as gender, age, emotions, and health conditions (DeGroot & Gooty, 2009; Pennycook, 1985). Thus, I expect that interviewees' para-verbal behaviors signal their personality traits during job interviews.

In view of signaling theory, a set of signals would be more useful when signalers (i.e., interviewees) provide a greater number of signals as more signals effectively reduce information asymmetry and make more efficient inferences (Connelly et al., 2011; Rynes et al., 1991). From this point of view, para-verbal behaviors may contain useful multifaceted signals, because people's acoustic features are influenced by not only their physical characteristics but also their own psychological characteristics (Guidi et al., 2019). For instance, while people who look tired are commonly expected to speak quietly, if they speak louder, they may be seen as extrovert people. Thus, I expect that interviewees' para-verbal behaviors could be a reliable indicator of personality traits by leveraging physical (i.e., looks) and psychological characteristics (i.e., personality).

In the field of hospitality businesses, service employees' appropriate vocal features can improve customers' perception of the service (Sundaram & Webster, 2000). At such raucous places as restaurants or hotel lobbies, employees are commonly required to have precise and accurate communication with customers. Not only with customers, the voice quality and how to convey their work order using proper acoustic features between supervisors and subordinates is essential to carry out efficient operations and improve job performance by sending clear messages (Hildebrand et al., 2020; Mistry et al., 2022). Thus, I assume that interviewees' para-verbal behaviors influence the interviewers' hiring decisions by making interviewees look like professional supervisors. Thus, the following hypotheses are suggested:

H5: Interviewees’ para-verbal behaviors would be significantly associated with their Big-five personality traits.

H5a: Interviewees’ para-verbal behaviors would be significantly associated with a neuroticism trait of interviewer-reported Big-five personality traits.

H5b: Interviewees’ para-verbal behaviors would be significantly associated with an extraversion trait of interviewer-reported Big-five personality traits.

H5c: Interviewees’ para-verbal behaviors would be significantly associated with an openness trait of interviewer-reported Big-five personality traits.

H5d: Interviewees’ para-verbal behaviors would be significantly associated with an agreeableness trait of interviewer-reported Big-five personality traits.

H5e: Interviewees’ para-verbal behaviors would be significantly associated with a conscientiousness trait of interviewer-reported Big-five personality traits.

H6: Interviewees’ para-verbal behaviors would be significantly associated with interviewers’ hiring decisions.

Similar to the relationships between verbal behaviors and self-reported and machine learning-inferred Big-five personality traits, I expect that interviewees’ para-verbal behaviors would also be related to self-reported and machine learning-inferred Big-five personality traits.

Interviewees' para-verbal behaviors can be another effective unique signal to differentiate themselves from others, as acoustic features in para-verbal behaviors are activated by their unique physical and psychological characteristics (Guidi et al., 2019; Rynes et al., 1991). For example, in the context of job interviews, interviewees who speak calm and stable during the job interview are more likely to perceive themselves as people with a lower level of neuroticism. Based on this perception, they would be more likely to rate a neuroticism trait low in self-reported surveys to emphasize their emotionally stable personality as a unique signal. This kind of impression management can be done in their professional social media to make themselves attractive job candidates (Kong & Ding, 2024; Tay et al., 2020). For instance, interviewees with a lower level of neuroticism may want to use more stable and sound language patterns rather than aggressive ones in their professional social media postings. Based on these discussions, it is expected that interviewees' para-verbal behaviors would be significantly related to self-reported and machine learning-inferred (from LinkedIn) Big-five personality traits:

H7: Interviewees' para-verbal behaviors would be significantly associated with self-reported Big-five personality traits.

H7a: Interviewees' para-verbal behaviors would be significantly associated with a neuroticism trait of self-reported Big-five personality traits.

H7b: Interviewees' para-verbal behaviors would be significantly associated with an extraversion trait of self-reported Big-five personality traits.

H7c: Interviewees' para-verbal behaviors would be significantly associated with an openness trait of self-reported Big-five personality traits.

H7d: Interviewees' para-verbal behaviors would be significantly associated with an agreeableness trait of self-reported Big-five personality traits.

H7e: Interviewees' para-verbal behaviors would be significantly associated with a conscientiousness trait of self-reported Big-five personality traits.

H8: Interviewees' para-verbal behaviors would be significantly associated with machine learning-inferred Big-five personality traits.

H8a: Interviewees' para-verbal behaviors would be significantly associated with a neuroticism trait of machine learning-inferred Big-five personality traits.

H8b: Interviewees' para-verbal behaviors would be significantly associated with an extraversion trait of machine learning-inferred Big-five personality traits.

H8c: Interviewees' para-verbal behaviors would be significantly associated with an openness trait of machine learning-inferred Big-five personality traits.

H8d: Interviewees' para-verbal behaviors would be significantly associated with an agreeableness trait of machine learning-inferred Big-five personality traits.

H8e: Interviewees' para-verbal behaviors would be significantly associated with a conscientiousness trait of machine learning-inferred Big-five personality traits.

Regarding interviewees' behaviors, finally, I argue that interviewees' non-verbal behaviors, such as facial movements or postures, can be another dimension of signals for interviewers to assess personality traits and make hiring decisions. While saying or not saying, interviewees continuously move any parts of their bodies (e.g., hands, heads, eyes, or faces), forming non-verbal behaviors (Burnett & Motowidlo, 1998; Kafetsios & Hess, 2022). Among several non-verbal behaviors, I concentrate on facial emotions made by facial movements, as facial emotions may provide straightforward information for personality inference. For instance, while non-verbal behaviors can be identified by various cues, such as head posture and hand movement (Fox & Spector, 2000), those cues may offer neutral information (i.e., locations of head and hands). Moreover, although other non-verbal behaviors, such as arrogant body posture and crossed legs, can be used to infer interviewees' personality traits (DeGroot & Motowidlo, 1999), those behaviors cannot be easily identified while seated. Rather, interviewers and interviewees spend much more time looking at each other's faces. Thus, I claim that interviewees' facial emotions can be useful to infer their personality traits. For example, people who smile a lot may be recognized as agreeable and extroverted people. In contrast, people showing more neutral emotions might be seen as introverted people (Senft et al., 2016). In terms of signaling theory, personality inference based on facial emotions would be useful because facial emotions are hard to fake (i.e., costly signal), making an efficacious signaling system (Bangerter et al., 2012). This tendency is more obvious in the job interview context because interviewees commonly feel external pressure and nervous which contribute to the challenge of faking facial emotions beyond conscious control during job interviews (Ho et al., 2021). Costly signals that are hard to deceive and/or mimic make signals valuable because costly signals readily differentiate signalers (i.e., interviewees) from others (Connelly et al., 2011; Spence, 1973). Thus, I hypothesize that interviewers may want to utilize interviewees' facial emotions the most in inferring their personality traits.

Furthermore, as a costly signal that apparently shows interviewees' personality traits (Alper et al., 2021; Keltner, 1996), interviewers may pay more attention to interviewees' non-verbal behaviors shown by their facial emotions in making the overall evaluations. Thus, by signaling personality traits that highly influence interviewees' attractiveness (Doan et al., 2021;

Leung & Law, 2010), interviewees' non-verbal behaviors captured by facial emotions would affect the interviewers' hiring decisions. Taken together, I suggest the following hypotheses:

H9: Interviewees' non-verbal behaviors would be significantly associated with interviewer-reported Big-five personality traits.

H9a: Interviewees' non-verbal behaviors would be significantly associated with a neuroticism trait of interviewer-reported Big-five personality traits.

H9b: Interviewees' non-verbal behaviors would be significantly associated with an extraversion trait of interviewer-reported Big-five personality traits.

H9c: Interviewees' non-verbal behaviors would be significantly associated with an openness trait of interviewer-reported Big-five personality traits.

H9d: Interviewees' non-verbal behaviors would be significantly associated with an agreeableness trait of interviewer-reported Big-five personality traits.

H9e: Interviewees' non-verbal behaviors would be significantly associated with a conscientiousness trait of interviewer-reported Big-five personality traits.

H10: Interviewees' non-verbal behaviors would be significantly associated with interviewers' hiring decisions.

Among the three communication types, non-verbal behaviors might be the most influential factor associated with self-reported and machine learning-inferred Big-five personality traits. By perceiving facial emotions as a unique signal that interviewers actively refer to, interviewees would want to consistently present signaling information through self-reported ratings and social media to be a distinguished job candidate (Connelly et al., 2011; Tay et al., 2020). Thus, I expect that non-verbal behaviors are significantly related to interviewees' self-reported and machine learning-inferred Big-five personality traits. For example, interviewees who know they gently and mildly smile rather than crack up may perceive themselves with higher emotional stability. Accordingly, they are more likely to give high scores to survey items regarding an emotional stability trait when conducting self-reported surveys. In a similar vein, they may want to avoid any forceful and aggressive words (e.g., "crazy") in LinkedIn postings based on their self-perceptions of facial emotion patterns. Consequently, machine learning-inferred Big-five personality traits from their LinkedIn pages would be more likely to assess the interviewees' agreeableness trait high. Taken together, I expect that interviewees' non-verbal behaviors would have significant relationships with self-reported and machine learning-inferred (from LinkedIn) Big-five personality traits:

H11: Interviewees' non-verbal behaviors would be significantly associated with self-reported Big-five personality traits.

H11a: Interviewees' non-verbal behaviors would be significantly associated with a neuroticism trait of self-reported Big-five personality traits.

H11b: Interviewees' non-verbal behaviors would be significantly associated with an extraversion trait of self-reported Big-five personality traits.

H11c: Interviewees' non-verbal behaviors would be significantly associated with an openness trait of self-reported Big-five personality traits.

H11d: Interviewees' non-verbal behaviors would be significantly associated with an agreeableness trait of self-reported Big-five personality traits.

H11e: Interviewees' non-verbal behaviors would be significantly associated with a conscientiousness trait of self-reported Big-five personality traits.

H12: Interviewees' non-verbal behaviors would be significantly associated with machine learning-inferred Big-five personality traits.

H12a: Interviewees' non-verbal behaviors would be significantly associated with a neuroticism trait of machine learning-inferred Big-five personality traits.

H12b: Interviewees' non-verbal behaviors would be significantly associated with an extraversion trait of machine learning-inferred Big-five personality traits.

H12c: Interviewees' non-verbal behaviors would be significantly associated with an openness trait of machine learning-inferred Big-five personality traits.

H12d: Interviewees' non-verbal behaviors would be significantly associated with an agreeableness trait of machine learning-inferred Big-five personality traits.

H12e: Interviewees' non-verbal behaviors would be significantly associated with a conscientiousness trait of machine learning-inferred Big-five personality traits.

Big-five Personality Traits and Hiring Decisions

Since job candidates' future job performance cannot be easily evaluated during job interviews, employers may refer to interviewees' interview performance and attractiveness to forecast their future job performance (McCarthy et al., 2013). Based on evaluations of interviewees, interviewers make hiring decisions as final decisions during the recruitment process (Cable & Judge, 1997; Huffcutt et al., 2001). To make better hiring decisions, interviewers consider various factors about interviewees, such as their knowledge, skills, work experiences, and characteristics (Raza & Carpenter, 1987; Schmidt & Hunter, 1998). Although strengths of influential factors on hiring decisions may differ depending on specific industry, organization, and job type, prior studies found that interviewees' social skills, personality traits, mental capacity, and knowledge and skills are, in general, assessed by interviewers when making hiring decisions (Cook et al., 2000; Huffcutt et al., 2001). It is plausible that employers in IT or engineering industries may pay more attention to knowledge and skills rather than personality traits to assess interviewees' competency. However, in the hospitality context, the role of personality traits in interviewees' evaluations is more emphasized than other factors because hospitality employees' caring attitudes and effective communication are commonly required to satisfy customers' diverse needs and increase service quality (Doan et al., 2021; Leung & Law, 2010).

In the context of hiring decisions, several meta-analyses outside of the hospitality industry emphasized the strong relationship of conscientiousness and extraversion traits with interview performance (Barrick et al., 2000; Cortina et al., 2000; Levashina et al., 2014; Roth et al., 2005). While hospitality studies have had little attention to the role of personality traits in the selection process, numerous previous studies have investigated the effects of Big-five personality traits on various individual and organizational consequences (Bellou et al., 2018; Doan et al., 2021; Kim et al., 2007; Köşker et al., 2019; O'Neill & Xiao, 2010; Shiwen and Ahn, 2023). For example, Kim et al. (2007) found that extraversion, agreeableness, and conscientiousness traits have negative effect on employees' job burnout while neuroticism has a positive effect, implying controlling emotional stability is important to decrease job burnout syndrome. A recent meta-analysis conducted by Doan et al. (2021) found that hospitality employees' extraversion, agreeableness, neuroticism, and conscientiousness traits have the strongest relationships with numerous relevant outcomes, such as organizational commitment, job satisfaction, and emotional exhaustion, implying a possible significant role of personality traits in interviewers' evaluation.

Due to its critical role in hospitality workplaces, it is expected that Big-five personality traits would be significantly associated with hiring decisions. Given that employees' personality traits are the strongest predictor of overall job performance in the hospitality industry, employers may actively try to understand interviewees' personality traits (Kwok et al., 2011). The employers' evaluations of interviewees' personality traits can be used when grading person-job and person-organization fit to predict future performance (P-J and P-O fit; Cable & Judge, 1997; Kwok et al., 2012). Accordingly, as interviewees are considered to have a higher P-J and P-O fit, they would be more likely to receive job offers (Bowen et al., 1991; Connelly & Ones, 2010). In sum, when interviewees show attractive personalities, interviewers would be more likely to perceive interviewees' competency, thus giving more job offers. Thus, I hypothesize that interviewees' personality traits would influence the hiring decisions made by interviewers as follows:

H13: Interviewer-reported Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H13a: A neuroticism trait of interviewer-reported Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H13b: An extraversion trait of interviewer-reported Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H13c: An openness trait of interviewer-reported Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H13d: An agreeableness trait of interviewer-reported Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H13e: A conscientiousness trait of interviewer-reported Big-five personality traits would be significantly associated with interviewers' hiring decisions.

While interviewer-reported Big-five personality traits might be the influential factor for hiring decisions made by interviewers, self-reported and machine learning-inferred Big five personality traits can be another informative source of the interviewers' hiring decisions. Several prior studies demonstrated that interviewer-reported Big-five personality traits have incremental validity over self-reported Big-five personality traits in predicting relevant outcomes, such as interview ratings and job performance (Barrick et al., 2000; Connelly & Ones, 2010; Klinger & Siangchokyoo, 2024; Oh et al., 2011). However, as one of humans who have limited cognitive resources, interviewers cannot easily fully understand others' (i.e., interviewees') personality traits. For instance, interviewers may have difficulties in understanding interviewees' personality traits that are innate and not readily apparent, such as emotional stability and openness to experience (Connolly et al., 2007). This is more evident in the job interview context, where interviewers need to evaluate Big-five personality traits of interviewees who have rarely met for a short time (Mount et al., 1994). Thus, it is important to utilize various sources of Big-five personality traits (i.e., interviewer-reported, self-reported, and machine learning-inferred) to better understand interviewees' Big-five personality traits and thus make better hiring decisions.

In terms of self-reported Big-five personality traits, I expect that interviewees' self-reported Big-five personality would have significant relationships with interviewers' hiring decisions. As one of the signals of their competency, interviewees present their personality traits, based on self-perceptions and judgment, in surveys which are used to measure self-reported Big-five personality traits. Although there is a possibility that self-reported ratings might be different from interviewer-reported ratings, self-reported ratings are still informative for interviewers to understand what they missed during the job interview and interviewees' perspectives regarding their personality traits (Klinger & Siangchokyoo, 2024; Oh et al., 2011). Accordingly, interviewees' self-reported Big-five personality traits would be used for employers to evaluate person-organization and person-job fit, and thus influencing hiring decisions (Bowen et al., 1991; Cable & Judge, 1997; Kwok et al., 2012).

Similarly, machine learning-inferred Big-five personality traits would be associated with interviewers' hiring decisions. Thanks to the advancement of information technology, employers actively utilize job candidates' professional social media, such as LinkedIn, for recruitment purposes (Roulin & Stronach, 2022). Employers may want to see job candidates' various activities and what they write to understand their personality traits (Tay et al., 2020). Big-five personality traits inferred from LinkedIn can be valuable for making hiring decisions because job candidates' activities and postings show their personality traits which interviewers may not see during job interviews (Fernandez et al., 2021). Thus, I expect that interviewees' Big-five personality traits from their LinkedIn using machine learning techniques would have significant relationships with the hiring decisions. Taken together, I hypothesized that:

H14: Self-reported Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H14a: A neuroticism trait of self-reported Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H14b: An extraversion trait of self-reported Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H14c: An openness trait of self-reported Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H14d: An agreeableness trait of self-reported Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H14e: A conscientiousness trait of self-reported Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H15: Machine learning-inferred Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H15a: A neuroticism trait of machine learning-inferred Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H15b: An extraversion trait of machine learning-inferred Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H15c: An openness trait of machine learning-inferred Big-five personality traits would be significantly associated with interviewers' hiring decisions.

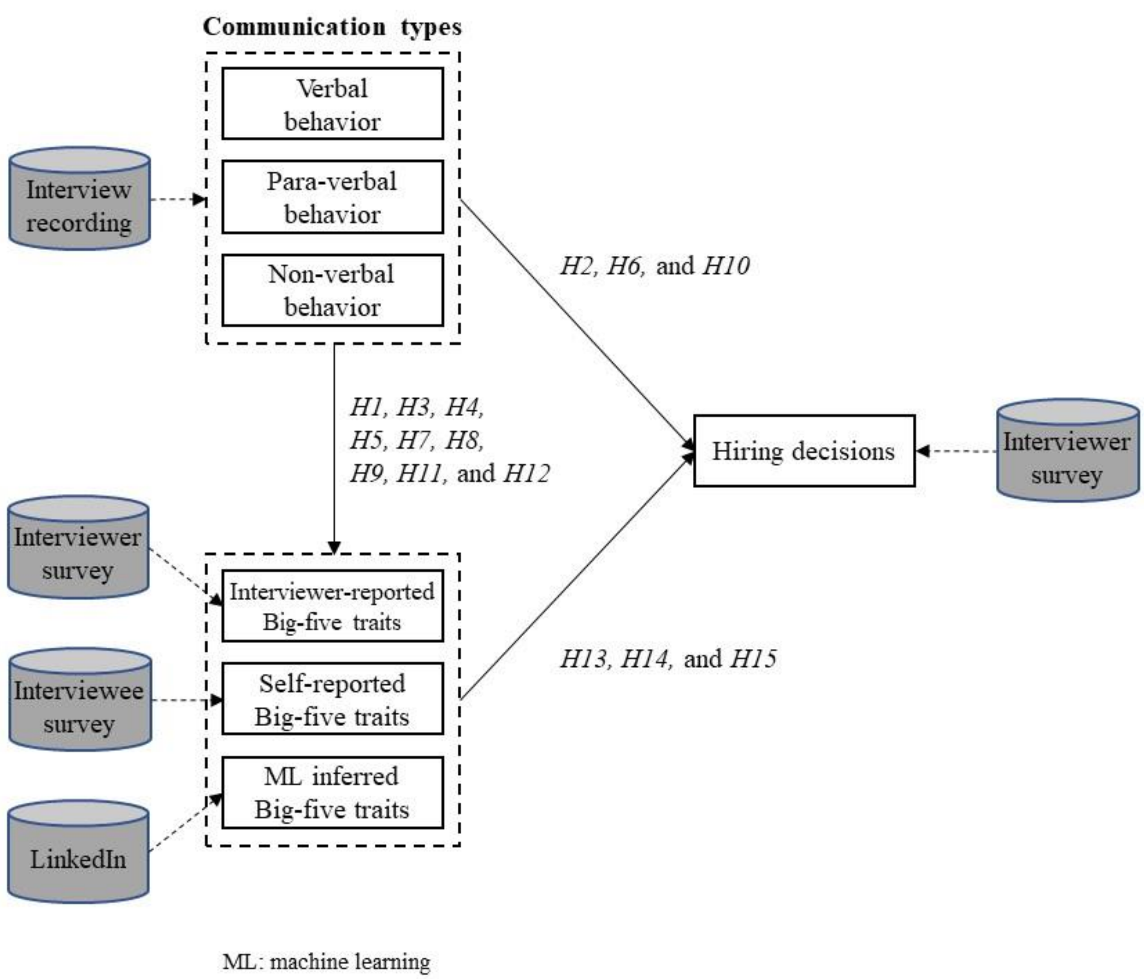
H15d: An agreeableness trait of machine learning-inferred Big-five personality traits would be significantly associated with interviewers' hiring decisions.

H15e: A conscientiousness trait of machine learning-inferred Big-five personality traits would be significantly associated with interviewers' hiring decisions.

Proposed Relationships

Figure 2.1 shows the overarching model of the proposed study. Data sources for each variable are included to easily differentiate the meanings of each variable, highlighted in gray. This study examines the effects of three communication types (i.e., verbal, para-verbal, and non-verbal behaviors) on Big-five personality traits (interviewer-reported, self-reported, and machine learning-inferred; neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness) and hiring decisions. The relationships between Big-five personality traits and hiring decisions are also analyzed.

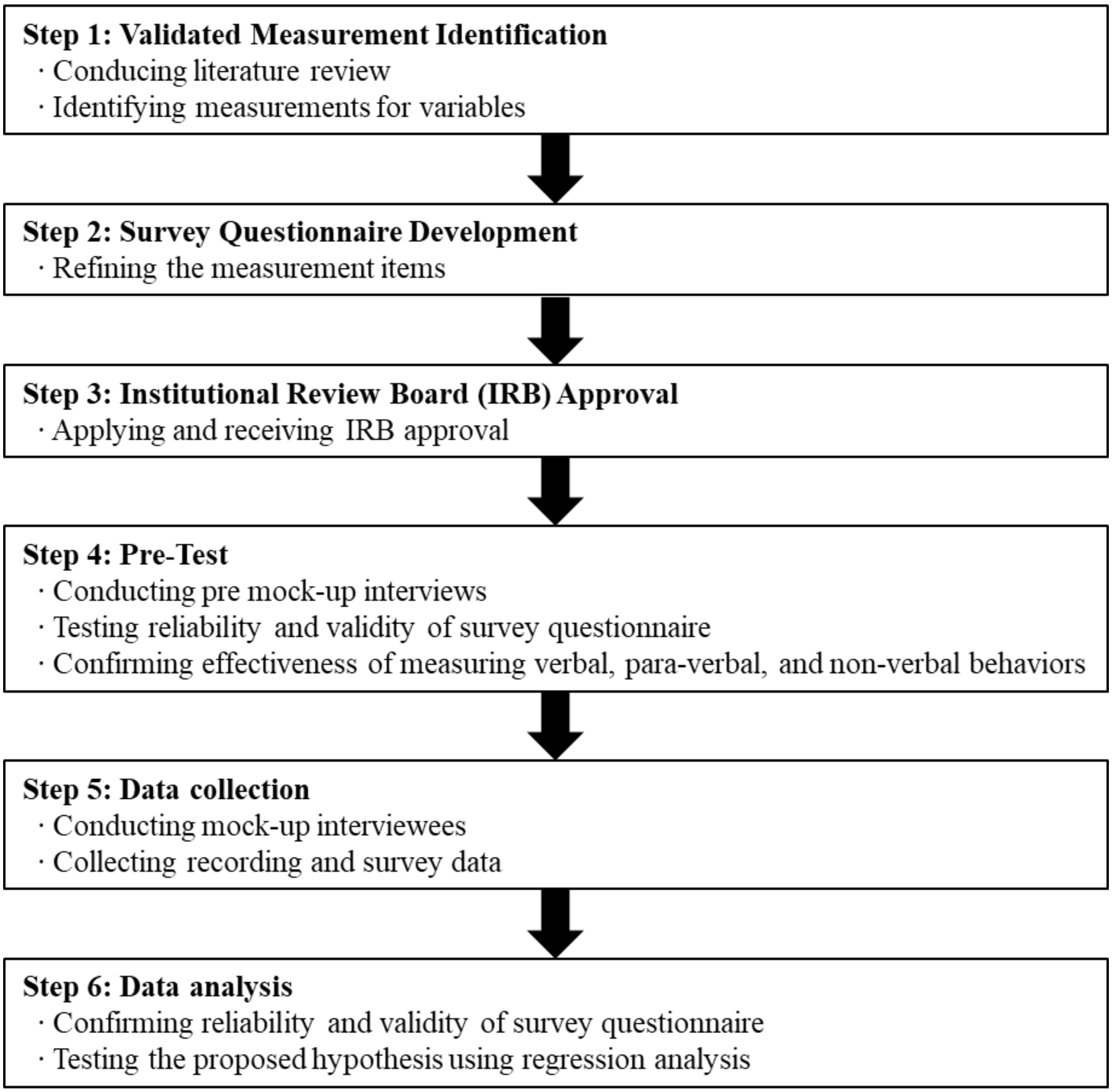
Figure 2.1 Overarching Research Model



Chapter 3 - Methodology

This chapter introduces this study's research methodology for empirical tests of the proposed hypothesis. The procedures for data collection and analysis are presented in Figure 3.1.

Figure 3.1 Procedures for Data Collection and Analysis



Measurements

Through the literature review, previously validated survey items and measurements were selected for the survey and three communication types. For the survey, all questionnaires were set in a format using a 7-point Likert-type scale, with 1 for 1 for strongly disagree, 2 for disagree, 3 for somewhat disagree, 4 for neither agree nor disagree, 5 for somewhat agree, 6 for agree, and 7 for strongly agree. Questions were revised to reflect the hospitality context. For the three communication types (i.e., verbal, para-verbal, and non-verbal behaviors), the values that pre-trained algorithms generated were standardized and aggregated to measure each communication type. Since this study measured different constructs by interviewees and interviewers, the following section is divided into two separate sub-sections for interviewees and interviewers.

Measurements for Interviewees

Verbal Behaviors

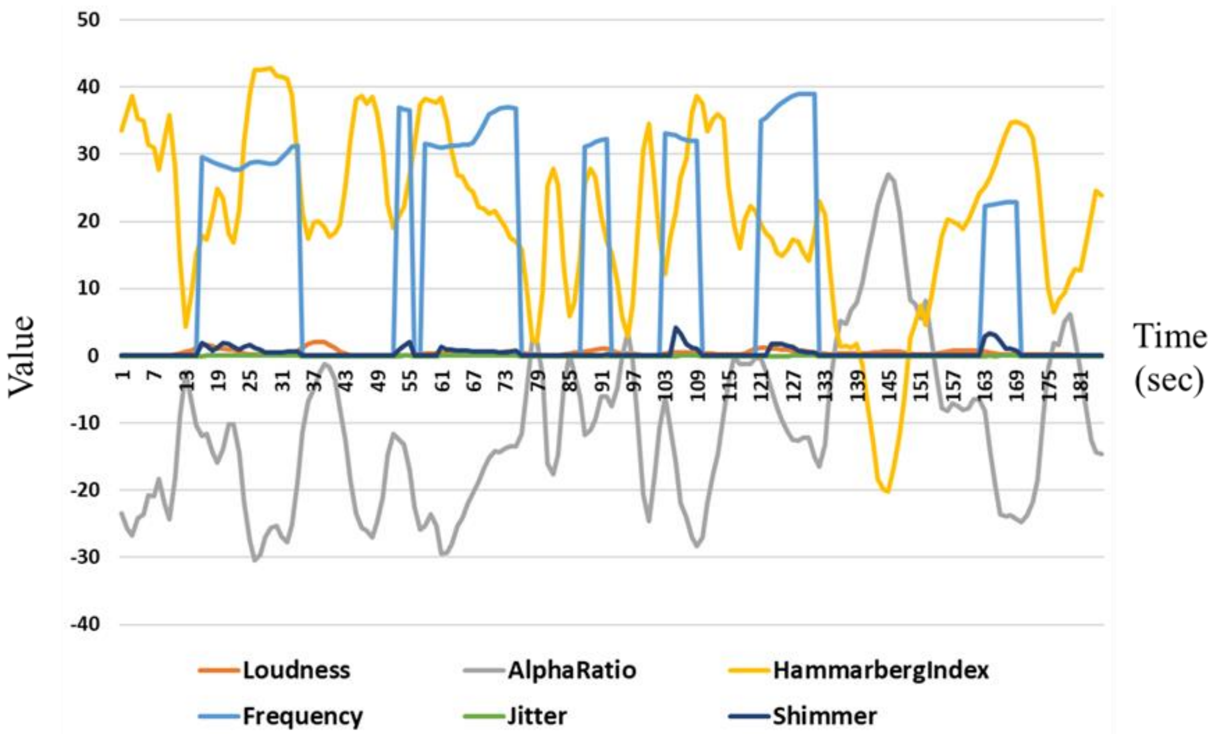
To measure interviewees' verbal language patterns, textual data were extracted from the interview recordings. To do this, IBM Watson speech-to-text performed to extract textual transcripts from each interview recording. IBM Watson speech-to-text provides highly accurate speech-to-text transformations based on pre-trained neural technologies (IBM, 2023). Linguistic Inquiry and Word Count (LIWC), content analysis software, then summarized the transcripts into four dimensions of psychological verbal language patterns: analytical thinking, clout, authenticity, and emotional tone. LIWC provides the percentages of words that present each dimension of psychological verbal language patterns, using a pre-determined word dictionary based on language research (Pennebaker et al., 2015). Verbal behaviors were measured by aggregating the values of four verbal language dimensions.

The analytical thinking dimension refers to an individual's complex and hierarchical thinking pattern, meaning rigid, logical, and formal rather than narrative, personal, friendly, heuristic, and intuitive characteristics (Pennebaker et al., 2014). The clout dimension represents an individual's certainty, confidence, leadership, and group-focused attitude rather than uncertain and self-focused thoughts (Farshid et al., 2019). The authenticity dimension shows how much individuals are honest and vulnerable rather than being guarded and making distance from others (Newman et al., 2003). Lastly, emotional tone dimension means the extent to which individuals feel positive emotions rather than negative emotions (Pennebaker et al., 2015). Using four dimensions, previous studies analyzed the differences in individual characteristics in the employee online reviews (Duncan et al., 2019), online dating applications (Farshid et al., 2019), and press releases context (Karačić et al., 2019).

Para-verbal Behaviors

To extract interviewees' acoustic features from the interview recordings, OpenSMILE, a Python library, was employed (Bayerl et al., 2023; Eyben et al., 2010). This study used a widely used acoustic feature set, called Geneva Minimalistic Acoustic Parameter Set (De Boer et al., 2023). Eleven acoustic features were extracted from the interview recordings: jitter, frequency, shimmer, loudness, alpha ratio, Hammarberg index, spectral loudness peaks per second, length of continuous voiced regions, length of continuous unvoiced regions, and voiced segments per second (Hickman et al., 2022). For instance, the jitter calibrates period-to-period variations of the frequency, indicating an irregular pitch level (De Boer et al., 2023). While OpenSMILE offers temporal changes (Figure 3.2) and mean values of acoustic features, this study utilized mean values of acoustic features because individual interview recordings were an analysis unit. Para-verbal behaviors were measured by standardizing and aggregating eleven acoustic features in each recording.

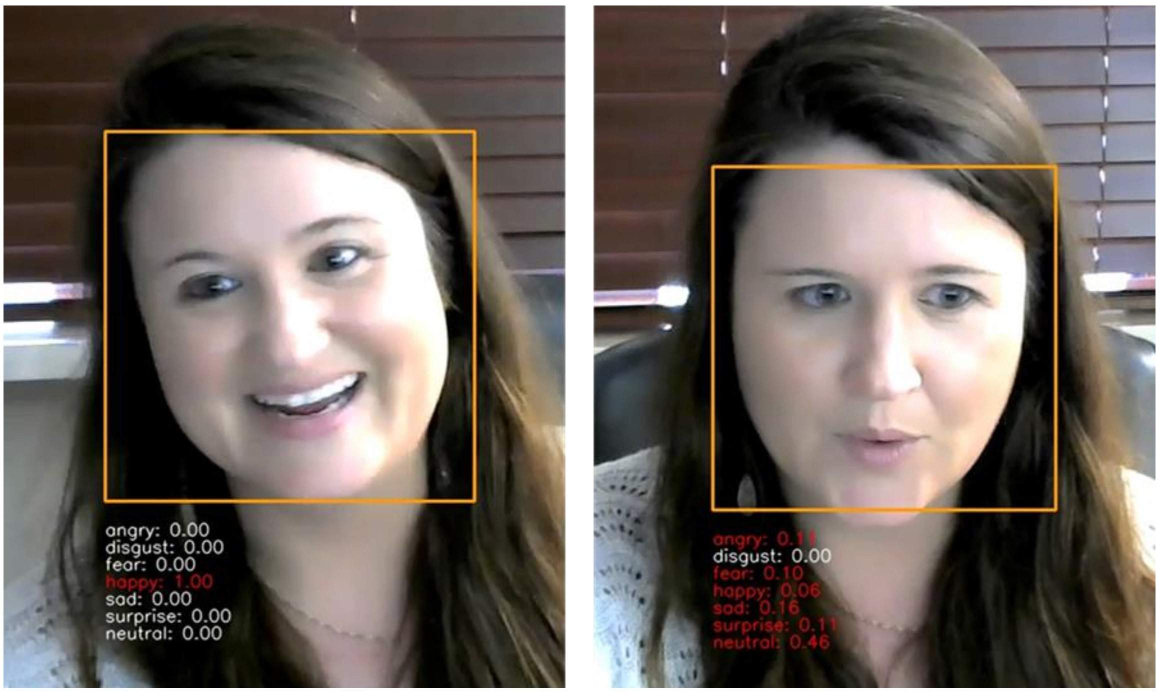
Figure 3.2 Example of Acoustic Features' Changes Using OpenSMILE



Non-verbal Behaviors

Among several non-verbal behaviors, such as postures or hand movements, this study focuses on facial emotions, as prior studies suggested that personality traits can be inferred by facial emotions created by facial movements (Keltner, 1996; Little & Perrett, 2007). Facial Expression Recognition (FER), a Python library, was utilized to measure seven facial emotional scores: happy, sad, fear, angry, surprise, disgust, and neutral (Goodfellow et al., 2013; Shenk, 2018). FER captures human emotions from facial movements using pre-trained multi-task cascaded convolutional networks-based emotion classification models and provides seven values of emotional scores, ranging from zero to one, per every second in a recording (Figure 3.3). Similar to para-verbal behaviors, since this study used individual interview recordings as an analysis unit, the sum of emotional scores over each interview recording was used. Non-verbal behaviors were measured by standardizing and aggregating seven summed emotional scores in each recording.

Figure 3.3 Example of Facial Emotion Analysis Using Facial Emotion Recognition



Self-reported Big-Five Personality Traits

Participants' Big-five personality traits (i.e., neuroticism, extraversion, openness, agreeableness, and conscientiousness) were measured by 25 items, 7-point Likert scale, developed by Yoo and Gretzel (2011). The 25 items were developed based on the original 100 items of Big-five personality traits (Goldberg, 1999) to enhance their simplicity and reduce participants' burden. Thus, 5 items measured each personality trait. Previous studies have reported Cronbach's alpha coefficients of, on average, for the five personality traits, .854 (Yoo & Gretzel, 2011), .821 (Jani & Han, 2014), and .87 (Talwar et al., 2022), using the 25 items. For instance, Big-five personality traits were measured by survey items for a neuroticism trait was measured by using a survey item ("I get stressed out easily"), a extraversion trait ("I talk a lot to different people at parties"), an openness trait ("I get excited by new ideas"), an agreeableness trait ("I sympathize with others' feelings"), and a conscientiousness trait ("I make plans and stick to them").

Machine Learning-inferred Big-Five Personality Traits

Machine learning-inferred Big-Five personality traits were measured by utilizing Receptiviti API, a commercial artificial intelligence-based personality traits inference model (Roulin & Stronach, 2022). Receptiviti infers Big-five personality traits ratings by utilizing textual data from job candidates' LinkedIn pages This study adopted Receptiviti API to measure machine learning-inferred Big-five personality traits from participants' LinkedIn pages, ranging from 0 to 100 for each trait.

Demographic Information

For participants demographic information, gender (female, male, prefer not to answer), age, ethnicity (Asian, African American, Caucasian, Hispanic/Latino, Pacific Islander, others, and prefer not to answer), marital status (single, married, widowed, divorced, separated, and prefer not to answer), the highest level of education (less than high school, high school, university, Masters/Ph.D., technical school, others, and prefer not to answer), specific hospitality industry that they want to work in the most (restaurant, event, casino, cruises, and others), and job experience in the hospitality industry were included.

Control Variables

Job experience was included as a control variable because job experience possibly influences interviewers' hiring decisions during the selection process. Increasing job experience means interviewees may have more job knowledge, thus more likely to have better future job performance (Schmidt & Hunter, 1998). Job experience was measured by the duration of job experience in the hospitality industry.

Measurements for Interviewers

Interviewer-reported Big-Five Personality Traits

Interviewers measured participants' Big-five personality traits using the same 25 items, 7-point Likert scale, developed by Yoo and Gretzel (2011). As Watson (1989) suggested, the same survey items were used for self-reported and interviewer-reported Big-five personality traits, in order to effectively compare the convergent validity of ratings made by participants and interviewers.

Hiring Decisions

Interviewers' hiring decisions were measured by asking two items, 7-point Likert scale, developed by Higgins and Judge (2004): "I would recommend extending a job offer to this candidate" and "Overall, I evaluate this candidate positively." Interviewers' hiring decisions reflect the interviewees' overall competency and fit with the organization shown during the interviews (Cable & Judge, 1997).

Table 3.1 Descriptions of Measurement

Dimensions	Measures	Source
Verbal behaviors	Aggregated value of four verbal language dimensions: analytical thinking, clout, authenticity, and emotional tone.	Farshid et al. (2019) Pennebaker et al. (2015)
Para-verbal behaviors	Standardized and aggregated value of eleven acoustic features: jitter, frequency, shimmer, loudness, alpha ratio, Hammarberg index, spectral loudness peaks per second, length of continuous voiced regions, length of continuous unvoiced regions, and voiced segments per second.	Hickman et al. (2022)
Non-verbal behaviors	Standardized and aggregated value of seven emotional scores: happy, sad, fear, angry, surprise, disgust, and neutral.	Goodfellow et al. (2013) Shenk (2018)
Self-reported Big-five personality traits	**Neuroticism** 1. I get stressed out easily. 2. I worry about things. 3. I fear for the worst. 4. I am filled with doubts about things. 5. I panic easily. **Extraversion** 6. I talk a lot to different people at parties. 7. I feel comfortable around people. 8. I start conversations. 9. I make friends easily. 10. I don't mind being the center of attention. **Openness** 11. I get excited by new ideas. 12. I enjoy thinking about things. 13. I enjoy hearing new ideas. 14. I enjoy looking for a deeper meaning in things.	Yoo and Gretzel (2011)

	15. I have a vivid imagination. **Agreeableness** 16. I sympathize with others' feelings. 17. I am concerned about others. 18. I enjoy hearing new ideas. 19. I respect others. 20. I believe that others have good intentions. **Conscientiousness** 21. I carry out my plans. 22. I pay attention to details. 23. I am always prepared. 24. I make plans and stick to them. 25. I am exacting in my work.	
Interviewer-reported Big-five personality traits	**Neuroticism** 1. This interviewee looks like he/she gets stressed out easily. 2. This interviewee looks like he/she worries about things. 3. This interviewee looks like he/she fears for the worst. 4. This interviewee looks like he/she is filled with doubts about things. 5. This interviewee looks like he/she panics easily. **Extraversion** 6. This interviewee looks like he/she talks a lot to different people at parties. 7. This interviewee looks like he/she feels comfortable around people. 8. This interviewee looks like he/she starts conversations.	Yoo and Gretzel (2011)

	9. This interviewee looks like he/she makes friends easily. 10. This interviewee looks like he/she doesn’t mind being the center of attention. **Openness** 11. This interviewee looks like he/she gets excited by new ideas. 12. This interviewee looks like he/she enjoys thinking about things. 13. This interviewee looks like he/she enjoys hearing new ideas. 14. This interviewee looks like he/she enjoys looking for a deeper meaning in things. 15. This interviewee looks like he/she has a vivid imagination. **Agreeableness** 16. This interviewee looks like he/she sympathizes with others’ feelings. 17. This interviewee looks like he/she is concerned about others. 18. This interviewee looks like he/she enjoys hearing new ideas. 19. This interviewee looks like he/she respects others. 20. This interviewee looks like he/she believes that others have good intentions. **Conscientiousness** 21. This interviewee looks like he/she carries out my plans. 22. This interviewee looks like he/she pays attention to details.	

	23. This interviewee looks like he/she is always prepared. 24. This interviewee looks like he/she makes plans and sticks to them. 25. This interviewee looks like he/she is exacting in my work.	
Machine learning-inferred Big-five personality traits	Predicted Big-five personality traits scores, ranging from 0 to 100, provided by Receptiviti API.	Biswas et al. (2023) Ramon et al. (2021) Rhea et al. (2022)
Hiring decisions	1. I would recommend extending a job offer to this candidate. 2. Overall, I evaluate this candidate positively.	Higgins and Judge (2004)

Pilot Study

A pilot study was conducted to clarify the survey items regarding Big-five personality traits and check the effectiveness of measuring verbal, para-verbal, and non-verbal behaviors. For the pilot study, 37 mock-up interviewees were recruited from Prolific 13 mock-up interviewees were hired from one of the universities in mid-west areas of US, respectively, who meet the four screening conditions: (1) 18 years or older, (2) currently living in the United States, (3) seeking supervisory job opportunities in the hospitality industry, and (4) having LinkedIn personal page. A well-trained graduate student conducted mock-up interviews by asking the same eleven structured interview questions to each interviewee through Zoom during which mock-up interviews were recorded. Regarding reliability and validity of self-reported Big-five personality traits, Cronbach’s alpha coefficients for each five dimensions were 0.968, 0.938, 0.917, 0.888, and 0.818, for neuroticism, extraversion, openness, agreeableness, and conscientiousness traits, respectively. The average variance extracted for all dimensions satisfied the threshold for convergent validity, higher than 0.5, that is, 0.803, 0.795, 0.657, 0.640, and 0.525 (Hair et al., 2010). For the effectiveness of measuring verbal, para-verbal, and non-verbal behaviors, the content of interview recordings and measurements of verbal, para-verbal, and non-verbal behaviors were manually compared. For instance, if an interviewee smiles a lot during the interview and the score of happiness in non-verbal behaviors is high, the effectiveness of Facial Expression Recognition, a Python library, was confirmed to measure non-verbal behaviors.

After the pilot study, two major things were modified. First, while eleven structured interview questions were asked during the pilot study, it was revised that five interview questions were going to be asked, and one follow-up question could be asked based on the interviewee's answer to enhance the reality of mock-up job interviews for the main study. Second, the interviewer's hiring decisions were measured by checking whether the interviewer would like to hire the interviewee (1) or not (0), as a binary variable. However, to capture more variations of hiring decisions by interviewers and to avoid any possible sample bias (e.g., too many rejects or accepts), the interviewer's hiring decisions were going to be measured by two survey items, a 7-point Likert scale (Table 3.1).

Sample Selection

The target sample of this study were people who are (1) 18 years or older, (2) currently living in the United States, (3) seeking supervisory job opportunities in the hospitality industry, and (4) having LinkedIn personal page. To determine the minimum sample size for this study, G*Power (3.1.8.7) was used. As suggested for social and behavior research, statistical power and effect size were set as 0.80 and 0.15, respectively (Cohen, 1988; Valentine et al., 2010). Since the proposed model has six predictors, the minimum sample size for this study is 98. Thus, this study aims to collect 100 samples.

Data Collection Procedures

Before collecting the data, an Institutional Review Board (IRB) application for the use of human subjects for this study was submitted (See Appendix A). From Prolific, 100 mock-up interviewees were recruited and six mock-up interviewees were hired from one of the universities in mid-west areas of US. Prolific is a crowd-sourcing community that provides highly reliable and wide range of panels (Ali et al., 2023; Filieri et al., 2021; Peer et al., 2017; Viglia & Dolnicar, 2020). By setting screening conditions, willing participants can be easily invited to this study from Prolific. This study used four screening conditions: (1) 18 years or older, (2) currently living in the United States, (3) seeking supervisory job opportunities in the hospitality industry, and (4) having LinkedIn personal page. After the participants entered the participation pool, they were required to complete self-reporting online surveys for self-reported Big-five personality traits and Doodle polls to find the date and time for mock-up interviews based on interviewers' availability.

Senior undergraduate students at one of the universities in mid-west areas of US were recruited by visiting several classes offered by the Department of Hospitality Management and promote the recruitment by showing a QR code (See Appendix B) by briefly introducing the purpose of this study, using four screening conditions: (1) 18 years or older, (2) currently living in the United States, (3) seeking supervisory job opportunities in the hospitality industry, and (4) having LinkedIn personal page. Ten mock-up interviewers were recruited from Prolific, who have at least three years of job experience in the hospitality industry. The mock-up interviewers were trained to act as mock-up interviewers and to ask five semi-structured interview questions and one following question if possible (Table 3.2). Specific dates and time for mock-up interviews were determined based on mock-up interviewees and interviewers' availability through Doodle poll.

Table 3.2 Five semi-structured Interview Questions

Number	Questions
1	Please introduce yourself.
2	What are your strengths and weaknesses?
3	What are your short-term and long-term goals?
4	Why did you apply for this job?
5	Do you have any last thing to say?

To encourage participants to this study, interviewee participants were compensated $8 per participant. Interviewer participants were compensated $16 per interview, considering their expertise. They were invited to mock-up job interviews on Zoom and informed that their responses, including audio and visual information, will be recorded and analyzed by our artificial intelligence algorithms. Consent forms were collected, accordingly. The cover letter of an online survey measuring self-reported Big-five personality traits was designed to meet all the minimum requirements of informed consent found in the Consent Form Template provided by The Institutional Review Board at Kansas State University. By checking an agreement button in the cover letter of an online survey, participation consent was collected. Appendices C and D present the final online survey questionnaires and the cover letter of the only survey questionnaires for mock-up interviewees and interviewers, respectively.

Before mock-up interviews, mock-up interviewees were asked to complete self-reporting online surveys measuring self-reported Big-five personality traits (Appendix C). After completing self-reporting online surveys, each interviewee and an interviewer were invited to Zoom at the same time by sending them the URL for a Zoom meeting room. Interviews were recorded by using the recording function available on Zoom. During mock-up interviews, mock-up interviewees were instructed to imagine that they are going to have a job interview for a supervisor position at a hospitality company. The semi-structured interview questions were asked by mock-up interviewers. One follow-up question can be asked based on interviewees' answers. Interview questions were asked in the order described in Table 3.2. The average time of mock-up interviewees was approximately six minutes. After mock-up interviews, mock-up interviewers measured interviewer-reported Big-five personality traits and hiring decisions for each mock-up interviewee (Appendix D). Machine learning-inferred Big-five personality traits were measured applying Receptiviti API to participants' LinkedIn pages, at any time during the data collection period.

Data Analysis

For the dataset regarding self-reported and interviewer-reported Big-five personality traits, data screening procedures, including normal distribution check and missing data and outlier handling, were conducted. After data screening procedures, confirmatory factor analysis (CFA) was performed to verify the validity and reliability of self-reported and interviewer-reported Big-five personality traits using SPSS. Reliability was tested based on Cronbach's alpha values (0.7 or higher; Cronbach, 1951). To check the convergent validity, the average variance extracted (AVE) was assessed with a threshold of 0.5 (Hair et al., 2010).

After checking the reliability and validity of self-reported, interviewer-reported, and machine learning-inferred Big-five personality traits, factor loading scores of the measurement items were used for hypothesis testing. For the relationships between three communication types and self-reported, interviewer-reported, and machine learning-inferred Big-five personality traits, three regression models were employed where three communication types were independent variables and each dimension of self-reported, interviewer-reported, and machine learning-inferred Big-five personality traits were a dependent variable for each regression model, respectively. For instance, for the relationship between three communication types and self-reported Big-five personality traits, verbal, para-verbal, and non-verbal behaviors have five relationships with each dimension of self-reported Big-five personality traits as a dependent variable (i.e., 1) neuroticism, 2) extraversion, 3) openness to experience, 4) agreeableness, and 5) conscientiousness) in the first regression model. For the association between three communication types and hiring decisions, regression analysis investigated the effects of three communication types on hiring decisions. Finally, for the relationship between self-reported, interviewer-reported, and machine learning-inferred Big-five personality and hiring decision, three regression models were developed where five dimensions of self-reported, interviewer-reported, and machine learning-inferred Big-five personality traits were independent variables and hiring decision was a dependent variable. For example, for the first regression model, five dimensions of self-reported Big-five personality traits as a dependent variable (i.e., 1) neuroticism, 2) extraversion, 3) openness to experience, 4) agreeableness, and 5) conscientiousness) were independent variables and hiring decision was a dependent variable.

Chapter 4 - Results

Demographic Profile of Respondents

Among 106 survey respondents in this study, 59.4% of respondents were male and 36.8% were female, and 3.8% preferred not to answer. As for their ethnicity, most respondents (43.4%) were Caucasian, followed by African American (30.2%), Hispanic/Latino (16.9%), and Asian (9.4%). The average of 106 respondents' age was 30.78. As for specific hospitality industry that respondents wanted to work in the most, 23.6% of respondents chose the hotel industry, followed by restaurant (17.9%), event (17.9%), casino (16.0%), cruises (12.3%), and other (e.g., tourism; 12.3%) industries. Among 106 respondents, 100 respondents had work experience in the hospitality industry. In specific, 25% of respondents chose the hotel industry, followed by restaurant (51%) event (19%), and casino (5%) industries. Among 100 respondents who had work experience in the hospitality industry, 51% chose part-time, 26% chose full-time, and 23% of them chose both for employment types. The average work experience was 24.94 months. Table 4.1 describes the demographic profile of respondents.

Table 4.1 Demographic Profile of Respondents (n = 106)

Characteristics	M	S.D	Min	Max	N	%
Age	30.78	5.907	21	59		
Work experience (Month)	24.94	43.507	0	240		
Gender						
Male					63	59.4
Female					39	36.8
Prefer not to answer					4	3.8
Ethnicity						
Asian					10	9.4
African American					32	30.2
Caucasian					46	43.4
Hispanic / Latino					18	16.9
Pacific Islander					0	0
Others					0	0
Prefer not to answer					0	0
Marital status						
Single					58	54.7
Married					27	25.5
Widowed					2	1.9
Divorced					17	16.0
Separated					2	1.9
Prefer not to answer					0	0
Education level						
High school					28	26.4
University					49	46.2
Masters / Ph.D.					6	5.7
Technical school					21	19.8
Others					2	1.9
Prefer not to answer					0	0

Hospitality industry that you want to work in the most						
Hotel					25	23.6
Restaurant					19	17.9
Event					19	17.9
Casino					17	16.0
Cruises					13	12.3
Others					13	12.3
Have you ever worked in the hospitality industry?						
Yes					100	94.33
No					6	5.66
Hospitality industry that you worked in						
Hotel					25	25
Restaurant					51	51
Event					19	19
Casino					5	5
Cruises					0	0
Others					0	0
Employment type						
Part-time					51	51
Full-time					26	26
Both					23	23

Descriptive Statistics

Among the three communication types, non-verbal behaviors had the greatest mean value ($M = 1.360$, $S.D = 3.649$), while para-verbal behaviors had the smallest mean value ($M = -.034$, $S.D. = 3.027$). In interviewer-reported Big-five personality traits, an agreeableness traits showed the biggest mean value ($M = 5.363$), followed by conscientiousness ($M = 5.339$), openness ($M = 4.928$), extraversion ($M = 4.426$), and neuroticism ($M = 4.164$) traits. Regarding self-reported Big-five personality traits, an openness trait had the largest mean value ($M = 6.05$), while a neuroticism trait had the lowest mean value ($M = 3.237$) which shows that interviewees tend to evaluate themselves having a greater level of emotional stability. In terms of machine learning-inferred Big-five personality traits, extraversion was the trait having the greatest mean value ($M = 57.139$), followed by agreeableness ($M = 51.33$), openness ($M = 50.395$), conscientiousness ($M = 44.445$), and neuroticism ($M = 28.461$).

Table 4.2 Descriptive Statistics

Dependent	M	S.D	Min	Max
Communication types				
Verbal behaviors	.0215	1.632	-3.570	3.650
Para-verbal behaviors	-.034	3.027	-8.365	7.466
Non-verbal behaviors	1.360	3.649	-4.730	16.370
Interviewer-reported Big-five personality traits				
Neuroticism	4.164	1.836	1	7
Extraversion	4.426	1.559	1	7
Openness	4.928	1.254	1	7
Agreeableness	5.363	1.08	2.25	7
Conscientiousness	5.339	1.099	2.2	7
Self-reported Big-five personality traits				
Neuroticism	3.237	1.537	1	7
Extraversion	5.684	1.08	2.25	7
Openness	6.05	0.852	4	7
Agreeableness	4.286	1.523	1	7
Conscientiousness	5.777	0.792	4	7
Machine learning-inferred Big-five personality traits				
Neuroticism	28.461	4.719	19.06	40.26
Extraversion	57.139	6.942	44.02	67.29
Openness	50.395	7.005	36.37	68.65
Agreeableness	51.33	6.172	39.77	68.82
Conscientiousness	44.445	5.212	35.57	59.28
Hiring decisions	4.632	1.766	1	7

Constructs Validity and Reliability

Confirmatory factor analysis (CFA) was performed to verify the validity and reliability of constructs, that is interviewer-reported, self-reported, machine learning-inferred Big-five personality traits, and hiring decisions by using R software and lavaan package (Rosseel, 2012). The results of CFA indicated a moderate fit of the model to data ($\chi^2(116) = 658.510$, $p < .001$, CFI = 0.837, TLI = 0.804, IFI = 0.840, RMSEA = .061), while the values of CIF > .9, TLI > .9, IFI > .9 and RMSEA < .05 are considered to have a good fit of the model to the data (Hoyle & Panter, 1995; Kline, 2005). The CFA results showed that composite reliability (CR) of two constructs that were measured by survey items (i.e., interviewer-reported and self-reported Big-five personality traits) ranged from 0.852 to 0.954 higher than the cut-off value of 0.7, which confirming convergent validity of the constructs (Hair et al., 2010). For discriminant validity, the square root of AVE for each latent factor was greater than each correlation, confirming discriminant validity (Fornell & Larcker, 1981). Tables 4.3, 4.4, and 4.5 show the results of validity and reliability of interviewer-reported and self-reported Big-five personality traits. Bivariate Correlations of the research variables are described in Table 4.6.

Table 4.3 Confirmatory Factor Analysis for Interviewer-reported Big-five Personality traits: Items, Loadings, C,R,, and AVE

Construct and Scale Item	Loading	C.R.	AVE
Neuroticism (α =.949)			
1. This interviewee looks like he/she gets stressed out easily.	0.859	0.911	0.673
2. This interviewee looks like he/she worries about things.	0.856		
3. This interviewee looks like he/she fears for the worst.	0.833		
4. This interviewee looks like he/she is filled with doubts about things.	0.701		
5. This interviewee looks like he/she panics easily.	0.840		
Extraversion (α = .961)			
6. This interviewee looks like he/she talks a lot to different people at parties.	0.811	0.883	0.602
7. This interviewee looks like he/she feels comfortable around people.	0.736		
8. This interviewee looks like he/she starts conversations.	0.710		
9. This interviewee looks like he/she makes friends easily.	0.753		
10. This interviewee looks like he/she doesn’t mind being the center of attention.	0.862		
Openness (α = .943)			
11. This interviewee looks like he/she gets excited by new ideas.	0.740	0.866	0.565
12. This interviewee looks like he/she enjoys thinking about things.	0.778		
13. This interviewee looks like he/she enjoys hearing new ideas.	0.735		
14. This interviewee looks like he/she enjoys looking for a deeper meaning in things.	0.792		
15. This interviewee looks like he/she has a vivid imagination.	0.712		
Agreeableness (α = .920)			
16. This interviewee looks like he/she sympathizes with others’ feelings.	0.890	0.900	0.694
17. This interviewee looks like he/she is concerned about others.	0.813		

19. This interviewee looks like he/she respects others.	0.852		
20. This interviewee looks like he/she believes that others have good intentions.	0.772		
Conscientiousness (α = .921)			
21. This interviewee looks like he/she carries out my plans.	0.554		
22. This interviewee looks like he/she pays attention to details.	0.713		
23. This interviewee looks like he/she is always prepared.	0.830	0.856	0.548
24. This interviewee looks like he/she makes plans and sticks to them.	0.747		
25. This interviewee looks like he/she is exacting in my work.	0.824		

Notes. C.R. = Composite reliability; AVE = Average variance extracted

Table 4.4 Confirmatory Factor Analysis for Self-reported Big-five Personality traits: Items, Loadings, C.R., and AVE

Construct and Scale Item	Loading	C.R.	AVE
Neuroticism (α = .959)			
1. I get stressed out easily.	0.872		
2. I worry about things.	0.894		
3. I fear for the worst.	0.904	0.954	0.805
4. I am filled with doubts about things.	0.923		
5. I panic easily.	0.893		
Extraversion (α = .907)			
6. I talk a lot to different people at parties.	0.857		
7. I feel comfortable around people.	0.848		
8. I start conversations.	0.875	0.913	0.679
9. I make friends easily.	0.779		
10. I don't mind being the center of attention.	0.754		
Openness (α = .850)			
11. I get excited by new ideas.	0.763		
12. I enjoy thinking about things.	0.805		
13. I enjoy hearing new ideas.	0.833	0.874	0.586
14. I enjoy looking for a deeper meaning in things.	0.847		
15. I have a vivid imagination.	0.538		
Agreeableness (α = .793)			
16. I sympathize with others' feelings.	0.870		
17. I am concerned about others.	0.885	0.881	0.651
19. I respect others.	0.788		
20. I believe that others have good intentions.	0.666		
Conscientiousness (α = .806)			
21. I carry out my plans.	0.730		
22. I pay attention to details.	0.767		
23. I am always prepared.	0.699	0.852	0.536
24. I make plans and stick to them.	0.804		
25. I am exacting in my work.	0.653		

Notes. C.R. = Composite reliability; AVE = Average variance extracted

Table 4.5 Composite Reliabilities, Correlations, and Squared Root of AVE

	CR	AVE	1	2	3	4	5	6	7	8	9	10
1. IN	0.911	0.673	0.82[a]									
2. IE	0.883	0.602	-.746**[b]	0.776								
3. IO	0.866	0.565	-.541**	.677**	0.752							
4. IA	0.9	0.694	-.255**	.462**	.706**	0.833						
5. IC	0.856	0.548	-.541**	.587**	.732**	.589**	0.74					
6.SN	0.954	0.805	0.112	0.037	-0.008	0.170	0.083	0.897				
7. SE	0.913	0.679	-.233*	.253**	0.075	-0.027	0.008	-.390**	0.824			
8. SO	0.874	0.586	0.103	0.0385	-0.012	0.040	-0.016	-0.020	.293**	0.765		
9. SA	0.881	0.651	.262**	-0.178	-0.004	0.067	-0.039	0.070	0.030	.224*	0.807	
10. SC	0.852	0.536	0.098	0.104	0.053	0.049	0.117	-0.115	.255**	.300**	0.023	0.732

Notes. [a] Square root of the AVE is along the diagonal; [b] Correlations are below the diagonal; * p < .05; ** p < .01; IN = Interviewer-reported neuroticism; IE = Interviewer-reported Extraversion; IO = Interviewer-reported openness; IA = Interviewer-reported agreeableness; IC = Interviewer-reported conscientiousness; SN = Self-reported neuroticism; SE = Self-reported extraversion; SO = Self-reported openness; SA = Self-reported agreeableness; SC = Self-reported conscientiousness.

Table 4.6 Bivariate Correlations of Variables

	VB	PB	NB	SN	SE	SO	SA	SC	IN	IE	IO	IA	IC	MN	ME	MO	MA	MC	HD
VB	1																		
PB	-.200*	1																	
NB	.286**	-.056	1																
SN	.034	-.152	-.037	1															
SE	.075	-.051	-.104	-.390**	1														
SO	-.062	-.334**	.162	-.02	.293**	1													
SA	-.147	.119	-.146	.07	.03	.224*	1												
SC	.019	.055	.003	-.116	.255**	.300**	.023	1											
IN	-.208*	-.075	-.19	.112	-.233*	.103	.262**	.099	1										
IE	.413**	-.057	.219*	.037	.253**	.039	-.178	.104	-.746**	1									
IO	.309**	.189	.301**	-.008	.075	-.012	-.004	.054	-.541**	.677**	1								
IA	.329**	-.056	.350**	.17	-.027	.04	.068	.049	-.255**	.462**	.706**	1							
IC	.166	.208*	.364**	.083	.007	-.016	-.039	.117	-.541**	.587**	.732**	.589**	1						
MN	.107	-.161	-0.145	-.241*	.205*	.221*	-.083	.052	-.038	.062	-.055	-.029	-.131	1					
ME	-.068	.222*	-.058	-.189	.226*	-.061	-.124	.038	-.287**	.196*	.13	.127	.084	.372**	1				
MO	-.042	-.132	-.021	-.031	.211*	.199*	-.119	.13	-.135	.186	.198*	.173	.031	.547**	.242*	1			
MA	.001	-.172	.137	-.177	.201*	.234*	-.117	.280**	-.016	.082	-.023	.026	.08	.420**	.066	.181	1		
MC	-.187	.154	.181	-.14	-.003	.261**	.266**	.101	-.079	-.028	.084	.062	.051	-.149	.114	.102	-.271**	1	
HD	.342**	-.037	.298**	.08	.162	.008	-.273**	-.086	-.701**	.749**	.727**	.570**	.658**	.022	.213*	.199*	.079	-.022	1

Notes. * p < .05; ** p < .01; IN = Interviewer-reported neuroticism; IE = Interviewer-reported Extraversion; IO = Interviewer-reported openness; IA = Interviewer-reported agreeableness; IC = Interviewer-reported conscientiousness; SN = Self-reported neuroticism; SE = Self-reported extraversion; SO = Self-reported openness; SA = Self-reported agreeableness; SC = Self-reported conscientiousness; MN = Machine learning-inferred neuroticism; ME = Machine learning-inferred extraversion; MO = Machine learning-inferred openness; MA = Machine learning-inferred agreeableness; MC = Machine learning-inferred conscientiousness; HD = Hiring decision

Hypothesis Test

The multiple linear regression analyses were conducted to test the proposed hypotheses and empirically investigate the relationships among three communication types, three types of Big-five personality traits, and hiring decisions. For the analyses, mock-up job candidates' work experience was included as a control variable due to its possible effect on hiring decisions because job candidates' work experience may show their job knowledge and thus impact employers' willingness to hire (Schmidt & Hunter, 1998). All multiple linear regression analyses were performed by IBM SPSS Statistics Version 29.0.1.1.

Table 4.6 shows the associations among three communication types, interviewer-reported Big-five personality traits, and hiring decisions made by interviewers. Regarding the relationships between three communication types and five dimensions of interviewer-reported Big-five personality traits, verbal behaviors were related to extraversion (β = .364, p < .01), openness (β = .227, p < .01), and agreeableness (β = .169, p < .01) traits, thus confirming *H1b, H1c,* and *H1d*. Para-verbal behaviors were significantly associated with openness (β = .108, p < .01) and consciousness (β = .090, p < .01) traits, supporting *H5c* and *H5e*. Finally, non-verbal behaviors had a significant relationship with openness (β = .079, p < .05), agreeableness (β = .083, p < .01), and conscientiousness (β = .104, p < .01) traits, confirming *H9c, H9d,* and *H9e*.

Regarding the associations between interviewer-reported Big-five personality traits and hiring decisions, neuroticism (β = -.406, p < .01), extraversion (β = .270, p < .01), agreeableness (β = .327, p < .01) were significantly associated with hiring decisions, supporting *H13a H13b,* and *H13d*.

Table 4.7 Results of Interviewer-reported Big-five Personality Traits

Models	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent	**N**	**E**	**O**	**A**	**C**	**Hiring decision**
Constant	3.306** (.178)	4.254** (.169)	4.815** (.135)	5.290** (.118)	5.204** (.119)	.931 (.824)
Control variable						
Work experience	.001 (.003)	0.004 (.003)	.000 (.003)	-.002 (.002)	.000 (.002)	.005* (.002)
Communication types						
Verbal	-.181 (.096)	.364** (.091)	.227** (.072)	.169** (.063)	.080 (.064)	
Para-verbal	-.060 (.051)	.026 (.048)	.108** (.038)	-.002 (.033)	.090** (.034)	
Non-verbal	-.060 (.042)	.026 (.045)	.079* (.032)	.083** (.028)	.104** (.028)	
Personality						
Neuroticism						-.406** (.099)
Extraversion						.270* (.109)
Openness						.281 (.140)
Agreeableness						.327* (.129)
Conscientiousness						.158 (.132)
Adjusted R^2	.040	.163	.178	.152	.165	.705
F statistics	2.088	6.130**	6.704**	5.713**	6.186**	42.919**

Notes. * *p* : <.05; ** *p* : <.01; N = Neuroticism; E = Extraversion; O = Openness; A = Agreeableness; C = Conscientiousness.

As can be seen in Table 4.7, the relationships among three communication types, interviewees' self-reported Big-five personality traits, and hiring decisions by interviewers were investigated. Specifically, about the relationships between three communication types and self-reported Big-five personality traits, while model 2 regarding an extraversion trait was significant ($F = 3.708$, $p < .01$), no communication type had a relationship with the extraversion trait. Both para-verbal behaviors ($\beta = -.096$, $p < .01$) and non-verbal behaviors ($\beta = .045$, $p < .05$) were significantly related to an openness trait, confirming *H7c* and *H11c*.

Regarding the associations between self-reported Big-five personality traits and hiring decisions made by interviewers, extraversion ($\beta = .288$, $p < .05$) and conscientiousness ($\beta = .486$, $p < .01$) traits were significantly associated with hiring decisions, supporting *H14b* and *H14e*.

Table 4.8 Results of Self-reported Big-five Personality Traits

Models	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent	**N**	**E**	**O**	**A**	**C**	**Hiring decision**
Constant	4.377** (.215)	4.080** (.172)	5.942** (.093)	5.724** (.127)	5.725** (.095)	6.655** (1.679)
Control variable						
Work experience	-.007 (.004)	.012** (.003)	.002 (.002)	.000 (.002)	.002 (.002)	.003 (.004)
Communication types						
Verbal	.031 (.116)	.084 (.092)	-.102 (.050)	-.064 (.069)	.012 (.051)	
Para-verbal	-.114 (.061)	.016 (.049)	-.096** (.027)	.034 (.036)	.023 (.027)	
Non-verbal	-.023 (.051)	-.061 (.040)	.045** (.022)	-0.034 (.030)	-.001 (.022)	
Personality						
Neuroticism						-.309 (.220)
Extraversion						.288* (.128)
Openness						.074 (.213)
Agreeableness						.185 (.097)
Conscientiousness						.486** (.156)
Adjusted R^2	.018	.094	.140	.042	.004	.137
F statistics	1.477	3.708**	5.262**	1.107	.457	5.162**

Notes. **p* : <.05; ** *p* : <.01; N = Neuroticism; E = Extraversion; O = Openness; A = Agreeableness; C = Conscientiousness.

The results regarding the relationships among three communication types, machine leaning-inferred Big-five personality traits, and hiring decisions are described in Table 4.8. Among three communication types, verbal (β = .650, $p < .05$) and non-verbal (β = .322, $p < .05$) behaviors were significantly related to an extraversion trait. Thus, *H4b* and *H12b* were supported. Among five dimensions of machine leaning-inferred Big-five personality traits, neuroticism (β = -.072, $p < .05$), extraversion (β = .063, $p < .05$), openness (β = .082, $p < .05$) had significant relationships with interviewers' hiring decisions, confirming *H15a*, *H15b*, and *H15c*. While model 4 for an agreeableness trait was significant (F = 6.095, $p < .01$), no communication type had a significant association with the agreeableness trait.

Table 4.9 Results of Machine Learning-inferred Big-five Personality Traits

Models	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent	**N**	**E**	**O**	**A**	**C**	**Hiring decision**
Constant	50.875** (.721)	44.485** (.583)	51.246** (.736)	27.170** (.511)	56.779** (.809)	.894 (2.429)
Control variable						
Work experience	.025 (.016)	-.021 (.011)	.004 (.014)	.042** (.010)	.020 (.016)	.004 (.004)
Communication types						
Verbal	.533 (.434)	.723* (.314)	-.263 (.396)	-.280 (.275)	-.081 (.435)	
Para-verbal	-.260 (.229)	.146 (.166)	-.284 (.209)	-.152 (.145)	.558* (.230)	
Non-verbal	-.376 (.190)	.373** (.138)	-.019 (.174)	.176 (.121)	-.087 (.191)	
Personality						
Neuroticism						-.072* (.033)
Extraversion						.063* (.026)
Openness						.082* (.033)
Agreeableness						.024 (.043)
Conscientiousness						-.028 (.035)
Adjusted R^2	.052	.104	.018	.163	.029	.070
F statistics	2.444	4.048**	.596	6.095**	1.796	2.309*

Notes. **p* : <.05; ** *p* : <.01; N = Neuroticism; E = Extraversion; O = Openness; A = Agreeableness; C = Conscientiousness.

Finally, Table 4.9 introduces the results regarding the relationships between interviewees' three communication types and interviewers' hiring decisions. Among three communication types, verbal (β = .304, p < .01) and non-verbal (β = .104, p < .05) were significantly associated with hiring decisions. Thus, *H2* and *H10* were supported.

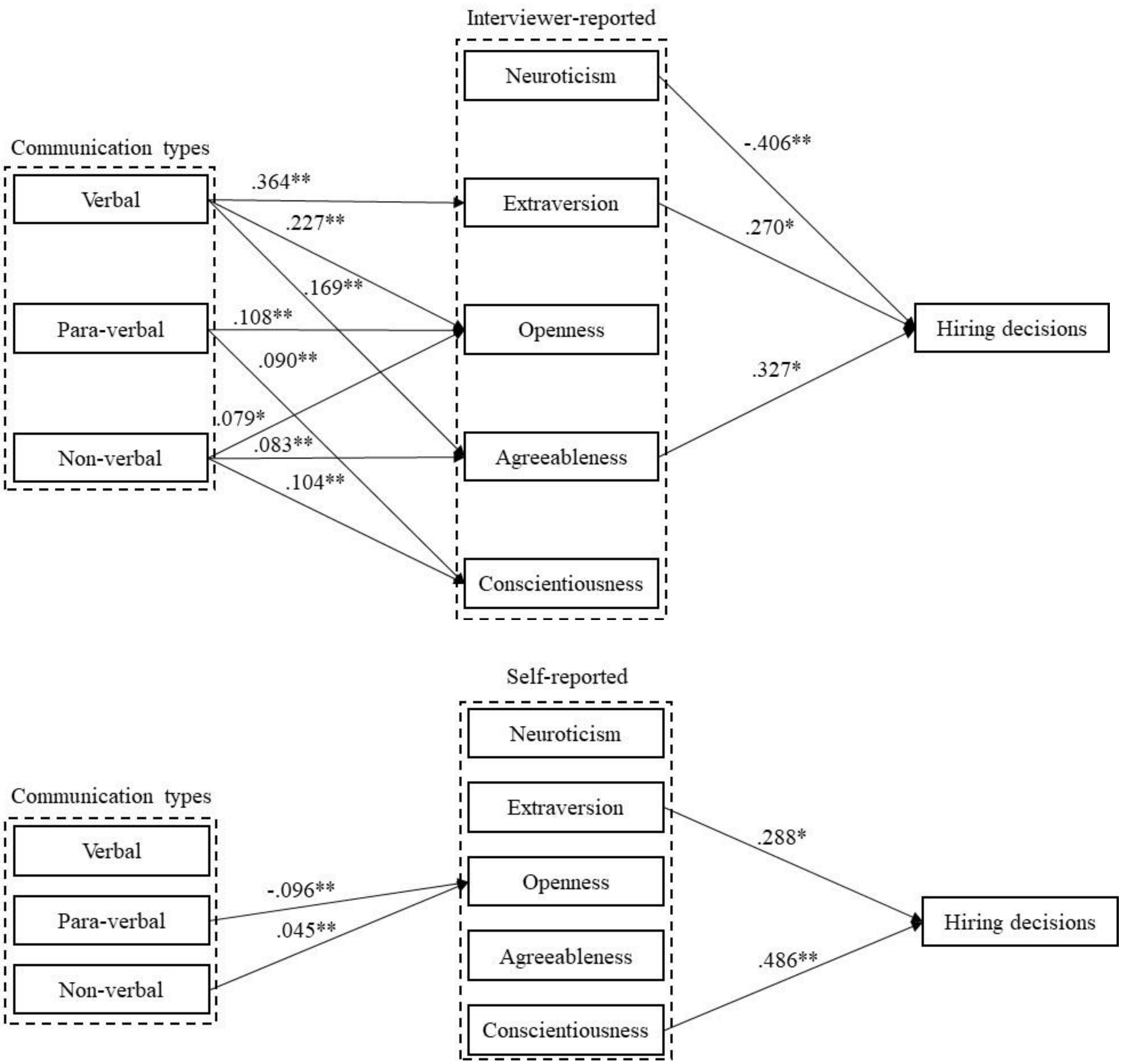
Table 4.10 Results of Communication Types And Hiring Decisions

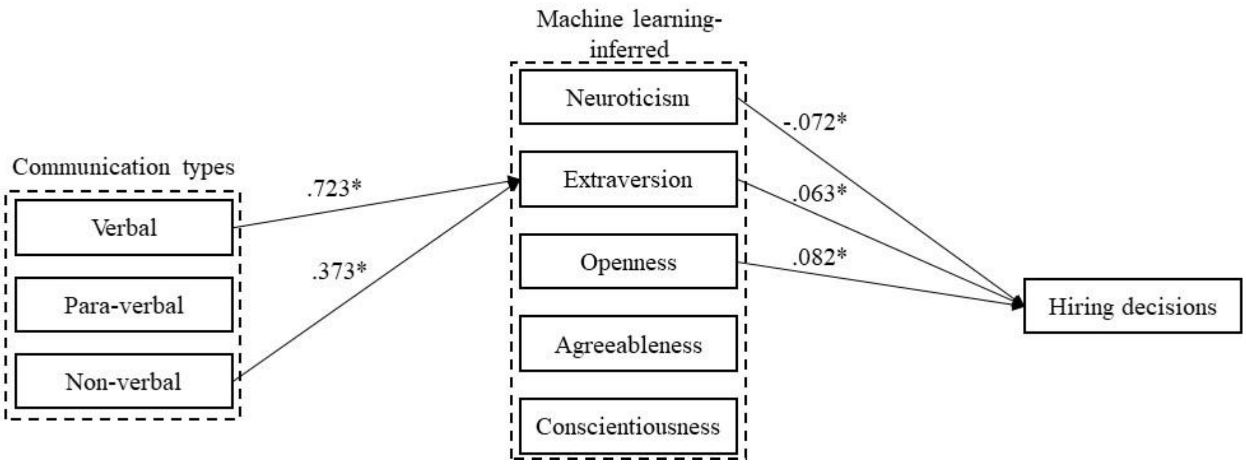
Dependent	**Hiring decision**
Constant	4.391** (.194)
Control variable	
Work experience	.004 (.004)
Communication types	
Verbal	.304**
	(.104)
Para-verbal	.030
	(.055)
Non-verbal	.104*
	(.046)
Adjusted R^2	.137
F statistics	5.162**

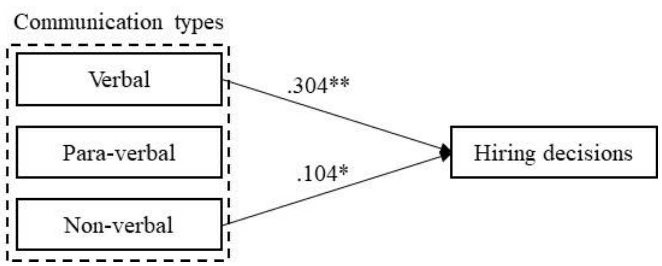
Notes. *p : <.05, **p : <.01

Figure 4.1 visually summarizes the results of this study.

Figure 4.1 The Results of The Current Study




Machine learning-inferred
Communication types
Verbal
Para-verbal
Non-verbal
.723*
.373*
Neuroticism
Extraversion
Openness
Agreeableness
Conscientiousness
-.072*
.063*
.082*
Hiring decisions


Communication types
Verbal
Para-verbal
Non-verbal
.304**
.104*
Hiring decisions

Chapter 5 - Conclusions

In the conclusions chapter, the major findings of the current study are discussed based on the results of testing research hypotheses (Table 5.1). Accordingly, theoretical and practical implications are discussed. Finally, limitations and recommendations for future research are suggested.

Table 5.1 Summary of Hypotheses Testing

Hypothesis	Supported	Hypothesis	Supported	Hypothesis	Supported
H1: V → IR		*H6*: PV→ HD	No	*H11e*	No
H1a	No	*H7*: PV → SR		*H12*: NV → ML	
H1b	Yes	*H7a*	No	*H12a*	No
H1c	Yes	*H7b*	No	*H12b*	Yes
H1d	Yes	*H7c*	Yes	*H12c*	No
H1e	No	*H7d*	No	*H12d*	No
H2: V → HD	Yes	*H7e*	No	*H12e*	No
H3: V → SR		*H8*: PV → ML		*H13*: IR → HD	No
H3a	No	*H8a*	No	*H13a*	Yes
H3b	No	*H8b*	No	*H13b*	Yes
H3c	No	*H8c*	No	*H13c*	No
H3d	No	*H8d*	No	*H13d*	Yes
H3e	No	*H8e*	No	*H13e*	No
H4: V → ML		*H9*: NV → IR		*H14*: SR → HD	
H4a	No	*H9a*	No	*H14a*	No
H4b	Yes	*H9b*	No	*H14b*	Yes
H4c	No	*H9c*	Yes	*H14c*	No
H4d	No	*H9d*	Yes	*H14d*	No
H4e	No	*H9e*	Yes	*H14e*	Yes
H5: PV → IR		*H10:* NV → HD	Yes	*H15*: ML → HD	
H5a	No	*H11*: NV → SR		*H15a*	Yes
H5b	No	*H11a*	No	*H15b*	Yes
H5c	Yes	*H11b*	No	*H15c*	Yes
H5d	No	*H11c*	Yes	*H15d*	No
H5e	Yes	*H11d*	No	*H15e*	No

Notes. V: Verbal behaviors, PV: Para-verbal behaviors, NV: Non-verbal behaviors, IR: Interviewer-reported Big-five personality traits, SR: Self-reported Big-five personality traits, ML: Machine learning-inferred Big-five personality traits, a: Neuroticism, b: Extraversion, c: Openness to experience, d: Agreeableness, and e: Conscientiousness

Summary of Major Findings

This study investigates the relationships among interviewees' three communication types (i.e., verbal, para-verbal, and non-verbal behaviors), three types of Big-five personality traits assessments (interviewer-reported, self-reported, and machine learning-inferred Big-five personality traits), and hiring decisions made by interviewers.

Relationships Between the Three Communication Types and Interview-reported Big-five Personality Traits

Overall, the three communication types showed even more significant relationships between interviewer-reported Big-five personality traits rather than self-reported and machine learning-inferred Big-five personality traits. While the three communication types had eight significant associations with extraversion, openness, agreeableness, and conscientiousness traits of interviewer-reported ratings, they also had two relationships with an openness trait of self-reported and two relationships with an extraversion trait of machine learning-inferred ratings. This tendency might be explained by prior studies that demonstrated that interviewer-reported Big-five personality traits have more validity and reliability than self-reported and machine learning-inferred Big-five personality traits (Barrick et al., 2000; Fan et al., 2023; Oh et al., 2011). Moreover, it can be explained by the nature of interviewer-reported ratings that interviewers conducted Big-five personality surveys based on their perceptions of interviewees' three communication types (Hickman et al., 2022). Thus, the three communication types had a greater number of significant relationships with interviewer-reported over self-reported traits and machine learning-inferred Big-five personality traits.

More specifically, the three communication types had no significant relationship with predicting a neuroticism trait by showing none of the three communication types had significant relationships with a neuroticism trait (*H1a, H5a*, and *H9a*). This result might be produced by the characteristics of a neuroticism trait that is related to interviewees' defensive tendencies and veiled behavioral tendencies (Peeters & Lievens, 2006). For example, it is possible that while interviewers want to capture a neuroticism personality based on interviewees' subconscious behaviors, interviewees may tend to naturally hide and suppress behaviors related to a neuroticism trait. Although the three communication types have several significant relationships with other personality traits, they may not effectively predict the neuroticism trait.

Openness, agreeableness, and conscientiousness traits had numerous significant relationships with the three communication types (*H1c*, *H1d*, *H5c*, *H5e*, *H9c*, *H9d*, and *H9e*). It has been known that, while openness, agreeableness, and conscientiousness traits are desired traits for organizations, they are harder recognize by others due to the innate and private nature of the three traits than an extraversion trait which can be more easily shown to others (Barrick et al., 2000; Oh et al., 2010). Although scant research provides a concrete rationale for numerous significant relationships between the three traits (i.e., openness, agreeableness, and conscientiousness) and three communication types, DeGroot and Gooty (2009) suggest possible reasons by showing that interviewees' visual cues (i.e., non-verbal behaviors in the current study) and vocal cues (para-verbal behaviors in the current study) are related to conscientiousness and openness traits but the agreeableness trait is not. DeGroot and Gooty (2009) also mentioned that their results may be caused by the interviewers' responsibility that the interviewers had to infer conscientiousness and openness traits as they are both desirable yet hardly noticeable. Based on DeGroot and Gooty's (2009) implications, this study supports their findings by additionally confirming the significant relationships between verbal behaviors and openness and agreeableness traits, in addition to para-verbal (i.e., vocal cues) and non-verbal behaviors (i.e., visual cues). Thus, our results may imply that interviewers use all three communication types to recognize the innate personality traits of openness, agreeableness, and conscientiousness.

However, this does not necessarily mean that interviewers do not try to understand interviewees' extraversion trait, especially in the hospitality industry, where employees' vital and active attitudes are one of the keys to enhance customers satisfaction (Doan et al., 2021). One of the findings of this study is that an extraversion trait had one significant relationship with verbal behaviors (*H1b*). This result can be supported by a prior study (Neff et al., 2010) demonstrating that, while both human language (i.e., verbal behaviors) and gestures (i.e., non-verbal behaviors) are adequate for predicting the perceptions of an extraversion trait, language plays a more significant role in shaping the perceptions of an extraversion trait, as human language is more nuanced and thus enhances the naturalness of extraversion perceptions. Thus, taken together, our results may imply that, while interviewers pay more attention and effort to interviewees' openness, agreeableness, and conscientiousness traits based on three communication types, interviewers use only verbal behaviors to understand an extraversion trait due to verbal behaviors' effectiveness.

Relationships Between the Three Communication Types and Self-reported Big-five Personality Traits

Contrary to the relationships between the three communication types and the interviewer-reported Big-five personality traits, three communication types had only two significant relationships with self-reported Big-five personality traits (*H7c* and *H11c*). The limited significant relationships with self-reported ratings is supported by a prior study that showed human language usage (i.e., verbal behaviors in the current study), on average, twice as accurately predicted self-reported rather than interviewer-reported Big-five personality traits (Hickman et al., 2000). They argue that language usage performs less in predicting self-reported ratings than interviewer-reported ratings due to a self-bias in self-reported ratings that draws on the self-other knowledge asymmetry model (Vazire, 2010). For example, it can happen that while interviewees use particular language usage related to extraversion and openness traits during job interviews, interviewees may rate a conscientiousness trait higher in self-reported surveys based on usual self-perceptions of their personality traits. On the other hand, interviewers would rate extraversion and openness traits higher based on the language usage they perceive. In this case, the interviewees' particular language usage would have more significant relationships with extraversion and openness traits of interviewer-reported Big-five personality traits. However, language usage would be less likely to have significant relationships with self-reported Big-five personality traits. Thus, due to self-bias in self-reported ratings, three communication types may not have significant relationship with self-reported Big-five personality traits in this study's results. This study supports Hickman et al.'s (2000) findings by additionally confirming the numerous insignificant relationships between the three communication types and self-reported Big-five personality traits, in addition to verbal behaviors (i.e., language usage).

Still, our study found significant relationships between para-verbal and non-verbal behaviors and an openness trait (*H7c* and *H11c*). The dominance of an openness trait rather than the other four dimensions of Big-five personality traits might be due to the characteristics of an openness trait. An openness trait is regarded as a trait related to aesthetic sensitivity, attentiveness to inner feelings, and being adaptive, which contributes to a higher level of stress tolerance (Lee-Baggley et al., 2005; Williams et al., 2009). In the job interview context, it might be plausible that interviewees who believe they have a higher stress tolerance level would evaluate an openness trait more correctly with fewer self-bias than other personality trait dimensions even after stressful situations, such as job interviews. Thus, two communication types (i.e., para-verbal and non-verbal behaviors) might be only associated with an openness trait of self-reported ratings, overshadowing significant relationships with the other four personality dimensions. One empirical study showed similar results that various acoustic features (e.g., jitter, shimmer, and intensity; para-verbal behavior in the current study) can be a strong predictor of an openness trait (Kasefy et al., 2020). While the acoustic features are significantly related to extraversion, openness, and agreeableness of self-reported Big-five personality traits, an openness trait has more numbers and stronger relationships with the acoustic features. Despite the possible significant relationships between verbal behaviors and an openness trait, verbal behaviors did not significantly predict an openness trait among the three communication types (not supported *H3c*). This might be explained by the interviewees' impression management strategy that they commonly use various verbal tactics (e.g., self-promotion, other-focused, and defensive) to create a desired impression to employers (Levashina et al., 2014). Thus, the discrepancies in interviewees' self-perceptions between usual verbal language and unusual verbal tactics during the job interviews may cause an insignificant association of verbal behaviors on an openness trait by making verbal behaviors during the job interviews a less reliable predictor.

Relationships Between the Three Communication Types and Machine Learning-inferred Big-five Personality Traits

Similar to the relationships between the three communication types and self-reported Big-five personality traits, our results found that the three communication types had only two significant associations with machine learning-inferred Big-five personality traits (*H4b* and *H12b*). The limited significant relationships of the three communication types with machine learning-inferred Big-five personality traits might be explained by the different context between the three communication types shown during the job interviews and social media activities used to measure machine learning-inferred Big-five personality traits (Roulin & Stronach, 2022). For example, during job interviews, interviewers present the three communication types while they answer interview questions and have conversations with interviewers. Thus, the implicature of the three communication types highly depends on the types of interview questions and the job interview atmosphere. However, LinkedIn postings are where machine learning-inferred Big-five personality traits can be written anytime job candidates want and even delicately revised before publication. Thus, the implicature of Big-five personality traits is more likely to be different than that of the three communication types shown during job interviews. Accordingly, the three communication types may have only a limited number of significant relationships with machine learning-inferred Big-five personality traits. Another possible reason can be the measurement system of machine learning-inferred Big-five personality traits (Yarkoni, 2010). Machine learning inference models commonly perform based on specific word libraries (Koutsoumpis et al., 2022). Thus, even though some words in LinkedIn postings are related to specific personality traits, they can be ignored if they do not exist in the word library. Scant relationships between the three communication types and machine learning-inferred Big-five personality traits support prior studies that showed machine learning-inferred Big-five personality traits have lower validity and reliability than other-reported and sometimes self-reported Big-five personality traits, although machine learning-inferred ratings would be additionally helpful in understanding a target's personality traits (Hickman et al., 2019; Roulin & Stronach, 2022).

Nevertheless, our result found significant relationships between verbal and non-verbal behaviors and an extraversion trait of machine learning-inferred Big-five personality traits (*H4b* and *H12b*). The preeminence of an extraversion trait instead of the other four dimensions of Big-five personality traits may be explained by the purposes of using social media (i.e., LinkedIn) to make connections and show various activities that are close to the meaning of an extraversion trait (Fernandez et al., 2021). Thus, job candidates who believe they are extraverted would be more likely to use words related to an extraversion trait in their LinkedIn postings and actively use communication types during job interviews. Accordingly, two communication types (verbal and non-verbal behaviors) may be only associated with an extraversion trait of machine learning-inferred ratings, overshadowing the significant relationships with the other four personality dimensions. Similar to our results, Kristof-Brown et al. (2002) showed that extroverted people use more non-verbal behaviors, such as smiling and eye contact. While para-verbal behaviors also have a possible significant relationship with an extraversion trait, it was not significant (not supported *H8b*). This result might be due to the characteristics of acoustic features that the variation of acoustic features highly depends on human factors, such as age and gender (Zhang et al., 2017). Since the interviewee sample of this study did not control those factors, the mixed effects of age and gender may attenuate a possible significant association between para-verbal behaviors and an extraversion trait.

Relationships Between the Big-five Personality Traits and Hiring Decisions

Regarding the relationships between the three types of Big-five personality traits assessments (i.e., interviewer-reported, self-reported, and machine learning-inferred) and hiring decisions, this study compares numerous significant relationships across the three types of Big-five personality traits assessments in predicting hiring decisions.

First, in terms of a neuroticism trait, it had a significant relationship on hiring decisions in interviewer-reported and machine learning-inferred Big-five personality traits (*H13a* and *H15*). A neuroticism trait does not have to be insignificant in self-reported ratings (not supported *H14a*), because controlling emotional stability is essential for employees, especially in various hospitality jobs related to emotional labor (Doan et al., 2021). The insignificance might be explained by the sensitive nature of a neuroticism trait that is associated with various mental health conditions and functions (Kotov et al., 2010). Due to its sensitivity, individuals tend to be challenged to objectively evaluate a neuroticism trait (Shabrina et al., 2022). This biased answer may attenuate a possible significant relationship between a neuroticism trait in self-reported ratings and hiring decisions.

Second, an extraversion trait solely was associated with hiring decisions across the three types of Big-five personality traits assessments (*H13b*, *H14b*, and *H15b*). This result is supported by prior studies saying employees with greater extraversion are more likely to build teamwork and job satisfaction in general (Cortina et al., 2000; Levashina et al., 2014; Roth et al., 2005). The significance of an extraversion trait is more evident in the hospitality industry, where active and energetic service provision is one of the most influential factors in enhancing service quality and satisfying customers (Doan et al., 2021; Silva, 2006). Thus, job candidates who are recognized as extroverted by interviewers (*H13b*), believe they are extraverted (*H14b*), and actively show extraversion in their LinkedIn postings (*H15b*) received more job offers in our study.

Third, in terms of an openness trait, an openness trait was exclusively significant in the relationships between machine learning-inferred Big-five personality traits and hiring decisions (*H15c*). This result might be explained by the characteristics of social media, where job candidates publicly make postings and build networks with unknown people (Fernandez et al., 2021). The characteristics of social media (i.e., LinkedIn) are related to the meaning of an openness trait, that is, being imaginative, curious, and board-mindedness (Goldberg, 1999). Job candidates who understand the characteristics of social media well would be more likely to use words related to an openness trait. Accordingly, machine learning models may more adequately capture the significant relationship between an openness trait and hiring decisions (*H15c*) rather than interviewer-reported and self-reported ratings (not supported *H13c* and *H14c*) in our study.

Fourth, about an agreeableness trait, it was solely significant in interviewer-reported Big-five personality traits (*H13d*). This significance may come from the awkward nature of job interviews, where interviewers often need to evaluate job candidates they meet for the first time (Mount et al., 1994). Thus, considering this aspect of job interviews, interviewees who present a greater level of agreeableness might receive higher scores in hiring decisions, signaling interpersonal warmth and cooperative attitudes. Conversely, of course, interviewers with warm attitudes can also be evaluated as agreeable people by interviewees. However, self-reported Big-five personality traits do not include interviewees' evaluation of interviewers. The characteristics of job interviews may make the significant association of an agreeableness trait on hiring decisions more evident in interviewer-reported ratings (*H13d*).

Finally, as to a conscientiousness trait, it was only significant in self-reported Big-five personality traits (*H14e*). This result might reflect the inherent and private nature of conscientiousness that is hardly recognizable by others (Barrick et al., 2000). Thus, a conscientiousness trait might not be effectively captured by interviewer-reported and machine learning-inferred ratings (not supported *H13e* and *H15e*), even though a conscientiousness trait is commonly desired by employers and job candidates know it.

Relationships Between the Three Communication Types and Hiring Decisions

Regarding the relationships between interviewees' three communication types and hiring decisions made by interviewers, our study found that verbal and non-verbal behaviors were significantly related to hiring decisions (H2 and H10). While all three communication types have a possible significant relationship with hiring decisions based on signaling theory, para-verbal behaviors were not significant in predicting hiring decisions (not supported H6). The significance of verbal and non-verbal behaviors may be explained by their high dependence on human's innate and solid cognitive and psychological structure in interviewees' language patterns and facial emotions (Hollandsworth Jr. et al., 1979; Kafetsios & Hess, 2022; Keltner, 1996; Tausczik & Pennebaker, 2010), making verbal and non-verbal behaviors more reliable signals than para-verbal behaviors. Conversely, the human voice system might be more unstable and changeable, depending on situational factors, such as weather or time (Everett et al., 2015; Lavan et al., 2019). Moreover, acoustic features highly rely on speakers' physical factors, such as age and gender, which are uncontrollable (Zhang et al., 2017). Thus, these factors may make para-verbal behavior less reliable and with fewer signals, thus having an insignificant association with hiring decisions.

Theoretical Implications

First, this study contributes to the hospitality literature by empirically investigating relationships between Big-five personality traits and hiring decisions in the selection process. Due to its importance in the hospitality industry, numerous hospitality researchers have documented the associations between Big-five personality traits and various outcomes, such as customer relationships, team relationships, organizational benefits, and individual benefits (Doan et al., 2021; Leung & Law, 2010; Silva, 2006; Tracey et al., 2007). Nevertheless, there are few empirical hospitality studies that examine the relationship between Big-five personality traits and hiring decisions, even though the hiring process is critical as the first step to obtaining competitive human resources (Carless, 2005; Kim et al., 2019). It is important to explore the specific relationships between the dimensions of Big-five personality traits and particular consequences because the effect of each dimension of Big-five personality traits can vary due to the multidimensional nature of human personality and the characteristics of specific consequences (Klinger & Siangchokyoo, 2024; Oh et al., 2011). Thus, this study adds to our knowledge about Big-five personality traits in the selection context to hospitality literature by empirically confirming significant dimensions of Big-five personality traits in predicting hiring decisions.

Second, the current study makes contributions to the literature in the recruitment context by examining the associations between interviewees' three communication types (i.e., verbal, para-verbal, and non-verbal behaviors) and Big-five personality traits. While prior studies have suggested the concept of three communication types to comprehend interviewees' behaviors and their relationships with hiring decisions (DeGroot & Gooty, 2009; DeGroot & Motowidlo, 1999; Feiler & Powell, 2016; Wilhelmy et al., 2016), they paid little attention to whether these three communication types are related to Big-five personality traits. The three communication types have potential benefits in explaining Big-five personality traits as they capture human's subconscious behaviors with fewer biases and interventions (Hickman et al., 2022). Based on signaling theory, this study empirically finds numerous significant relationships between the three communication types and Big-five personality traits based on the characteristics of each communication type and dimension of Big-five personality traits. Thus, the current study extends the usefulness of three communication types relating to the Big-five personality traits in order to better understand job candidates' personality traits.

Furthermore, this study also found significant relationships of verbal and non-verbal behaviors with hiring decisions, while para-verbal behaviors were insignificant. The significance of verbal and non-verbal behaviors can be explained by prior studies that emphasize unique and solid cognitive and psychological systems in human language patterns and facial emotions (HKafetsios & Hess, 2022; Keltner, 1996; Tausczik & Pennebaker, 2010). On the other hand, acoustic features in para-verbal behaviors were found to be less reliable signals due to their variability influenced by situational and human physical factors (Everett et al., 2015; Lavan et al., 2019; Zhang et al., 2017). This finding supports the signaling theory that posits the reliability of signals determines the quality of signals, thus receiving more attention (Connelly et al., 2011).

Third, our study contributes to the body of personality identification in the selection process by using three types of the Big-five personality traits assessments (i.e., interviewer-reported, self-reported, and machine learning-inferred) and investigating their relationships with hiring decisions. Prior studies in personality identification have confirmed the psychometric properties, that is, the validity and reliability of three types of Big-five personality trait assessments in explaining relevant outcomes, such as job performance or academic performance

(Connelly & Ones, 2010; Fan et al., 2023; Hickman et al., 2022; Klinger & Siangchokyoo, 2024; Mount et al., 1994; Oh et al., 2011). By extending this theoretical foundation, the current study empirically investigates and compares influential dimensions from three types of Big-five personality traits assessment on hiring decisions. As discussed in the summary of findings, several significant results reflect the characteristics of each Big-five personality assessment and dimensions (Barrick et al., 2000; Doan et al., 2021; Fernandez et al., 2021; Shabrina et al., 2022). Thus, our study provides empirical evidence of using three types of Big-five personality traits assessments in the hiring process.

Practical Implications

First, this study provides practical guidance for hospitality employers to find the right people by understanding interviewees' Big-five personality traits using subconscious communication types. Our results highlight the importance of an extraversion trait by finding extraversion traits from all three types of Big-five personality traits are significantly related to hiring decisions. Furthermore, an extraversion trait is mainly predicted by verbal behaviors across the three types of Big-five personality traits. This result implies that employers should pay more attention to interviewees' verbal behaviors (i.e., language patterns) to understand their extraversion level better rather than para-verbal and non-verbal behaviors. To understand an openness trait, interviewers may need to consider all three communication types, implying that a comprehensive assessment of interviewees' verbal, para-verbal, and non-verbal communication would help identify the openness of interviewees.

Moreover, the current study offers valuable information that HR managers may want to refer to when training interviewers in terms of the three communication types. Among the three communication types, verbal and non-verbal behaviors are the only influential factors in predicting hiring decisions. This suggests that when making hiring decisions, rather than understanding specific personality traits, interviewees' verbal and non-verbal behaviors should be considered more closely. Rather, paying attention to interviewees' para-verbal behaviors rather than their verbal and non-verbal behaviors would be less meaningful and may provide a possible bias when making hiring decisions. Also, it should be noted that verbal behaviors have a larger effect size than non-verbal behaviors with hiring decisions. Thus, interviewers may want to put more emphasis on interviewees' verbal answers rather than their facial emotions.

Finally, our study shows how employers better understand job candidates' Big-five personality traits using the three types of Big-five personality assessments-interviewer-reported, self-reported, and machine learning-inferred ratings-when making hiring decisions. Our results provide effective guidance of using specific Big-five personality traits assessments for each dimension of Big-five personality traits, because they provide different rating patterns. For example, employers may refer to self-reported ratings for conscientiousness level over the other two assessment types. At the same time, machine learning-based personality traits can help measure openness levels on job candidates' LinkedIn pages. When identifying the agreeableness of job candidates, interviewer-reported ratings would be the most helpful. The relative importance of the three types of Big-five personality traits may depend on specific personality traits that employers are looking for. Thus, based on the current organizational culture and/or characteristics of job positions, employers may want to select specific types of Big-five personality traits to better understand the particular personality traits of job candidates.

Limitations and Suggestions for Future Research

This study has several limitations. First, we used the Big Five personality framework to measure job candidates' personality traits due to its applicability and predictive validity. Still, more personality assessment frameworks exist, such as the Eysenck Personality Questionnaire, Minnesota Multiphasic Personality Inventory, and Myers-Briggs Type Indicator, which capture different aspects of human personality traits (Wiggins & Trapnell, 1997). Thus, although Big-five personality framework has been widely used in personality measurement, future studies may want to consider various frameworks to make more generalizable results, which might be helpful to fully understand human personality.

Second, our study measures interviewees' three communication types by aggregating specific measurements' values. For example, when measuring para-verbal behaviors, we aggregate the values of eleven acoustic features to effectively interpret the results. However, this aggregation may hinder researchers from more deeply understanding the research variables and phenomenon (Orcutt et al., 1968; Taghiyeh et al., 2023). For instance, possible significant associations of loudness, pitch, and pause with Big-five personality traits may provide even more specific and novel findings in understanding interviewees' personality traits. Thus, future studies have opportunities to utilize specific measurements for three communication types (not necessarily all of them at once) for a deeper understanding of personality traits.

Third, among the five dimensions of Big-five personality traits, our study was not able to find significant relationships between three communication types and a neuroticism trait. Nevertheless, hospitality employers may want to hire job candidates with a greater level of emotional stability because of the emotionally stressful working environment of the hospitality industry (Doan et al., 2021). The insignificant relationships between three communication types and a neuroticism trait may come from the aggregated values of specific measurements for the three communication types mentioned above. Therefore, future research may use specific measurements and/or find other behaviors beyond three communication types to predict a neuroticism trait of job candidates.

Fourth, while the current study mainly focuses on the associations among three communication types, Big-five personality traits, and hiring decisions, possible moderators may exist in terms of relationships between interviewees and interviewers. For example, gender or ethnicity differences between interviewees and interviewers may affect the hiring decisions in terms of diversity and inclusion (Derous & Pepermans, 2019). Future studies would supplement the body of personality assessment literature by identifying and empirically investigating various moderators.

Finally, this study examines the relationships of three communication types and Big-five personality traits with hiring decisions, assuming interview performance (i.e., hiring decisions) as a possible indicator of future job performance (McCarthy et al., 2013). However, relevant measurements related to job performance might be obtained by conducting a longitudinal study (Tims et al., 2015). A longitudinal study may require researchers to cooperate with practitioners in the field. Thus, future researchers may want to work with practitioners for a longitudinal study, which may help achieve a true meaning of prediction using three communication and Big-five personality traits during job interviews.

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Appendix A - IRB Approval

Kansas State University | University Research Compliance Office

TO: Jichul Jang
Hospitality Management
Manhattan, KS 66506

Proposal Number: IRB-11676

FROM: Lisa Rubin, Chair
Committee on Research Involving Human Subjects

DATE: 05/04/2023

RE: Proposal Entitled, "Investigating the effects of the Big five personality traits on interview performance: Using voice and face recognition techniques using a job interview."

The Committee on Research Involving Human Subjects / Institutional Review Board (IRB) for Kansas State University has reviewed the proposal identified above and has determined that it is EXEMPT from further IRB review. This exemption applies only to the proposal - as written – and currently on file with the IRB. Any change potentially affecting human subjects must be approved by the IRB prior to implementation and may disqualify the proposal from exemption.

Based upon information provided to the IRB, this activity is exempt under the criteria set forth in the Federal Policy for the Protection of Human Subjects, **45 CFR §104(d), category:Exempt Category 2 Subsection ii.**

Certain research is exempt from the requirements of HHS/OHRP regulations. A determination that research is exempt does not imply that investigators have no ethical responsibilities to subjects in such research; it means only that the regulatory requirements related to IRB review, informed consent, and assurance of compliance do not apply to the research.

Any unanticipated problems involving risk to subjects or to others must be reported immediately to the Chair of the Committee on Research Involving Human Subjects, the University Research Compliance Office, and if the subjects are KSU students, to the Director of the Student Health Center.

Electronically signed by Lisa Rubin on 05/04/2023 3:28 PM ET

KANSAS STATE UNIVERSITY | University Research Compliance Office

TO: Jichul Jang
Hospitality Management
Manhattan, KS 66506

FROM: Lisa Rubin, Chair
Committee on Research Involving Human Subjects

DATE: 03/13/2024

RE: Proposal #IRB-11676, entitled "Investigating the effects of the Big five personality traits on interview performance: Using voice and face recognition techniques using a job interview."

MODIFICATION OF IRB PROTOCOL #IRB-11676, ENTITLED, "Investigating the effects of the Big five personality traits on interview performance: Using voice and face recognition techniques using a job interview"

EXPIRATION DATE: Exempt

The Committee on Research Involving Human Subjects (IRB) has reviewed and approved the request identified above as a modification of a previously approved protocol. **Please note that the original expiration remains the same.**

All approved IRB protocols are subject to continuing review at least annually, which may include the examination of records connected with the project. Announced in-progress reviews may also be performed during the course of this approval period by a member of the University Research Compliance Office staff. Unanticipated adverse events involving risk to subjects or to others must be reported immediately to the Chair of the IRB, and / or the URCO

It is important that your human subjects activity is consistent with submissions to funding / contract entities. It is your responsibility to initiate notification procedures to any funding / contract entity of any changes in your activity that affects the use of human subjects.

KANSAS STATE UNIVERSITY | University Research Compliance Office

Electronically signed by Lisa Rubin on 03/13/2024 3:59 PM ET

Appendix B - Promotional QR code

1. Purpose of study
- To predict interviewers' personality traits based on behaviors

2. Requirement
- Have **LinkedIn**

3. What you will do
1) **Online survey** regarding personality traits (5 mins)
2) **A mock-up interview** through Zoom (10-15 mins)

4. When?
- Feb 19 ~ 29
- Specific time and date will vary

5. Risk and benefit
- No risk at all
- **Experience job interview** and **compensation of $8**

Any questions?

Juhwan Lim (jhlim90@ksu.edu)

Appendix C - Cover letter and online survey questionnaires for mock-up interviewees

KANSAS STATE UNIVERSITY

Thanks for participating in an online pre-survey about personality traits and mock-up job interview! This is a research project being conducted by Juhwan, Lim (limjuhwan3411@gmail.com), a Ph.D. candidate at the department of hospitality management, Kansas state university. The purpose of this research is to investigate the role of personality traits during the selection process.

PARTICIPAION

Your participation in this pre-survey and online mock-up job interview is completely voluntary. You may stop and refuse the pre-survey and mock-up job interview at any time with no penalty. You are free to decline to answer any particular question you do not wish to answer for any reason. If you decide to participate in this pre-survey and experiment, please take a few minutes to answer each question on the pre-survey as accurately and completely as possible.

BENEFITS

You will receive no direct benefits from participating in this pre-survey and mock-up job interview. However, your responses may provide us a better understanding of the role of personality traits during the selection process, so that you may work for a more suitable job position and company in the future.

RISK

There are no foreseeable risks involved in participating in this pre-survey and mock-up interview.

CONFIDENTIALITY

Your responses will be processed confidentially and remain anonymous. No individual responses will not be reported. Only aggregated data will be used. Your responses will be stored online using Qualtrics and OneDrive where the data is protected with the password encryption from each researcher university Qualtrics and OneDrive account. No one will be able to identify you and your answers, and no one will know whether you participated in this pre-survey and mock-up job interview or not.

A summary of results will be available at K-state Research Exchange (http://krex.k-state.edu/dspace/) when the study is completed. Further, the subjects will be asked to leave their e-mail if they have any questions on this study.

If you agree to participate, please check the agreement button below.

Agree

The following questions are about your **demographics**.

Please provide your Prolific ID

1. Please indicate your gender.

- Male
- Female
- Prefer not to answer

2. Please indicate your age.

3. Please select your ethnicity.

- Asian
- African American
- Caucasian
- Hispanic / Latino
- Pacific Islander
- Other
- Prefer not to answer

4. Please select your marital status.

- Single
- Married
- Widowed
- Divorced
- Separated
- Prefer not to answer

5. Please select the highest level of education that you have completed.

- Less than high school
- High school
- University
- Masters / Ph.D.
- Technical school
- Others
- Prefer not to answer

6. Please select the specific hospitality industry that you want to work in the most.

- Hotel
- Restaurant
- Event
- Casino
- Cruises
- Other

7. Have you ever worked in the hospitality industry?

- Yes
- No

7.1 If yes, please select the specific hospitality industry that you worked in.

- Hotel
- Restaurant
- Event
- Casino
- Cruises
- Other

7.2 If yes, how long did you work in the hospitality industry?

Year	
Month	

7.3 If yes, please indicate the type of employment.

- Part-time
- Full-time
- Both

8. Please share your LinkedIn (https://linkedin.com) webpage URL.

9. Please share your email address.

Listed below are statements about your personality traits regarding Neuroticism. Please indicate how much you agree or disagree with the statements.

1-1. I get stressed out easily.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

1-2. I worry about things.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

1-3. I fear for the worst.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

1-4. I am filled with doubts about things.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

1-5. I panic easily.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

Listed below are statements about your personality traits regarding Extraversion. Please indicate how much you agree or disagree with the statements.

2-1. I talk a lot to different people at parties.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

2-2. I feel comfortable around people.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

2-3. I start conversations.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

2-4. I make friends easily.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

2-5. I don't mind being the center of attention.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

Listed below are statements about your personality traits regarding Openness. Please indicate how much you agree or disagree with the statements.

3-1. I get excited by new ideas.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

3-2. I enjoy thinking about things.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

3-3. I enjoy hearing new ideas.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

3-4. I enjoy looking for a deeper meaning in things.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

3-5. I have a vivid imagination.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

4-1. I sympathize with others' feelings.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

4-2. I am concerned about others.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

4-3. I enjoy hearing new ideas.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

4-4. I respect others.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

4-5. I believe that others have good intentions.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

5-1. I carry out my plans.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

5-2. I pay attention to details.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

5-3. I am always prepared.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

5-4. I make plans and stick to them.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

5-5. I am exacting in my work.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree

Appendix D - Cover letter and online survey questionnaires for mock-up interviewers

KANSAS STATE UNIVERSITY

Thanks for participating in an online pre-survey about personality traits and mock-up job interview! This is a research project being conducted by Juhwan, Lim (limjuhwan3411@gmail.com), a Ph.D. candidate at the department of hospitality management, Kansas state university. The purpose of this research is to investigate the role of personality traits during the selection process.

PARTICIPAION
Your participation in this pre-survey and online mock-up job interview is completely voluntary. You may stop and refuse the pre-survey and mock-up job interview at any time with no penalty. You are free to decline to answer any particular question you do not wish to answer for any reason. If you decide to participate in this pre-survey and experiment, please take a few minutes to answer each question on the pre-survey as accurately and completely as possible.

BENEFITS
You will receive no direct benefits from participating in this pre-survey and mock-up job interview. However, your responses may provide us a better understanding of the role of personality traits during the selection process, so that you may work for a more suitable job position and company in the future.

RISK
There are no foreseeable risks involved in participating in this pre-survey and mock-up interview.

CONFIDENTIALITY
Your responses will be processed confidentially and remain anonymous. No individual responses will not be reported. Only aggregated data will be used. Your responses will be stored online using Qualtrics and OneDrive where the data is protected with the password encryption from each researcher university Qualtrics and OneDrive account. No one will be able to identify you and your answers, and no one will know whether you participated in this pre-survey and mock-up job interview or not.

A summary of results will be available at K-state Research Exchange (http://krex.k-state.edu/dspace/) when the study is completed. Further, the subjects will be asked to leave their e-mail if they have any questions on this study.

If you agree to participate, please check the agreement button below.

Agree

1. Please indicate your gender.

- ◯ Male
- ◯ Female
- ◯ Prefer not to answer

2. Please indicate your age.

3. Please select the specific hospitality industry that you worked or are working in.

- ◯ Hotel
- ◯ Restaurant
- ◯ Event
- ◯ Other

4. How long did you work in the hospitality industry?

Year (approximately)

Listed below are statements about first interviewee' personality traits regarding Neuroticism (emotional stability). Please indicate how much you agree or disagree with the statements.

1.1 This interviewee looks like he/she gets stressed out easily.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

1.2 This interviewee looks like he/she worries about things.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

1.3 This interviewee looks like he/she fears for the worst.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

1.4 This interviewee looks like he/she is filled with doubts about things.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

1.5 This interviewee looks like he/she panics easily.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

Listed below are statements about first interviewee' personality traits regarding Extraversion. Please indicate how much you agree or disagree with the statements.

2.1 This interviewee looks like he/she talks a lot to different people at parties.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

2.2 This interviewee looks like he/she feels comfortable around people.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

2.3 This interviewee looks like he/she starts conversations.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

2.4 This interviewee looks like he/she makes friends easily.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

2.5 This interviewee looks like he/she doesn't mind being the center of attention.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

Listed below are statements about first interviewee' personality traits regarding Openness. Please indicate how much you agree or disagree with the statements.

3.1 This interviewee looks like he/she gets excited by new ideas.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

3.2 This interviewee looks like he/she enjoys thinking about things.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

3.3 This interviewee looks like he/she enjoys hearing new ideas.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

3.4 This interviewee looks like he/she enjoys looking for a deeper meaning in things.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

3.5 This interviewee looks like he/she has a vivid imagination.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

Listed below are statements about first interviewee' personality traits regarding Agreeableness. Please indicate how much you agree or disagree with the statements.

4.1 This interviewee looks like he/she sympathizes with others' feelings.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

4.2 This interviewee looks like he/she is concerned about others.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

4.3 This interviewee looks like he/she enjoys hearing new ideas.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

4.4 This interviewee looks like he/she respects others.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

4.5 This interviewee looks like he/she believes that others have good intentions.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

Listed below are statements about first interviewee' personality traits regarding Conscientiousness. Please indicate how much you agree or disagree with the statements.

5.1 This interviewee looks like he/she carries out my plans.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

5.2 This interviewee looks like he/she pays attention to details.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

5.3 This interviewee looks like he/she is always prepared.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

5.4 This interviewee looks like he/she makes plans and sticks to them.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

5.5 This interviewee looks like he/she is exacting in my work.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

Listed below are statements about your hiring decisions on the first interviewee. Please indicate how much you agree or disagree with the statements.

6.1 I would recommend extending a job offer to this candidate.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

6.2 Overall, I evaluate this candidate positively.

Entirely disagree	Mostly disagree	Somewhat disagree	Neutral	Somewhat agree	Mostly agree	Entirely agree
○	○	○	○	○	○	○

6.3 On a scle of 1 to 100, please indicate the extent to which you would like to hire the first interviewee.