THE REPUBLIC OF TÜRKİYE
SOCIAL SCIENCES UNIVERSITY OF ANKARA
THE GRADUATE SCHOOL OF SOCIAL SCIENCES

THE MEDIATING ROLE OF DYNAMIC CAPABILITIES IN THE RELATIONSHIP BETWEEN BIG FIVE PERSONALITY TRAITS AND INNOVATION PERFORMANCE OF STARTUP BUSINESSES: EVIDENCE FROM SAUDI ARABIA

Master's Thesis

Mohammed Abdullah Salem BA GUBAIR

Master of Science in Business Administration (English)

November 2023

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Mohammed Abdullah Salem BA GUBAIR

DECLARATION

I am Mohammed Abdullah Salem BA GUBAIR hereby declare that this thesis entitled *"The Mediating Role of Dynamic Capabilities in The Relationship Between Big Five Personality Traits and Innovation Performance of Startup Businesses: Evidence from Saudi Arabia"* is the result of my own work and under supervision and guidance of my advisor Dr. Mustafa ÇOLAK. Also, I declare that this thesis was conducted based on academic ethics and rules. I have undertaken that all materials which were taken from previous studies to support this research were referenced and quoted. Finally, as for the rules of writing, it was done in accordance with the rules and regulations of the Social Sciences University of Ankara.

22/11/2023

Mohammed Abdullah Salem BA GUBAIR

TABLE OF CONTENTS

ÖZET

Beş Büyük Kişilik Özellikleri ve Startup İşletmelerinin İnovasyon Performansı Arasındaki İlişkide Dinamik Yeteneklerin Aracı Rolü: Suudi Arabistan'dan Kanıtlar

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Günümüzün rekabetçi kurumsal ortamında, startup'lar ekonomik kalkınma ve inovasyon açısından kritik öneme sahiptir. Yenilikçilik açısından startupların performansını etkileyen faktörlerin anlaşılması da kritik önem taşımaktadır. Bu tez çalışması, startup kurucularının Beş Büyük kişilik özellikleri ile bu kurucuların işletmelerinin inovasyon performansı arasındaki bağlantıyı ve dinamik yeteneklerin bu ilişkide aracı olarak oynadığı rolü incelemektedir. Bu çalışma özellikle, startup inovasyon performansının olası göstergeleri olarak vicdanlılık, dışadonukluk, deneyime açıklık, uyumluluk ve nevrotiklik gibi Büyük Beş kişilik özelliğine bakmaktadır. Bu çalışma, bu özelliklerin, kurucuların engellerle nasıl başa çıktıkları, fırsatları nasıl aradıkları ve çevreleriyle nasıl etkileşime geçtikleri üzerinde etkili olabileceğini ve bunların hepsinin de firmalarının yenilikçi performansı üzerinde etkili olabileceğini varsaymaktadır. Ayrıca bu ilişkide aracı değişken olarak dinamik yetenekler ele alınmaktadır. Bu çalışmada kurucuların kişilik özelliklerinin, startuplarındaki dinamik yeteneklerin gelişimini etkilediği ve bunun da inovasyon performansını etkilediği öne sürülmektedir.

Öne sürülen argümanları incelemek için toplam 11 hipotez geliştirilmiştir. Bu hipotezleri araştırmak için 185 startup sahibine veya yöneticisine anketler gönderildi. Bu örnekleme çerçevesinden 128 ankete yanıt alındı. Veriler SPSS 29 ve Smart-PLS 4 yazılımları ile analiz edildi.

Sonuçlar, kullanılan ölçüm ölçeklerinin ne güvenilir ne de geçerli olduğunu; bu da resmi prosedürler yoluyla (örneğin, çoklu regresyon analizi veya yapısal eşitlik modellemesi kullanılarak) hipotez test edilmesinin anlamlı olmadığını ortaya koydu. Araştırmanın değişkenleri arasındaki korelasyonlar incelendiğinde, beş büyük kişilik özelliği, dinamik yetenekler ve

inovasyon performansı arasında istatistiksel olarak anlamlı bir ilişkinin bulunmadığı; ve dolayısıyla önerilen hipotezlerin hiçbirinin desteklenmediği ortaya çıkmıştır.

Bu çalışmada kullanılan ölçeklerin güvenirlik ve geçerlilik açılarından yetersiz kalmasının olası bazı nedenleri belirlenmiştir. Ölçeklerin güvenilirliği ve geçerliliğinin olmayışı, özellikle Suudi Arabistan bağlamında, kurucuların kişilik özellikleri, startupların dinamik yetenekleri ve inovasyon performansları arasındaki karmaşık etkileşimi kapsamlı bir şekilde incelemek için ölçüm araçlarının daha fazla araştırılması ve geliştirilmesi gerekliliğini önermektedir.

Anahtar Kelimeler: Beş büyük kişilik özelliği, dinamik yetenekler, yenilikçilik performansı, startup, Suudi Arabistan

ABSTRACT

The Mediating Role of Dynamic Capabilities in The Relationship Between Big Five Personality Traits and Innovation Performance of Startup Businesses: Evidence from Saudi Arabia

Mohammed Ba-Gubair
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In today's competitive corporate environment, startups are pivotal for economic development and innovation. Understanding the factors influencing startup performance, particularly in terms of innovation, is crucial. This thesis investigates if startup founders’ Big Five personality traits are related to the innovation performance of their businesses, along with the mediating role of dynamic capabilities in this relationship. Specifically, this study explores how the Big Five personality traits (i.e., conscientiousness, extraversion, openness to experience, agreeableness, and neuroticism) potentially affect startup innovation performance. The study posits that these traits might influence founders' approaches to challenges, identification of opportunities, and engagement with their environment, thereby impacting their firms' innovative performance. Additionally, the study introduces dynamic capabilities as a mediator, proposing that founders' personality traits influence the development of dynamic capabilities within their startups, which in turn affects innovation performance.

Total of 11 hypotheses were developed to examine the posited arguments. To investigate these hypotheses, questionnaires were sent to 185 startup owners or executives. 128 responses were received from the sampling frame. Data were analyzed by SPSS 29 and Smart-PLS 4 statistical software packages.

The results indicated that the measurement scales used were not neither reliable nor valid, suggesting that hypothesis testing through formal procedures (e.g., by using multiple regression analysis or structural equation modeling) was not doable. Examination of the correlations among the study’s variables indicated that there were no statistically significant relationships among big five personality traits, dynamic capabilities and innovation performance, suggesting that none of the proposed hypotheses were supported.

Some possible reasons for the lack of reliability and validity of the scales used in this current study is identified. The lack of reliability and validity of the measurement scales prompt further exploration and refinement of measurement tools to comprehensively examine the intricate interplay between founders' personality traits, dynamic capabilities, and innovation performance in the startup context, in particular in the context of Saudia Arabia.

Keywords: Big five personality traits, dynamic capabilities, innovation performance, startup, Saudi Arabia

LIST OF ABBREVIATIONS

Neuro: Neuroticism

Extrv: Extraversion

Consc: Conscientiousness

Open: Openness

Agree: Agreeableness

DC: Dynamic Capabilities

Dyn Cap: Dynamic Capabilities

Sens: Sensing

Seiz: Seizing

Reconf: Reconfiguring

Inno Per: Innovation Performance

Prd Inov: Product Innovation

Prcs Inov: Process Innovation

IV: Independent Variable

DV: Dependent Variable

RBV: Resource-Based View

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1. Background

In today's ever-evolving global economy, the success and sustainability of startups hold a prominent position, driving economic growth and fostering innovation. Startups play a vital role in driving innovation. They are one of the main actors driving change in the innovation ecosystem (Korper et al., 2020).

While startups continue to gain significance in the business landscape, it becomes imperative to understand the multifaceted factors that underpin their success. A critical aspect of this success lies in the innovation performance of startups, which is influenced by various internal and external factors. Pietro et al. (2017) pointed out that innovation performance stands as a pivotal aspect in the success of startup enterprises, given its inherent connection to their capacity to foster progress, stimulate economic advancement, and ensure long-term viability.

Among the internal factors, individual personalities of founders and key decision-makers have recently garnered attention as potential determinants of startup innovation. Samašonok & Juškevičienė (2022) found that individuals with low conscientiousness, high extraversion, openness, and emotional stability were more likely to exhibit creativity which ultimately leads to innovation. This research however, seeks to investigate the relationship between the Big Five personality traits and the innovation performance of startups, with a particular focus on the mediating role of dynamic capabilities. Furthermore, this study draws upon evidence from the unique entrepreneurial ecosystem of Saudi Arabia.

The Big Five personality traits, which include openness, conscientiousness, extraversion, agreeableness, and neuroticism, are enduring psychological characteristics that influence how individuals think, feel, and behave in various contexts (Al-Hawari, 2015). Startups, being dynamic and often resource-constrained, heavily rely on the cognitive, emotional, and social dimensions of their founders and leaders. It is reasonable to postulate that these personality traits may influence the innovative behaviors and decision-making processes that drive startup success (Bergner, 2020).

Dynamic capabilities assume a pivotal role in the intricate innovation mechanisms inherent to startup enterprises. These capabilities are instrumental in equipping firms with the capacity to effectively adjust and transform their operations in light of swiftly changing external conditions. These capabilities involve the integration, building, and reconfiguration of internal and external competencies (Zollo & Winter, 2002). This research posits that dynamic capabilities may mediate the relationship between the Big Five personality traits and the innovation performance of startups. In other words, the personality traits of startup founders may influence their firm's ability to develop and leverage dynamic capabilities, which in turn affects innovation outcomes.

Saudi Arabia's startup ecosystem is a compelling context for this study. The Kingdom has undertaken a series of ambitious economic reforms and initiatives to diversify its economy and reduce dependence on oil revenues. As a result, it has witnessed a surge in entrepreneurial activities and government support for startups. However, the influence of individual personalities on the innovation performance of Saudi startups and the mediating role of dynamic capabilities in this context remains an underexplored area.

This research, therefore, endeavors to make a contribution to the existing reservoir of knowledge by conducting a thorough and comprehensive investigation into the complex interconnections among the Big Five personality traits, dynamic capabilities, and the innovation performance of startup enterprises, all within the distinct socio-economic and cultural context of Saudi Arabia. The outcomes of this study are expected to offer valuable insights that extend their applicability to entrepreneurs, policymakers, and investors operating in the Saudi Arabian landscape, while also enriching the global conversation surrounding the factors influencing the success of startups. Ultimately, the findings of this research are poised to serve as a compass for devising precision-targeted measures and strategies aimed at nurturing a more resilient and innovative startup ecosystem, thereby delivering benefits to both the local and international business communities. Consequently, this research endeavors to make a substantial contribution to the extant corpus of knowledge. It seeks to provide an examination of the intricate interrelationships among the Big Five personality traits, dynamic capabilities, and the innovation performance of startups within the distinctive socio-economic and cultural milieu of Saudi Arabia. The outcome of this inquiry may generate valuable insights with significant applicability to diverse stakeholders, including entrepreneurs, policymakers, and investors operating within the Saudi Arabian entrepreneurial landscape. Furthermore, this research is poised to extend its reach to the global discourse surrounding the factors that underpin the success of startup ventures. In summation, the discerned outcomes of this research are envisioned to serve as a guiding compass for the development of precisely targeted interventions and strategies, with the overarching goal of nurturing a more innovative and enduring startup ecosystem. Such endeavors, in turn, stand to accrue benefits not only to the local business community in Saudi Arabia but also resonate on an international scale.

1.2. Statement of The Problem

The dynamic and highly competitive landscape of the Saudi Arabian startup ecosystem necessitates an understanding of the factors shaping innovation performance among emerging enterprises. While the influence of individual personality traits, specifically the Big Five personality Traits (openness, conscientiousness, extraversion, agreeableness, and emotional stability), on entrepreneurial success has been explored in various contexts, there is a need to investigate their specific impact on the innovation performance of startups in Saudi Arabia. The main purpose of this thesis is to examine the question of how the Big Five personality traits of executives of startups influence the startups' innovation performance and to what extent this relationship is mediated by the dynamic capabilities exhibited by these startups in the context of Saudi Arabia. By addressing this knowledge gap, the study seeks to provide evidence-based insights that can inform strategies for fostering innovation in startup sector.

1.3. Research Questions

Based on what have been mentioned related to research problem, this study attempts to address the following main questions:

-Do Big Five personality traits of executives of startups influence the startups' innovation performance?

-To what extent this relationship is mediated by the dynamic capabilities exhibited by these startups?

1.4. Purpose of The Study

The main objective of this study is to investigate the mediating role of dynamic capabilities in the relationship between big five personality traits and innovation performance of startup businesses in the context of Saudi Arabia. In a broader academic context, this research endeavors to augment the existing body of knowledge pertaining to the intrinsic influence of human factors, specifically personality traits, within the entrepreneurial and innovation processes operational in the Saudi Arabian startup ecosystem. By discerning the intricate interplay of these factors, it aspires to yield valuable insights that are pertinent to both scholars and industry practitioners. This, in turn, facilitates a more profound comprehension of the multifaceted dynamics that may increase the innovative endeavors within this particular organizational landscape. Furthermore, through a systematic inquiry into the intermediary role of dynamic capabilities, the study is poised to unveil strategic pathways and operational mechanisms that startups can harness to bolster and optimize their innovation performance, offering practical guidance to entrepreneurial leaders navigating the intricacies of this burgeoning sector.

1.5. Significance of The Study

The study explores how the Big Five personality traits (i.e., openness, conscientiousness, extraversion, agreeableness, and neuroticism) influence the innovation performance of startups. This could provide valuable insights into the relationship between individual differences and entrepreneurial success, shedding light on the psychological aspects of innovation. The study also examines the mediating role of dynamic capabilities for the relationship between personality traits and innovation performance. This is significant as it adds a layer of complexity to the relationship. Understanding how dynamic capabilities mediate the influence of personality on innovation performance can provide actionable knowledge for entrepreneurs looking to improve their business strategies.

Focusing on Saudi Arabia, the study could offer specific insights into the cultural and contextual factors that affect the relationship between personality traits and innovation performance in this region. This information could be particularly valuable for policymakers, investors, and entrepreneurs operating in Saudi Arabia.

1.6. Justification of The Study

This research serves as a significant contribution to the expanding body of knowledge pertaining to startups, a pivotal driver of economic advancement. The investigation aims to elucidate the psychological factors (e.g., personality traits) that exert influence upon innovation within the realm of startups, thereby affording valuable insights of significance to scholars, and industry practitioners. Furthermore, through the examination of the intermediary function of dynamic capabilities, this study adopts an interdisciplinary approach, amalgamating facets of psychology and business management. This cross-disciplinary perspective is poised to furnish a more comprehensive overview of the innovation process within startup enterprises. The research addresses a conspicuous lacuna in the existing literature, as extant scholarship primarily investigates the connection between personality traits and entrepreneurial success, while comparatively fewer inquiries delve into the dynamics surrounding innovation performance and the mediating role played by dynamic capabilities. In this vein, this research endeavors to bridge that gap and offer a more comprehensive understanding of how personality influences innovation performance.

1.7. Organization of The Thesis

This chapter introduces the study topic and discusses its relevance literature review. While providing justifications for the chosen topic, the problem statement of the research is formulated, research questions are introduced and the purpose of this research is presented.

In the next chapter, the literature review is presented. While the topics and previous findings in relation are discussed the significance of the study will become clearer. This chapter will conclude with the presentation of the research model and the hypotheses. Chapter three details the research methodology explaining research design, sample characteristics, the measurement of the variables in the study, the data collection and analysis procedures. Chapter four reports the finding from data analysis including descriptive statistics, findings from correlation analyses, and the results of hypotheses testing. Chapter five is the last chapter of this study and it is devoted to the discussion and conclusion; which start with the restatement of the problems, the hypotheses or the relationships of the variables. Furthermore, it covers the recommendations and suggestions for the future research.

2. LITERATURE REVIEW

2.1. Overview

This chapter provides explanations for variables of the study, based on previous studies. It is organized around five parts. The first part focuses on the Big Five Personality traits. The second part deals with the concept of dynamic capability. The third part provides explanation for the concept of innovation performance. The fourth part gives a short explanation of startups vs SMEs (small-to-medium sized enterprises). Finally, the fifth part concludes this chapter with the research model and hypotheses of the study.

2.2. Big Five Personality Traits

The Five-Factor Model (FFM), colloquially known as the Big Five personality traits, stands as a firmly established and widely embraced conceptual framework within the discipline of personality psychology, as posited by McCrae and John in (1992). The five core dimensions of personality encompass openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. The broad scope and practical applicability of these Big Five traits have rendered them subjects of extensive scholarly exploration spanning diverse academic domains, including psychology, business, education, and entrepreneurship. The present literature review endeavors to offer a comprehensive synthesis of extant research pertaining to the Big Five personality traits and their multifaceted implications across various spheres of academic inquiry.

For example, Şahin et al. (2019) conducted a study in that delved into the interplay between the Big Five personality traits, entrepreneurial self-efficacy (ESE), and entrepreneurial intention. Their findings shed light on the significance of specific combinations of personality attributes, particularly elevated levels of ESE, in conjunction with specific configurations of the Big Five traits, in predicting an increased inclination toward entrepreneurial endeavors. This investigation underscores the critical importance of elucidating the intricate dynamics by which individual characteristics intersect and wield influence over entrepreneurial conduct.

In a similar vein, Lee et al. (2005) embarked on an exploration of personality attributes that extend beyond the traditional Big Five framework by investigating their association with the HEXACO model of personality. The research outcomes revealed the substantial explanatory power of the Big Five traits while also uncovering distinct personality dimensions that are not encapsulated within either the Big Five or HEXACO paradigms. This empirical inquiry underscores the necessity for a more nuanced and all-encompassing understanding of personality traits that transcends the confines of the Big Five paradigm.

Similarly, Bazkiaei et al. (2020) embarked on an investigation into the nexus between entrepreneurial education, the Big Five personality traits, and entrepreneurial intention. Their study ascertained a positive relationship between entrepreneurial education and certain personality traits, such as openness to experience and extraversion, and the inclination towards entrepreneurial endeavors. These findings posit the prospect that educational interventions, in conjunction with the cultivation of specific personality traits, have the potential to augment entrepreneurial attitudes and intentions among university students.

Moreover, Rahim & Rahim (2018) conducted a study examining the influence of personality traits, encompassing the Big Five, materialism, and stress, on compulsive buying behavior within the context of Malaysian Generation Y consumers. Their research unveiled that traits like agreeableness, neuroticism, and materialism significantly impact compulsive buying behavior, with materialism emerging as the most potent predictor. This exploration accentuates the pivotal role of personality traits, including those constituting the Big Five framework, in comprehending consumer behavior and, by extension, its implications for marketing and business strategies.

In an entirely different domain, Kwang & Rodrigues (2002) undertook an investigation into the Big Five personality profiles of adaptors and innovators. Their study unearthed distinctive personality-based disparities between these two creative archetypes, with adaptors exhibiting higher conscientiousness levels, while innovators manifested heightened extraversion and openness to experience. The recognition of these personality-driven distinctions in creative styles between adaptors and innovators signifies their potential to instigate interpersonal discord. This research underscores the imperative of recognizing and valuing divergent creative styles to mitigate conflict and foster collaboration among dissimilar creative cohorts.

Furthermore, Sharma et al. (2013) scrutinized the roles of personality traits, cognitive abilities, and emotional intelligence in predicting negotiation outcomes. Their study contravened the prevailing consensus positing that individual dissimilarities possess limited predictive efficacy in forecasting negotiation results. Contrarily, the research established the predictive validity of cognitive ability, emotional intelligence, and assorted personality traits across a spectrum of outcome measures. This inquiry underscores the critical importance of accounting for individual variances in negotiation processes and their subsequent ramifications.

In a study conducted by Iqbal et al. (2021) they explored how the Big Five personality traits impact customer's intentions to make purchases. Their research specifically focused on the role of trust, as a mediator in this process. The findings revealed that all personality traits, except for neuroticism directly influence customer's likelihood to make purchases. This scholarly work is valuable in enhancing our understanding of how personality traits shape consumer behavior in the realm of e commerce.

Moving on to another research endeavor by Shane & Nicolaou (2013) their investigation examined the influence of genetics on performance with a specific emphasis on the Big Five personality traits. Through their study they discovered that income earned by self-employed individuals can be associated with factors. Moreover, they found genes that contribute to the correlations between agreeableness, openness to experience, extraversion and self-employment income. Overall, Shane and Nikolaou's research provided insights into the interplay among genetics, personality traits and entrepreneurial performance. It emphasized the importance of considering factors when studying outcomes and highlighted how these factors may interact with environmental influences to shape an individual's path as a self-employed person and their financial achievements. This study served as a step in bridging our understanding between genetics and entrepreneurship while shedding light on the nature of success, in entrepreneurial endeavors. This study implies that the combination of inclinations and personal characteristics play a role, in achieving success as an entrepreneur.

Haris et al. (2021) conducted an investigation into the moderating influence of the Big Five personality traits on the correlation between Islamic financial planning and financial outcomes. Their study unveiled that individuals characterized by limited financial literacy and a heightened inclination toward openness to experience were more likely to engage in Islamic financial planning. This study enhances our comprehension of the roles played by personality traits, particularly in the context of Islamic financial planning. On a broader scale, it deepens our understanding of how personality traits can interact with financial behaviors, particularly in the realm of financial planning, which holds considerable significance in the context of business startup management. It underscores the notion that personality is not a universal concept and can exert an impact on financial decision-making.

In a different context, Chen et al. (2013) scrutinized the predictive capacity of the Big Five personality traits with respect to managerial coaching behaviors. Their findings illuminated positive associations between extraversion, openness to experience, agreeableness, conscientiousness, and various coaching behaviors, while neuroticism displayed a negative relationship. This research underscores the potential of personality traits, particularly extraversion, openness to experience, and conscientiousness, in forecasting managerial coaching behaviors. By discerning the link between personality traits and coaching behaviors, organizations can make well-informed decisions in the selection and training of managers.

Nga & Yien (2013) examined the impact of personality traits and demographic factors on financial decision-making among Generation Y individuals. Their research discerned that conscientiousness, openness, and agreeableness exerted substantial influence on risk aversion and cognitive biases in financial decision-making. This investigation underscores the pivotal roles played by personality traits in shaping financial behaviors and decision-making processes. This investigation underscores the pivotal roles played by personality traits in shaping the financial behaviors and decision-making processes of Generation Y individuals. It highlights the fact that financial decision-making is not solely a rational, objective process but is deeply influenced by individual differences in personality.

In a broader theoretical context, Ashton & Lee (2001) proposed a theoretical foundation for major dimensions of personality, including those encapsulated by the Big Five traits. Their research posited Surgency, Conscientiousness, and Intellect/Imagination as traits imbued with active engagement in social, task-related, and idea-related pursuits. This theoretical proposition furnishes a framework for comprehending the major dimensions of personality and their implications.

Moreover, Barrick & Mount (1991) undertook a meta-analysis probing the relationship between the Big Five personality dimensions and job performance. Their research substantiated the validity of extraversion, conscientiousness, emotional stability, and openness to experience as predictors of job performance across a spectrum of occupational domains. This scholarly endeavor underscores the critical import of considering personality traits in the realms of personnel selection, training, and performance evaluation. It highlights the significant importance of taking personality traits into account when making decisions related to personnel selection, training, and evaluating job performance.

Zhao et al. (2009) conducted a comprehensive meta-analytical investigation that sought to elucidate the intricate relationship between personality traits and entrepreneurial intentions and performance. Their research findings established a compelling association between the Big Five personality traits, in conjunction with risk propensity, and the formation of entrepreneurial intentions. However, the interplay between personality traits and entrepreneurial performance was observed to be notably nuanced. This study underscores the multifaceted roles that personality traits assume in the genesis and realization of entrepreneurial pursuits. The literature review underscores the significant impact of personality traits, alongside risk propensity, in influencing an individual's motivation to embark on an entrepreneurial path. Nevertheless, it underscores the indispensability of recognizing that entrepreneurial success hinges on a multifaceted interplay of factors, with personality being just one component of this intricate equation. A comprehensive understanding of how personality traits contribute to the emergence and achievement of entrepreneurial endeavors holds substantial value for both prospective entrepreneurs and scholars engaged in entrepreneurship research and education.

In summary, the extensive body of literature pertaining to the Big Five personality traits provides substantial empirical evidence to support their relevance and influence across a diverse range of domains, encompassing entrepreneurship, consumer behavior, negotiation, job performance, financial decision-making, and educational contexts. The collective research findings underscore the pivotal roles played by personality traits, particularly those encompassed within the Big Five framework, in shaping a wide spectrum of behaviors, attitudes, and outcomes. Appreciating and taking into account these traits carry profound implications for the development of theoretical frameworks, educational curricula, practical applications, and policy formulation within various academic and professional domains. Furthermore, the subsequent sections of this literature review will dissect the dimensions comprising the Big Five framework.

2.2.1. Conscientiousness

Conscientiousness, as a personality trait, has been a subject of substantial investigation concerning its implications for success within the realm of business, with a specific focus on the dynamic context of startups. Numerous empirical studies have endeavored to elucidate the intricate relationship between conscientiousness and various facets of startups, encompassing entrepreneurial intentions, performance metrics, and overall success.

A study conducted by Nga and Shamuganathan (2010) aimed to scrutinize the influence of personality traits, including conscientiousness, on the intentions to initiate social entrepreneurship ventures. The empirical findings unveiled that individual exhibiting higher levels of conscientiousness demonstrated heightened attributes such as leadership acumen, self-efficacy, and ambition, factors that significantly augmented their inclination to embark on entrepreneurial pursuits. This discernment underscores the pivotal role played by conscientiousness in shaping the entrepreneurial intentions of individuals, particularly in the context of social entrepreneurship.

In a parallel vein, other research Sarwoko & Nurfarida (2021) embarked on an inquiry into the interplay between entrepreneurial personality traits, among which conscientiousness was a central focus, and business performance outcomes. The research outcomes illuminated a constructive association between conscientiousness and business performance, wherein heightened conscientiousness was linked to behaviors typified by organization, diligence, and responsibility. These qualities, in turn, were identified as instrumental contributors to the overall success of entrepreneurial ventures.

Baluku et al. (2016) delved into the nuanced role of conscientiousness in moderating the relationship between startup capital infusion and entrepreneurial success. In an intriguing finding, it was discerned that neuroticism, a personality trait inversely correlated with entrepreneurial success, exhibited a more pronounced moderating effect in comparison to conscientiousness. This observation posits that individuals characterized by heightened conscientiousness may be adept at efficaciously leveraging startup capital, thereby enhancing the likelihood of realizing success in their entrepreneurial endeavors.

Furthermore, Setia (2018) conducted an investigation into the personality profiles of successful entrepreneurs, wherein conscientiousness emerged as a pivotal trait associated with entrepreneurial triumph. The study underscored the observation that individuals endowed with conscientious attributes tend to exemplify qualities such as diligence, organizational proficiency, and meticulous attention to detail—qualities that are intrinsically aligned with effective business management and decision-making processes.

In a broader empirical context, Freiberg and Matz (2023) embarked on a comprehensive field study focusing on technology startups. Their research endeavors sought to unravel the influence of founder personality traits, including conscientiousness, on critical milestones indicative of startup success. The study discerned a positive correlation between conscientiousness and pivotal markers of success, notably, the likelihood of securing venture capital and the prospect of acquisition. This empirically supported insight posits that individuals characterized by conscientious tendencies are more likely to attract external funding and attain successful outcomes within the purview of their startup endeavors.

Collectively, the extant literature underscores the significant import of conscientiousness as a personality trait that can exert a constructive influence on various facets of startups. Notably, it wields an impact on the formative stage, delineating entrepreneurial intentions, as well as on the subsequent performance metrics and ultimate success trajectories of ventures. Individuals imbued with conscientious attributes tend to manifest organizational prowess, diligence, and a proclivity for meticulous resource management, qualities that, in tandem, contribute to the effective stewardship of entrepreneurial undertakings. It is, however, germane to recognize that the interplay between conscientiousness and startup outcomes may be contingent upon a myriad of contextual factors, encompassing the specific industry, the prevailing business environment, and the confluence of other personality traits and resources. These intricate nuances necessitate ongoing scholarly inquiry to deepen our understanding of the multifaceted relationship between conscientiousness and startups and whether there is any mediating of moderating variables.

2.2.2. Openness to Experience

Butz et al. (2018) conducted a study titled "Beyond the Big Five: Does Grit Influence the Entrepreneurial Intent of University Students in the US?" This research delves into the intricate connection between grit and entrepreneurial intent, offering valuable insights into the role of personality traits in shaping intentions to initiate startups.

In a similar vein, Burch et al. (2022) authored a study entitled "An Examination of How Personal Characteristics Moderate the Relationship between Startup Intent and Entrepreneurship Education." This investigation explores the nuanced interplay between individual characteristics, such as confidence, and their potential to moderate the association between startup intent and entrepreneurship education. This inquiry contributes to the broader understanding of the influence of openness to experience in the pursuit of entrepreneurial education.

Saptadjaya and Gunawan (2020) conducted a study titled "The Effect of Self-Efficacy and Big Five Personality Traits towards Entrepreneurial Intention on International Business Management." This research comprehensively examines the impact of self-efficacy and the Big Five personality traits, including the pertinent dimension of openness to experience, on entrepreneurial intention. The findings of this study provide valuable insights into the intricate relationship between openness to experience and intentions to embark on entrepreneurial ventures.

Freiberg and Matz (2023) authored a study titled "Founder Personality and Entrepreneurial Outcomes: A Large-Scale Field Study of Technology Startups." This comprehensive investigation explores the ramifications of founder personality, encompassing dimensions such as openness to experience, on the outcomes of technology startups. The research endeavors to deepen our understanding of how openness to experience influences the trajectory and ultimate success of startup ventures.

In a slightly different context, Scherer et al. (2018) conducted a study titled "To Internationalize or Not to Internationalize? A Descriptive Study of a Brazilian Startup". This research delves into the decision-making processes of startups concerning internationalization, a strategic move that may inherently involve the dimension of openness to experience as a factor influencing their exploration of new markets and opportunities.

Lastly, Zhou et al. (2019) contributed to the body of literature with their study. This investigation adopts a nuanced approach to differentiate between pattern and level effects of personality traits, including openness to experience, on entrepreneurship. The study strives to shed light on the specific influence exerted by openness to experience on behaviors and outcomes intimately linked with startups.

In sum, these studies collectively offer valuable insights into the multifaceted relationship between openness to experience and various dimensions of startups, spanning entrepreneurial intent, education, success, internationalization, and specific behaviors and outcomes. By delving into these facets, they significantly contribute to the comprehensive understanding of how openness to experience shapes the entrepreneurial process and impacts outcomes within the dynamic context of startups. It is imperative to mention that the Big Five model does not represent the only framework employed for the comprehension of personality. In the sphere of leadership and decision-making, alternative models, such as the trait theory of personality, have been subject to exploration, as indicated by the work of Kreiner et al. (2018). Nevertheless, it is worth emphasizing that the Big Five model holds significant prominence and widespread recognition, affording a comprehensive and holistic framework for the examination of personality traits, as substantiated by Bergner (2020).

2.2.3. Extraversion

Schlaegel et al. (2021) conducted a comprehensive study titled "Personal Factors, Entrepreneurial Intention, and Entrepreneurial Status: A Multinational Study in Three Institutional Environments," which was published in the Journal of International Entrepreneurship in 2021. This research undertakes an examination of the intricate role played by personal factors, inclusive of broad personality traits such as extraversion, in shaping entrepreneurial outcomes within diverse countries and under varying institutional contexts.

In a similar vein, Tsoai and Chipunza (2022) authored a scholarly contribution. This empirical inquiry embarks on a comprehensive exploration of the nuanced relationship between personality traits, specifically delving into extraversion, conscientiousness, and openness to experience, and their impact on the performance of internet cafes.

Furthermore, Wang et al. (2015) contributed to the body of knowledge with their research study titled "The Contribution of Self-Efficacy to the Relationship between Personality Traits and Entrepreneurial Intention," published in Higher Education in 2015. This scholarly endeavor undertakes a rigorous investigation into the mediating role of self-efficacy in elucidating the intricate relationship between personality traits, with a specific focus on extraversion, and the entrepreneurial intentions of agricultural students.

The collective insights garnered from these scholarly references shed valuable light on the multifaceted relationship between extraversion and diverse dimensions of startups. These dimensions encompass entrepreneurial outcomes, performance metrics, and intentions to engage in entrepreneurial pursuits. In sum, these studies significantly contribute to the burgeoning body of knowledge concerning the pivotal influence exerted by extraversion on the entrepreneurial process and its subsequent ramifications within the dynamic milieu of startups.

2.2.4. Neuroticism

Sarwoko and Nurfarida (2021) conducted a scholarly inquiry, titled "Entrepreneurial Marketing: Between Entrepreneurial Personality Traits and Business Performance," which was published in the Entrepreneurial Business and Economics Review in 2021. This research undertakes a comprehensive examination of the pivotal role played by entrepreneurial personality traits, with a specific focus on neuroticism, in shaping the landscape of entrepreneurial marketing practices and their consequential impact on business performance.

In a parallel vein, Bazkiaei et al. (2020) made a significant scholarly contribution with their study. This research engages in a systematic investigation into the intricate relationship between the big-five personality traits, encompassing neuroticism, and their potential influence on the entrepreneurial intentions harbored by university students.

These scholarly references collectively provide illuminating insights into the multifaceted relationship between neuroticism and a spectrum of dimensions pertinent to startups. These dimensions encompass entrepreneurial marketing strategies, business performance metrics, and the formulation of entrepreneurial intentions, particularly among the student population. In sum, these studies significantly enrich our understanding of the nuanced impact exerted by neuroticism within the entrepreneurial milieu, shedding light on its implications for the entrepreneurial process and subsequent outcomes within the dynamic sphere of startups.

2.2.5. Agreeableness

Agreeableness, one of the fundamental personality traits, has garnered substantial attention in the realm of organizational psychology due to its multifaceted impact on various facets of organizational performance and dynamic capabilities (Tsoai & Chipunza, 2022). A study conducted by Tsoai and Chipunza (2022) has unveiled an intriguing relationship between agreeableness and entrepreneurial pursuits. Their findings suggest that individuals possessing higher levels of agreeableness are more inclined to embark on entrepreneurial ventures, while those exhibiting neuroticism personality traits display little interest in initiating new business endeavors (Tsoai & Chipunza, 2022). This observation underscores the potential role of agreeableness in shaping entrepreneurial behavior and the willingness to undertake risks.

Moreover, the work of Galvão and Pinheiro (2019) adds another layer to the significance of agreeableness within the entrepreneurial context. Their study posits that agreeable individuals may possess an advantage in networking capabilities, as they tend to excel in building and maintaining interpersonal relationships, a skill set that proves advantageous for networking and accessing valuable resources (Galvão & Pinheiro, 2019).

In the context of team innovation, Hartog and colleagues (2019) advance a compelling argument regarding the evolving importance of personality traits, such as extraversion and agreeableness, within teams over time. Their research posits that personality characteristics oriented towards interpersonal relationships, like agreeableness, grow in significance for fostering team innovation (Hartog et al., 2019). This implies that agreeableness can facilitate effective collaboration and teamwork, ultimately contributing to enhanced innovation capabilities within a team setting.

In the broader context of personality research, the Big Five personality traits, including agreeableness, have been the subject of extensive theoretical and empirical scrutiny (Soylemez, 2021). These traits, which encompass openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism, have been demonstrated to exert significant influence over employees' attitudes, behaviors, and overall work performance (Hu & Lin, 2021).

In conclusion, the existing body of literature underscores the pivotal role of agreeableness in shaping various aspects of organizational performance and dynamic capabilities. Its impact spans entrepreneurial endeavors, networking competencies, teamwork and collaboration dynamics, strategic human resource management, and the attitudes and behaviors of employees. Consequently, agreeableness emerges as a vital element within the complex fabric of organizational psychology, with implications that extend to diverse facets of contemporary work environments.

2.3. Dynamic Capabilities

The concept of dynamic capabilities has gained significant attention in the fields of entrepreneurship, innovation, and strategic management. Dynamic capabilities refer to a firm's ability to adapt, integrate, and reconfigure its resources and competencies in response to rapid changes in the business environment (Barney et al., 2011; Teece, 2007). Numerous studies have explored the concept of dynamic capabilities and its implications for firm performance and competitiveness. A systematic literature review conducted to identify relevant articles within the entrepreneurship, innovation, and strategic management literature found that dynamic capabilities play a crucial role in firms' ability to innovate and achieve global performance (Arend and Bromiley; Giudici and Reinmoeller). However, despite the extensive research on dynamic capabilities, there is still much room for further operationalization and empirical validation of key propositions in this field.

The concept of dynamic capability has been extensively examined and defined in various ways within the academic literature. Scholars posit that dynamic capability plays a pivotal role in the pursuit of competitive advantage within the realm of strategic management. Theoretical perspectives on management strategy diverge in their interpretations of the origins of dynamic capabilities. Nevertheless, a prevailing consensus among many scholars underscores the significance of dynamic capabilities as a critical means to attain and sustain competitive advantages (Teece et al., 1997; Teece, 2007; Helfat et al., 2007; Ambrosini & Bowman, 2009; Helfat & Peteraf, 2009). Wang and Ahmed (2007) also align with this viewpoint, characterizing dynamic capability as "the firm's behavioral orientation constantly to integrate, reconfigure, renew, and recreate its resources and capabilities and, most importantly, upgrade and reconstruct its core capabilities in response to the changing environment to attain and sustain competitive advantage."

The concept of dynamic capabilities is often regarded as an extension of the resource-based view (RBV), wherein the central objective is to achieve sustainable competitive advantage (Barney, 1991). RBV posits that a firm's advantage arises from its possession of bundles of resources and core competencies, encompassing both tangible and intangible assets. Criticism has been leveled at the RBV for providing limited guidance on how managers can cultivate such competencies, particularly in highly turbulent, fast-paced environments. Barney (2001) introduced the notion of resource benefits and emphasized the idea that resources meeting the VRIO criteria are no longer easily imitated by competitors.

One of the most widely accepted definitions in the literature, proposed by Teece et al. (1997), characterizes dynamic capabilities as "the firm's ability to integrate, build, and reconfigure internal and external resources and competencies to address and shape rapidly changing business environments." Augier and Teece (2009) subsequently modified this definition to emphasize dynamic capabilities as "the ability to sense and then seize new opportunities and to reconfigure and protect knowledge assets, competencies, and complementary assets with the aim of achieving a sustained competitive advantage." Teece (1997) elucidates the term "dynamic" by highlighting the need for continuous competency renewal to align with the evolving business environment. He underscores the role of strategic management in adapting, integrating, and reconfiguring organizational skills, resources, and functional competencies in response to environmental shifts.

Teece (2007) further refines the concept, positing that continuous renewal entails a set of ongoing activities and adjustments categorized into three clusters: sensing, seizing, and transforming. Sensing involves identifying and assessing opportunities by learning about the environment and the skills needed to gain a competitive edge. Seizing involves mobilizing resources to address opportunities and capture value, while transforming entails ongoing renewal and implementation of strategic plans. Teece (2018) reintroduces these three dynamic capabilities to address contemporary industry challenges, emphasizing the need for enterprises to sense rapid changes in the competitive environment, seize opportunities, and continuously transform aspects of the organization and culture to proactively respond to emerging threats and opportunities.

Eisenhardt and Martin (2000) define dynamic capabilities as specific processes such as product development, strategic decision-making, and alliancing. Barreto (2010) views dynamic capabilities as the firm's potential to systematically solve problems, driven by its ability to sense opportunities and threats, make market-oriented decisions, and adapt its resource base. Other scholars, following Teece's framework, disaggregate dynamic capabilities into the capacity to sense and shape opportunities and threats, to seize opportunities, and to maintain competitiveness through enhancing, combining, protecting, and reconfiguring intangible and tangible assets (Teece, 2007).

Li and Liu (2011) characterize dynamic capability as a firm's potential to systematically solve problems, rooted in its capacity to sense opportunities and threats, make timely decisions, and efficiently implement strategic changes. Teece's (2007) perspective further underscores the importance of sensing capacity in obtaining relevant external information and transforming capacity in translating valuable information into actionable strategies.

In summation, the literature on dynamic capabilities unequivocally suggests that the ultimate aim of this concept is to generate value that bestows a sustainable competitive advantage upon organizations. Competitive advantage, as elucidated, emanates from dynamic capabilities, which encompass technological innovation and other strategic resources. Competitive advantage can be understood as the set of resources and capabilities that confer an edge over competitors (Wiggins & Ruefli, 2002), emphasizing attributes such as location, technology, and product features. It is evident from the literature review that the majority of definitions underscore a firm's capacity to navigate a rapidly changing and turbulent environment while continuously renewing competencies to secure a lasting competitive advantage.

Within the framework of the Big Five personality traits, extant research has elucidated a discernible nexus between these personality dimensions and the construct of dynamic capabilities. For instance, conscientiousness, characterized by attributes such as organizational proclivity, responsibility, and a predisposition towards achievement, has been empirically established as positively correlated with dynamic capabilities (Durán et al., 2022). The underpinning rationale resides in the propensity of individuals possessing elevated conscientiousness to engage in proactive initiatives, evince a predilection for taking initiative, and evince a tenacious resolve when confronted with adversities, all of which are germane to the cultivation and operationalization of dynamic capabilities (Durán et al., 2022).

Concomitantly, openness to experience, denoting traits of curiosity, imaginative disposition, and openness to novel ideas, has similarly been ascertained to exhibit a constructive association with dynamic capabilities (Durán et al., 2022). This linkage derives its cogency from the inclination of individuals characterized by high levels of openness to experience to actively seek out fresh information, explore nascent opportunities, and adapt adeptly to environmental vicissitudes, all of which are foundational prerequisites in the cultivation of dynamic capabilities.

Beyond the confines of the Big Five taxonomy, other personality attributes have also been observed to bear relevance to the realm of dynamic capabilities. Notably, hubris, typified by excessive pride and overconfidence, has been identified as possessing an adverse relationship with dynamic capabilities (Guo et al., 2022). This antithetical connection arises from the proclivity of individuals imbued with hubristic tendencies to exhibit unwarranted overconfidence in their competencies and manifest resistance towards change, thereby impeding their capacity to engender and implement dynamic capabilities (Guo et al., 2022).

Conversely, entrepreneurial self-efficacy, which denotes an individual's belief in their aptitude to efficaciously execute entrepreneurial endeavors, has been established to be positively linked to dynamic capabilities (Şahin et al., 2019). This association emanates from the proclivity of individuals characterized by robust entrepreneurial self-efficacy to evince a readiness for risk-taking, innovate proactively, and adeptly adapt to environmental vicissitudes, all of which are pivotal attributes in the cultivation of dynamic capabilities (Şahin et al., 2019).

In summation, it becomes evident that the interplay between personality traits and dynamic capabilities is a multifaceted and intricate phenomenon. Distinct personality traits proffer diverse effects on the development and operationalization of dynamic capabilities. For instance, traits such as conscientiousness and openness to experience generally exhibit propitious ramifications, while traits such as hubris can engender deleterious consequences. Consequently, organizations must be cognizant of the personality profiles of their employees and leaders when devising and implementing dynamic capabilities, as these individual traits wield a discernible influence on the efficacy and potency of these capabilities.

In the domain of entrepreneurship, scholarly inquiries into the concept of dynamic capabilities have yielded substantial insights into their significance in fostering organizational growth and adaptability within a rapidly evolving business milieu. This discourse delves into three pivotal studies conducted by Chang (2012), Klofsten et al. (2021), and Vu (2020), which collectively underscore the relevance and implications of dynamic capabilities in the entrepreneurial context.

Chang's investigation (2012) focused on the dynamic capabilities of IT entrepreneurs. The study illuminated the paramount role played by dynamic capabilities in the pursuit of corporate expansion, particularly within a landscape marked by perpetual change. Central to its findings was the assertion that entrepreneurs must exhibit adept resource deployment and a continuous adaptation to market dynamics to thrive in such a volatile environment.

Building upon this foundation, Klofsten and colleagues (2021) contributed to the discourse by examining the applicability of dynamic capabilities within the startup ecosystem, with a specific emphasis on entrepreneurship. Their work elucidated how the dynamic capabilities framework can serve as a valuable managerial instrument. It enables the creation of competitive advantages through the strategic application of entrepreneurial techniques within established organizational structures. This study reinforces the adaptability and versatility of dynamic capabilities across diverse entrepreneurial contexts.

Additionally, Vu (2020) advanced a comprehensive conceptual model, illuminating the intricate interconnections among dynamic capabilities, innovation prowess, entrepreneurial competencies, and financial as well as strategic performance. His research accentuated the pivotal role of dynamic capabilities in catalyzing innovation and entrepreneurial triumph. This inquiry underscores the multifaceted nature of dynamic capabilities and their far-reaching influence on various dimensions of organizational performance in entrepreneurial ventures.

The cumulative body of research by Chang (2012), Klofsten et al. (2021), and Vu (2020) collectively attests to the paramount importance of dynamic capabilities in the entrepreneurial arena. They underscore how adept resource mobilization, adaptability to changing market dynamics, and the strategic application of dynamic capabilities can be instrumental in achieving corporate growth and competitive advantages. Consequently, these studies contribute substantially to our understanding of the intricate interplay between dynamic capabilities and entrepreneurial success, highlighting their centrality in navigating the complexities of today's dynamic business environments.

2.4. Innovation Performance

Innovation Performance is a crucial element for the success and growth of organizations in today's competitive business environment. A plethora of scholars and researchers have delved into the intricate realm of innovation performance, exploring diverse dimensions and frameworks to comprehend its profound implications on organizational prosperity. The conceptualization of innovation performance can be succinctly delineated as the evaluation of an enterprise's adeptness in conducting technological innovation endeavors (Li & Hou, 2023). The scholarly discourse has yielded an array of definitions and perspectives concerning innovation performance.

Within the annals of academic investigation, considerable attention has been accorded to the dimensions of product and process innovation performance, both recognized as pivotal constituents of organizational innovation performance, with scholars underscoring the imperative necessity of assessing and appraising these facets to obtain a holistic grasp of an organization's innovation prowess (Li & Hou, 2023).

Product innovation, a dimension of innovation performance, occupies a prominent position in scholarly discourse. It pertains to the development and introduction of novel or enhanced products into the market. Evaluation of this dimension of innovation performance frequently hinges on metrics such as investments in research and development, market share, and levels of customer satisfaction (Jin & Lee, 2020).

Innovation performance, within the organizational context, pertains to the systematic evaluation and quantification of the efficacy and triumph of innovation endeavors undertaken by an entity. It encompasses the ideation and execution of initiatives directed towards both the augmentation of product offerings and the enhancement of internal operational processes (Hagedoorn & Cloodt, 2003). Specifically, product innovation denotes the creation and market introduction of novel or refined goods, whereas process innovation centers on the optimization of the efficiency and effectiveness of internal workflows and mechanisms within the organizational framework.

Moreover, innovation performance can be construed within the ambit of knowledge management and the harnessing of knowledge assets inherent to an organization. The processes governing knowledge and the intensity of knowledge resources assume pivotal roles in propelling innovation performance. Efficient mechanisms for sharing knowledge, encompassing both information and communication technology (ICT)-facilitated platforms and interpersonal interactions, contribute substantively to the augmentation of innovation competencies and project management, eventually concurring with the enhancement of organizational performance (Sáenz et al., 2012).

It is noteworthy that the purview of innovation performance measurement is not confined to individual enterprises but can be extended to the level of clusters or entire industries. Continuous innovation and performance assessment methodologies can be harnessed to manage the collective performance of a cluster of firms, thus facilitating the enactment of enhancement strategies congruent with strategic objectives, and the ongoing monitoring of outcomes for further refinement (Carpinetti et al., 2007).

To encapsulate, innovation performance, as a construct, encompasses both product and process innovation facets and can be gauged through a multifaceted array of indicators spanning financial and non-financial dimensions. The conceptualization of innovation performance is amenable to diverse emphases, with certain studies underscoring the prominence of product innovation, while others accentuate the importance of process innovation. The domain of knowledge management and collaborative endeavors assumes an instrumental role in shaping innovation performance. Additionally, innovation performance measurement is amenable to application at the cluster or industry level, offering a comprehensive perspective on the collective performance of multiple enterprises.

Furthermore, the conceptualization of innovation performance can be approached from diverse vantage points. Some studies underscore the prominence of product innovation and its ramifications on the performance of the organization. For instance, research has underscored that entities in supporting sectors should concentrate on process, marketing, and organizational innovations to elevate both their innovative capacities and organizational performance (Tuan et al., 2016). Conversely, other investigations underscore the centrality of process innovation and its potential to engender cost efficiencies and gains in efficacy. The initial phases of process development and process innovation are shown to be pivotal in the attainment of favorable outcomes (Frishammar et al., 2013).

The measurement of innovation performance assumes paramount significance for organizations, as it furnishes them with valuable insights into the effectiveness of their innovation endeavors and serves as a diagnostic tool to pinpoint areas necessitating refinement. Multiple evaluative indices can be employed to gauge innovation performance, encompassing financial metrics such as sales growth and profitability, alongside non-financial benchmarks such as the quantity of newly introduced products, patent filings, and levels of customer contentment (Hagedoorn & Cloodt, 2003).

2.4.1. Process Innovation

Process innovation encompasses the conception and deployment of novel or enhanced procedures within an organizational framework, with the overarching objective of augmenting efficiency, productivity, and overall performance (Damanpour et al., 2009). This multifaceted endeavor entails the modification of task execution modalities, the sequencing of activities, the utilization of technological tools, and the harmonization of distinct functions and departments (Ju et al., 2020). Notably, process innovation finds its applicability across a spectrum of industries and sectors, spanning service-oriented establishments (Damanpour et al., 2009), manufacturing enterprises (Cheng et al., 2014), and the realm of environmental technology (Radnejad et al., 2020).

Research posits a symbiotic relationship between process innovation and other forms of innovation, prominently product innovation (Damanpour et al., 2009). This interdependence engenders a reciprocal dynamic, wherein advancements in one sphere catalyze progress in the other (Damanpour et al., 2009). For instance, the integration of product and technological process innovations often unfolds as a mutually reinforcing endeavor, with enhancements in either domain precipitating innovation in the counterpart (Damanpour et al., 2009). This intricate interplay underscores the strategic significance of accommodating both product and process innovation within organizational paradigms.

The contours of process innovation manifest in a diverse array of typologies, comprising incremental and radical innovations (Cheng et al., 2014). Incremental process innovations entail the gradual refinement of extant operational methodologies, while radical process innovations herald substantial alterations and disruptions to entrenched procedural norms (Radnejad et al., 2020). Organizations may opt for radical process innovations as a means to attain competitive ascendancy or to respond to external exigencies, such as environmental regulatory mandates (Radnejad et al., 2020). Nonetheless, the implementation of radical process innovations is not bereft of challenges, including impediments to commercialization (Radnejad et al., 2020).

The adoption of process innovation exerts a salutary influence on organizational performance. Evidentiary support underscores its capacity to engender enhanced innovation performance, as organizations innovate novel products and services (Tajudeen et al., 2022). Furthermore, process innovation is instrumental in amplifying efficiency, curtailing expenses, and elevating customer satisfaction levels (Damanpour et al., 2009). Beyond these immediate benefits, process innovation can be instrumental in advancing sustainability objectives, particularly within the purview of green process innovation (Feng et al., 2018). Through the infusion of environmental considerations into their operational processes, organizations can attenuate their ecological footprint and contribute to the advancement of sustainable development (Feng et al., 2018).

To foster process innovation, organizations must judiciously consider a constellation of factors. These encompass the availability of informational and knowledge reservoirs, both internal and external in origin (Gómez et al., 2016). A robust access to pertinent information undergirds the identification of process innovation opportunities while keeping organizations attuned to industry dynamics and competitive undertakings (Gómez et al., 2016). Additionally, the shaping influence of organizational culture and leadership looms large in the cultivation of a conducive milieu for process innovation (Tajudeen et al., 2021). A corporate ethos that venerates experimentation, learning, and the ethos of continuous amelioration is pivotal in nurturing an environment that galvanizes employees to conceive and actualize innovative concepts (Tajudeen et al., 2021).

In sum, process innovation represents the conceptualization and implementation of fresh or enhanced operational methodologies within an organizational setting. It stands inextricably entwined with other facets of innovation, notably product innovation, and bears the potential to exert a momentous impact on organizational performance. Process innovation can adopt diverse profiles, spanning from incremental refinements to revolutionary transformations. Its fruition necessitates access to pertinent information, an encouraging organizational culture, and effective leadership. Embracing process innovation endows organizations with the capacity to elevate efficiency, productivity, and sustainability.

2.4.2. Product Innovation

Product innovation encompasses the process of conceiving and introducing novel or enhanced products into the commercial sphere (Shu et al., 2014). This multifaceted endeavor entails the creation and delivery of offerings imbued with augmented value for consumers, achieved through the incorporation of fresh attributes, functionalities, designs, or heightened performance capabilities. Notably, product innovation exhibits a diverse array of manifestations, ranging from incremental enhancements applied to pre-existing products to the inauguration of entirely unprecedented offerings (Shu et al., 2016).

Empirical inquiry has illuminated the intricate nexus between product innovation and an array of factors, encompassing the management paradigms of organizations and the exogenous institutional milieu. For instance, the cultivation of green management practices, which pivot on the tenets of environmental sustainability, has emerged as a salient factor with the potential to exert a constructive impact on the trajectory of product innovation (Shu et al., 2014). Within this purview, governmental backing and the conferment of social legitimacy emerge as two instrumental institutional enablers that mediate the interplay between green management practices and the sphere of product innovation (Shu et al., 2014). It is noteworthy that the influence of government support primarily manifests in the catalysis of radical product innovation, whereas the sway of social legitimacy tends to be more pronounced in the context of incremental product innovation.

In the realm of fostering product innovation, the establishment of a conducive work milieu that stimulates creativity emerges as a pivotal imperative (Dul & Ceylan, 2014). A work environment oriented towards nurturing creativity is one that accords employees the requisite resources, autonomy, and encouragement requisite for the conception and operationalization of innovative ideas (Dul & Ceylan, 2014). This encompasses the cultivation of a corporate culture that extols experimentation, risk-taking, and the cultivation of a learning-oriented ethos, as well as the provision of unfettered access to pertinent information and opportunities for collaborative endeavors (Dul & Ceylan, 2014). Organizations that accord preeminence to the cultivation of a creativity-supporting work environment are apt to realize superior performance outcomes in the realm of product innovation (Dul & Ceylan, 2014).

In the overarching framework of organizational efficacy and competitiveness, product innovation assumes an indomitable role. It serves as the vanguard through which companies can demarcate themselves from rival entities, allure prospective patrons, and retain extant clienteles (Shu et al., 2014). Furthermore, product innovation is demonstrably capable of engendering augmented market share, expanded revenue streams, and ameliorated financial performance (Shu et al., 2014). Notably, its impact extends beyond the commercial realm, as product innovation can be instrumental in advancing sustainability objectives via the development of environmentally conscientious products and solutions (Shu et al., 2014).

In summary, the ambit of product innovation encompasses the genesis and introduction of fresh or ameliorated products to the marketplace, a process critically contingent upon multifarious determinants, including green management practices, governmental support, social legitimation, and the cultivation of creative workspace. Product innovation stands as an indispensable linchpin for organizations, underpinning their competitive stature, customer appeal, and prospects for sustainable growth.

2.5. Startups vs. SMEs

Startups and Small and Medium-sized Enterprises (SMEs) have both differences and similarities. Startups manifest a distinct array of attributes that demarcate them from established enterprises and SMEs. These attributes can be categorized across various dimensions, encompassing the qualities of the individuals who initiate the venture, the organizational structure they instantiate, the ambient milieu within which the new enterprise operates, and the procedural mechanisms employed in its establishment (Thurik et al., 2005).

One pivotal attribute of startups lies in the constitution of the entrepreneurial team. Scholarly inquiry has ascertained that the attributes of team members, including their proficiencies, experience, and diversity, exert a substantial influence on the performance of the nascent venture (Jin et al., 2017). Furthermore, the characteristics of the founders, such as their socioeconomic standing and political inclinations, can wield an impact on the formation of formal political affiliations by the fledgling enterprise (Mai et al., 2015).

Another distinctive trait of startups resides in their pronounced emphasis on innovation and the development of novel products, services, processes, or platforms designed to address extant market exigencies (Sivicka, 2018). Startups frequently distinguish themselves by their capacity to introduce disruptive technologies or business models that pose challenges to established entities within their industry (Chesbrough & Tucci, 2020). This predilection for innovation is intrinsically linked to the entrepreneurial mindset and the willingness to undertake calculated risks (Thurik et al., 2005).

The financial characteristics of startups also serve to set them apart from established corporations. Startups typically emerge as newly-established, rapidly-evolving entities with the goal of formulating a sustainable business model centered on their innovative offerings (Sivicka, 2018). Often, these enterprises rely on external funding sources, notably venture capital, to bolster their expansion and development (Bottazzi et al., 2008). The valuation of startups constitutes a multifaceted process that takes into account an array of factors, encompassing the capabilities of the team, market potential, and the intellectual property assets associated with the venture (Miloud et al., 2012).

Moreover, startups navigate a dynamic and unpredictable operating environment, necessitating agility and adaptability. Their objectives and priorities often diverge from those of established corporations. The competitive landscape confronting startups can prove to be arduous, with success contingent upon factors such as industry-specific characteristics, market demand, and competitive intensity (Homburg et al., 2013). In addition to these challenges, startups must grapple with the intricacies of the regulatory and legal landscape, which can significantly impact their innovation management processes (Denysenko et al., 2023).

In summation, startups are distinguished by their focal point on innovation, reliance on external financial backing, the composition of their entrepreneurial team, and their capacity to navigate a dynamic and uncertain milieu. These distinctive attributes collectively shape the unique challenges and opportunities that startups encounter in their pursuit of growth and success.

Startups and Small and Medium-sized Enterprises (SMEs) exhibit a set of overlapping characteristics while encountering akin challenges within their respective operational domains. Both categories of enterprises typically manifest diminutive scale, accompanied by restricted resource allocations and the presence of informal organizational structures, as corroborated by extant literature (Ghezzi et al., 2021; Cavallo et al., 2020). A recurring impediment faced by these entities is the formidable task of securing ample capital infusion, owing to their less-than-ideal credit ratings and limited access to primary financial markets (Binh et al., 2020). Nevertheless, it is imperative to underscore that startups diverge from SMEs in distinct respects, primarily concerning their emphasis on innovation, fervent ambitions for rapid growth, and a pronounced proclivity for risk-taking (Weiblen & Chesbrough, 2015). Startups are particularly characterized by their nimbleness, the integration of disruptive technologies or business models, and the prospect of substantial workforce expansion and revenue augmentation (Braak et al., 2018).

A pivotal facet pertinent to both startups and SMEs revolves around their involvement in open innovation and collaborative endeavors. Both these organizational types stand to gain immensely from forging partnerships with external entities, encompassing startups, established corporate entities, or academic research institutions, in order to bolster their innovation capabilities and broaden their market reach (Ghezzi et al., 2021). The critical roles played by open business models and value co-creation cannot be overstated, as they act as facilitators for fostering collaboration between startups and SMEs (Ghezzi et al., 2021). It is noteworthy that startups, in particular, exhibit an inclination toward the embrace of open innovation practices, in order to harness external knowledge pools and resource endowments (Korber & McNaughton, 2017).

The domain of digital transformation presents yet another sphere replete with opportunities for the mutual betterment of startups and SMEs. Both categories of organizations possess the potential to leverage digital technologies for the augmentation of their marketing efforts, improvement of customer engagement, and enhancement of overall operational efficiency (Verhoef, 2021). In this regard, they may avail themselves of customer knowledge management techniques and exploit digital platforms as tools for gaining insights into the predilections and behavioral patterns of their customer base (Verhoef, 2021). This proactive approach can, in turn, enable them to customize their products and services more effectively, attuned to the needs and preferences of their clientele.

The entrepreneurial ecosystem constitutes an instrumental milieu within which both startups and SMEs function, engendering substantial contributions to economic development and job creation. These entities serve as bedrocks underpinning the growth and sustainability of national economies. Furthermore, it is imperative to recognize that startups and SMEs are faced with a litany of shared challenges that span the domains of access to financial resources, market competitiveness, regulatory compliance, and resource constraints (Ramachandran & Yahmadi, 2019; Jones-Evans, 2015). Additionally, both categories of enterprises confront the onerous task of navigating intricate regulatory frameworks and surmounting impediments that hinder market entry. The cultivation of robust brand identities and the formulation of effective marketing strategies assume paramount significance for startups and SMEs, as these initiatives serve as pivotal mechanisms for differentiation and customer attraction (Bresciani & Eppler, 2010; Merrilees, 2007).

In summary, startups and SMEs, while distinguished by certain unique attributes, share in common the characteristics of limited resources, informal organizational structures, and analogous challenges vis-à-vis access to finance and market competitiveness. It is noteworthy that startups are characterized by their conspicuous proclivity for innovation, fervent growth aspirations, and the embracing of risk. Both these categories of enterprises stand to accrue substantial advantages from the adoption of open innovation practices, engagement in digital transformation, and active participation in the entrepreneurial ecosystem.

2.6. Research Model and Hypotheses

The present study proceeds to examine the research model depicted in Figure 2.1 below:

See next page for Figure 2.1.

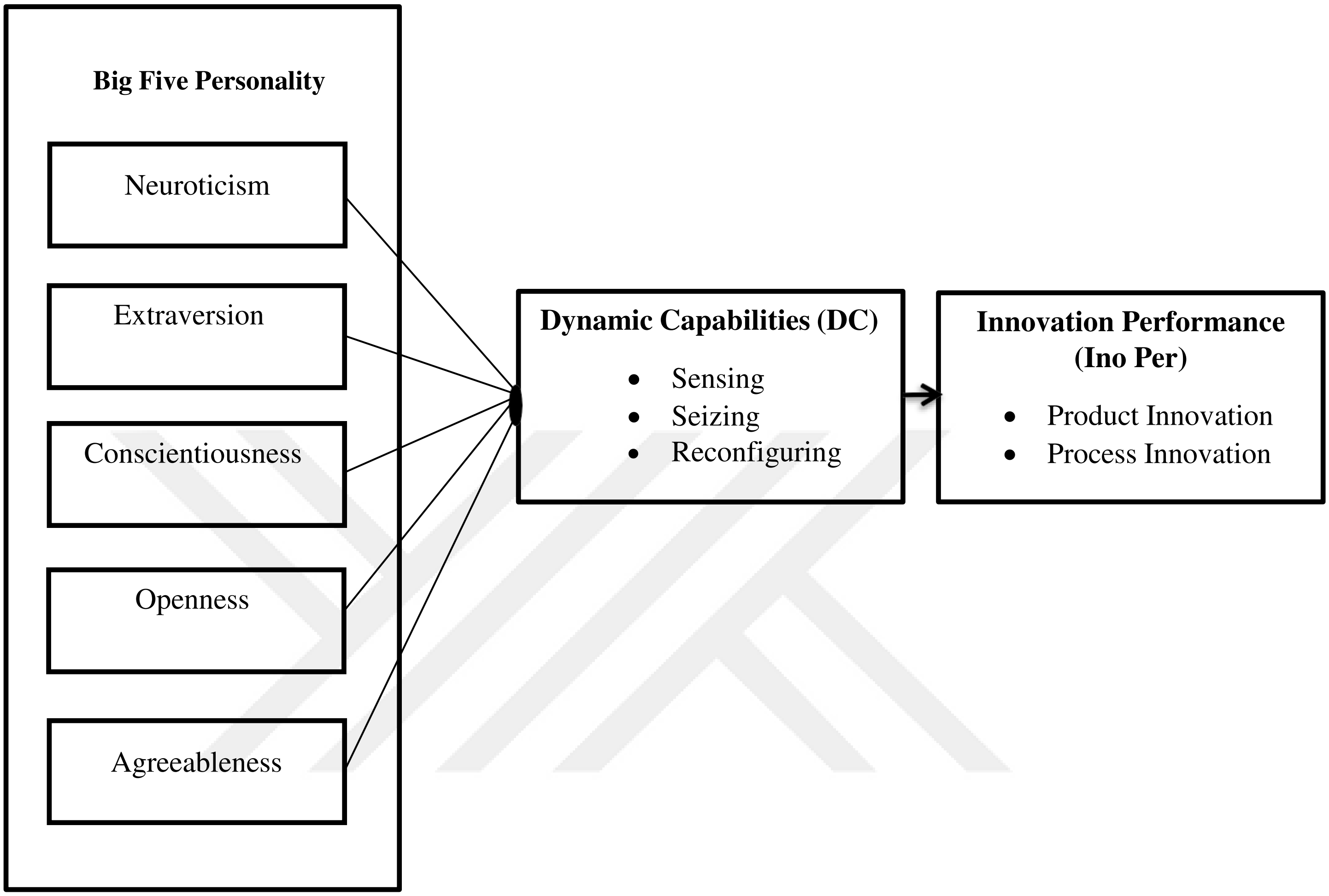

Figure 2.1. Research Model

In the contemporary competitive and dynamic landscape of business, emerging enterprises confront a myriad of challenges and uncertainties. One factor that may contribute to the success or failure of a startup is the personality of its managers, the personality traits exhibited by their managerial personnel emerge as a critical factor. Specifically, this discourse postulates that the dimension of neuroticism in managers' personalities may exert a detrimental influence on the dynamic capabilities of their respective startups. Substantiating this hypothesis, various scholarly sources contribute empirical evidence.

One such source posits that individuals characterized by high levels of neuroticism tend to possess traits of self-consciousness and heightened self-monitoring, attributes deemed crucial in the realms of financial management and resource allocation within the business context (Baluku et al., 2016). In a similar vein, extant research demonstrates a noteworthy negative correlation between neuroticism and entrepreneurial intention, while concurrently highlighting the positive impact of traits such as conscientiousness, openness, and extraversion (Li et al., 2022). Furthermore, investigations reveal an adverse relationship between neuroticism and both professional and leadership self-efficacies (Adebusuyi & Adebusuyi, 2022). Collectively, these findings substantiate the notion that neuroticism is intricately linked to unfavorable outcomes within the entrepreneurial sphere. Moreover, the literature underscores the adverse impact of individual-level neuroticism on entrepreneurial success, reinforcing the discernible negative association between neuroticism and entrepreneurial outcomes.

In conclusion, the evidence from various sources converges to underscore the significant role of neuroticism in shaping the fate of startups. While certain aspects of neuroticism may initially appear beneficial, the overarching narrative aligns with its negative repercussions on entrepreneurial intention, self-efficacies, and ultimately, the success of startups. Entrepreneurs and stakeholders alike would do well to recognize and address the potential pitfalls associated with neurotic managerial personalities, fostering an environment conducive to the dynamic capabilities and longevity of startups in today's competitive business environment. Building upon the aforementioned insights and the extant literature, I posit the hypothesis that:

H1: Neuroticism dimension of managers’ personality is negatively related to the dynamic capabilities of their startups.

The investigation into the correlation between the extraversion dimension of managers' personality and the dynamic capabilities exhibited by their startups h has been a subject of interest in the literature. Lovrincevic (2022) underscores the significance of entrepreneurial personality traits in the context of startup success, asserting that these traits play a pivotal role during both the early and growth stages of startups. Ameer et al. (2022) further accentuate the influence of a manager's personality traits, including extraversion, on the success of projects, with particular attention to the moderating effects of project management maturity. This observation implies that the extraversion dimension of a manager's personality exerts an influence on the project outcomes within the startup environment.

Contrastingly, Zhao and Jung (2017) discovered that extraversion and conscientiousness lack statistically significant impacts on the quality of relationships between firms and their supply-chain partners. This incongruent result suggests that the association between extraversion and startup performance may be contingent upon various contextual factors. Additionally, Sarwoko and Nurfarida (2021) shed light on the entrepreneurial personality traits of Small and Medium-sized Enterprise (SME) owners and managers, including extraversion, and their role in cultivating marketing capabilities to enhance competitive advantage. This implies that extraversion may contribute to augmenting specific capabilities within the startup milieu.

Within the realm of startup founders, Sundermeier and Kummer (2019) underscore the relevance of personality attributes such as charisma and hubris in the context of securing seed funding online. This underscores that certain personality traits, including those associated with extraversion, such as charisma, may exert influence on the fundraising success of startups. Consequently, while extraversion may not exert a direct impact across all facets of startup performance, it may play a discernible role in specific domains such as project success, marketing capabilities, and fundraising.

In summation, the extant literature offers divergent findings concerning the direct influence of extraversion on startup performance. While certain studies underscore its importance in specific contexts such as project success and fundraising, others posit that its impact is contingent upon a multitude of factors. Consequently, further empirical inquiry is imperative to comprehensively elucidate the intricate relationship between the extraversion dimension of managers' personality and the dynamic capabilities inherent in their startups.

Therefore, this study posits a hypothesis suggesting a positive relationship between the extraversion dimension of managers' personalities and the dynamic capabilities of their startups. This implies that as the level of extraversion in managers increases, the dynamic capabilities of their startups also witness a corresponding augmentation. Accordingly, the second hypothesis can be formulated as follows**:**

H2: Extraversion dimension of managers’ personality is positively related to the dynamic capabilities of their startups.

The conscientiousness dimension of managers' personality has been found to be positively related to the dynamic capabilities of their startups. Dynamic capabilities are crucial for startups as they enable them to adapt to environmental changes, innovate, and achieve sustainable business model innovation (Dias et al., 2022). Research has shown that certain accelerator practices enhance startups' dynamic capabilities, indicating the importance of managerial conscientiousness in driving these capabilities (García-Ochoa et al., 2020). Additionally, the study by highlights the significant role of dynamic capabilities in transforming entrepreneurial resources into performance, particularly in technology-intensive dynamic markets, further emphasizing the relevance of conscientiousness in managerial personality (Farhana & Swietlicki, 2020).

Furthermore, the impact of personality traits, including conscientiousness, on entrepreneurial intentions and behavior has been widely studied. Personality traits, such as conscientiousness, have been found to mediate the relationship between technology entrepreneurship education and entrepreneurial behavior, underscoring their influence on entrepreneurial activities (Ngah et al., 2018). Moreover, the relationship between entrepreneurial intentions and personality traits has been established, indicating that conscientiousness may play a role in shaping individuals' intentions to engage in entrepreneurial activities (Ahmed et al., 2022).

In conclusion, the conscientiousness dimension of managers' personality is indeed positively related to the dynamic capabilities of their startups. This relationship is crucial for the success and sustainability of startups, as dynamic capabilities enable them to innovate and adapt to changing environments. Additionally, the influence of conscientiousness and other personality traits on entrepreneurial intentions and behavior further emphasizes the significance of conscientiousness in the context of startup management. Therefore, we hypothesis that:

H3: Conscientiousness dimension of managers’ personality is positively related to the dynamic capabilities of their startups.

The openness dimension of managers' personality plays a crucial role in the dynamic capabilities of their startups. This openness allows managers to embrace new ideas, perspectives, and opportunities, which in turn enables their startups to adapt and innovate in response to environmental changes and uncertainties. This is supported by many scholars in different research domains, such as entrepreneurial capability, which found a positive relationship between entrepreneurship and firm performance under dynamic environmental conditions (Pangeran, 2015). Furthermore, studies have shown that the entrepreneurial orientation of a firm, which includes traits such as being proactive, innovative, and risk-taking, positively influences business performance. Additionally, the ability to adapt and respond quickly to unexpected circumstances, known as agility, is a vital capability for companies in today's ever-changing market (Khristianto et al., 2021).

Moreover, the relationship between the openness dimension of managers' personality and the dynamic capabilities of their startups has also been supported by several studies. For instance, Pundziene et al. (2022) found that open innovation mediates the relationship between dynamic capabilities and competitive firm performance, emphasizing the importance of investing in innovation and engaging customers in the innovation process (Pundziene et al., 2022; . Aro & Perez, 2021) identified the importance of dynamic capabilities in the strategic management of internal and external knowledge in the company as a source of competitive advantage. Additionally, Chabbouh & Boujelbene (2023) confirmed the significant relationship between dynamic organizational capacities and innovation performance through the mediating role of open innovation, providing valuable guidance for entrepreneurs and innovation managers in SMEs.

Moreover, Barrick & Mount (1991) found a link between openness to experience and job proficiency, indirectly supporting the idea that the openness dimension of managers' personality can influence the dynamic capabilities of their startups. This is further reinforced by the findings of (Bogers et al., 2019), who emphasized the critical role of open strategy in effectuating the dynamic capabilities of innovating firms.

Therefore, the evidence from these studies collectively supports the positive relationship between the openness dimension of managers' personality and the dynamic capabilities of their startups, emphasizing the importance of open innovation, managerial cognition, and dynamic organizational capacities in driving innovation performance and competitive firm performance. Building upon the aforementioned insights and the extant literature, I posit the hypothesis that:

H4: Openness dimension of managers' personality is positively related to the dynamic capabilities of their startups.

The success of startups is heavily influenced by various factors, including the personality traits of their managers. One such trait that has been found to positively impact the dynamic capabilities of startups is agreeableness. This relationship between the agreeableness dimension of managers' personality and the dynamic capabilities of their startups has been a subject of interest in the field of entrepreneurship. Freiberg & Matz (2023) found that agreeableness is positively related to the likelihood of raising an initial round of funding for technology startups. This suggests that the agreeableness of managers may play a role in the early-stage success of startups by influencing their ability to secure funding.

Moreover, Olteanu and Fichter (2022) introduced the concept of transformative capacity in startups, encompassing resources, competencies, and entrepreneurial orientation. Drawing on the resource-based view of the firm and the dynamic capability perspective, they underscored internal factors crucial for predicting the growth and impact of nascent ventures. Entrepreneurial orientation, a pivotal factor in this framework, could potentially be influenced by the agreeableness of managers, thus playing a role in shaping the dynamic capabilities of startups.

In addition, Lovrincevic (2022) classified startup success factors into entrepreneurial (individual level) and organizational (startup level) categories, with important entrepreneurial personality traits being among the factors instrumental to success. This suggests that the personality traits of managers, including agreeableness, may have a direct impact on the success of startups at the individual level.

Therefore, the evidence from these references supports the idea that the agreeableness dimension of managers' personality is positively related to the dynamic capabilities of their startups, particularly in terms of securing funding, influencing transformative capacity, and contributing to individual-level success factors. Drawing from the previously discussed insights and the existing body of literature, I propose the following hypothesis:

H5: Agreeableness dimension of managers’ personality is positively related to the dynamic capabilities of their startups.

The dynamic capabilities of startups play a crucial role in their innovation performance. These capabilities enable startups to adapt to rapidly changing environments, create and capture wealth, and achieve sustainable business model innovation (Teece et al., 1997). Startups with strong dynamic capabilities are more likely to achieve breakthrough innovation and subsequent success in niche markets (Farhana & Swietlicki, 2020). Additionally, dynamic capabilities are identified as key antecedents to innovation and growth in startups, highlighting their significance in driving startup performance (García-Ochoa et al., 2020). Furthermore, startups are characterized as agile organizations with dynamic capabilities that allow them to take risks and pursue innovation-driven goals, ultimately influencing their success or failure (Oliva & Kotabe, 2019).

The influence of dynamic capabilities on startup success is further emphasized by the fact that these capabilities for innovation performance reside in the startup's origin, history, and goals (Hernandez et al., 2021). Moreover, the study by suggests that dynamic capabilities such as out-of-box management and high-performance work practices influence the relationship between various challenges and the success of frugal eco-innovative startups. The role of dynamic capabilities in explaining better firm performance and competitiveness is also highlighted in a cross-cultural study focusing on startups in India and China (Behl, 2022).The moderating effect of market orientation on the relationship between dynamic capabilities and firm performance further underscores the significance of these capabilities in driving startup success (Hernández-Linares et al., 2021).

In conclusion, the dynamic capabilities of startups positively contribute to their innovation performance by fostering adaptability, continuous learning, resource flexibility, collaboration, risk-taking, and an entrepreneurial mindset. As startups navigate the challenges of the business environment, their ability to develop and leverage dynamic capabilities becomes a key determinant of their success in innovation. Building upon the aforementioned insights and the extant literature, I posit the hypothesis that:

H6: Dynamic capabilities of startups are positively related to their innovation performance.

Figure 2.1. suggest that dynamic capabilities mediate the relationship between each dimension of big five personality traits and innovation performance. In other words:

H7: Dynamic capabilities of startups mediate the relationship between neuroticism dimension of managers' personality and startups' innovation performance.

H8: Dynamic capabilities of startups mediate the relationship between extraversion dimension of managers' personality and startups' innovation performance.

H9: Dynamic capabilities of startups mediate the relationship between conscientiousness dimension of managers' personality and startups' innovation performance.

H10: Dynamic capabilities of startups mediate the relationship between openness dimension of managers' personality and startups' innovation performance.

H11: Dynamic capabilities of startups mediate the relationship between agreeableness dimension of managers' personality and startups' innovation performance.

3. METHODOLOGY

3.1. Introduction

The steps taken by the researcher during the study are described in details in this chapter. Sampling, measurement of the variables, study method, study design, study sample, preparation of the research questionnaire, and identification of the scale utilized in this study are all discussed in the following sections.

3.2. Sampling

In the context of Saudi Arabia, this study aims to test the proposed relationship on startup business drawn from the database of the Saudi Chamber of Commerce and Saudi national startup business incubator as the sampling frame of this study. I decided to choose Saudi Arabia as a location due to the notable openness to non-oil business activities. This might be an indicator of successful business practices in such a highly dynamic and competitive business domain worldwide. This study employs purposive sampling, also called judgmental sampling, a nonprobability sampling method. Even though this sampling method is less representative of the population and has low external validity, it is used especially in those situations where the target population is difficult to find or reach. Furthermore, it gives the researcher the ability to choose only those informants whom they deemed fit to participate in the research stud; that is, to accurately judge and answer the measurement questions.

The sampling frame is characterized by the age of the firm, where this study is focusing only on the startups that have at least two years in operation to insure the indicator of innovation performance. The sample size is 185 startup managers or owners from the targeted population, one executive per each firm. Data structure of this study is cross-sectional self-administered email survey.

3.3. Measurement

3.3.1. Dependent Variable: Innovation Performance

Innovation performance was measured using nine items which consisted of product and process innovations adapted from Prajogo & Ahmed (2006); and Sözbilir (2018), they were the following product innovation indicators: 1) novelty, 2) use of the latest technology, 3) product development speed, 4) number of new products, 5) the first product to enter the market (early market entrants), while the process innovation indicators were: 1) technological competitiveness, 2) adoptability the latest technology quickly, 3) the novelty of the technology used, 4) the rate of technological change.…”. In this scale respondents were asked to indicate their firm's priorities in operations on a five-point scale from 1 (most unimportant) to 5 (most important).

3.3.2. Independent Variable: Big-Five Personality Traits

The independent variable of this study, “Big-Five Personality Traits”, was be measured by using the measurement scale adopted from Hamplová, Kelley& Evans (2021). The scale measures the items key personality traits The scale items are straightforward to capture the following aspects: Extraversion, Emotional Stability, Agreeableness, Conscientiousness, and Openness to Experience. The scale uses a five-point Likert scale, ranging from strongly disagree to strongly agree.

3.3.3. Mediating Variable: Dynamic Capabilities

The mediating variable of this study “Dynamic capabilities”. Its measurement scale was adopted from Kump et. al (2019). The adopted scale was developed based on Teece’s (2007) famous dynamic capability framework that assesses (DC) dimensions: sensing, seizing, and transforming as conceptualized by scholar Teece. The authors of the adopted scale collected empirical data to employ an exploratory factor analysis (EFA) in order to assess the internal consistency of the sensing, seizing, and transforming subscales as well as to remove items of low psychometric quality. The measurement scale at hand formulated all items in a depersonalized manner to ask organizations instead of individual attitudes and outcomes as reported in their article, which is perfectly complies with the propose of this study that aims to measure the variables at the organizational level. (e.g., We are always up-to-date with market trends, instead of I am always up-to-date with market trends). The scale however, used gradual responses with six-point Likert scale. Kump et. al (2019) reported that the overall alpha coefficient is 0.91 which considered as ideal. The authors also reported that the subscales show high internal consistency, and the overall scale indicates high construct validity as the authors also reported that the scale has shown solid criterion validity.

3.4. Data Collection

Taking into account the nature of the research, the approach that we used, the objectives of the study that determine the type and data collection tools, the time allocated to this study, and the available material resources, the researcher relied on the questionnaire as an appropriate tool because this tool helps to save time and effort reduces cost, and analyzing its data is less complicated. Thus, questionnaires were sent to 185 informants and 128 responded questionnaires were received from the sampling frame that was drawn from the Saudi Chamber of Commerce and Saudi National Startup Business Incubator. When embarking on data collection, I sought assistance from a trusted friend, who has expertise in the field working at National Startup Business Incubator and other privet sector Incubators, a hub for innovation and entrepreneurial endeavors.

3.5. Data Analysis

The acquired data was loaded into the computer using the statistical program SPSS 29 and Smart-PLS 4 in order answer to the study's questions and test its hypotheses. Descriptive and inferential analysis were conducted including reliability, validity, regression analysis and mediation analysis to test the research hypotheses and the mediating role of dynamic capabilities.

4. DATA ANALYSIS AND FINDINGS

4.1. Introduction

This chapter presents the results of data analysis using SPSS version 29 and Smart-PLS 4. The chapter has been divided into several parts, which include data verification, normality assumption, demographic profile, descriptive statistics and correlation table, reliability and validity assessments, and hypothesis testing.

4.2. Data Verification

The process of data verification in this study encompassed various components, including addressing missing data, identifying outliers, assessing data distribution for normality, and conducting a thorough descriptive analysis of the respondents.

4.2.1. Missing Values

Field (2019) indicated that the management of missing values encompasses a range of strategies, including imputation, which entails estimating missing values using the information available, the removal of problematic cases, the use of special codes to identify missing data, or the utilization of more advanced techniques like multiple imputation to handle uncertainty associated with missing data. The selection of the appropriate method should be guided by the nature of the dataset and the research objectives. Additionally, it is crucial to maintain transparency by thoroughly documenting and reporting the procedures employed to handle missing values in the analysis. This transparency is vital for ensuring the reproducibility of results, as emphasized by Sekaran (2013).

As per Hair et al. (2018), the approach to addressing missing values depends on both the extent of missing data and its specific characteristics. When the proportion of missing values is below 10%, researcher have the option to either eliminate the cases with missing data from the dataset or employ various imputation methods to fill in the missing values. However, if the missing data constitutes a larger proportion, falling between 10% and 20%, specific techniques become more suitable for structural equation modeling (SEM) data. In such cases, methods like hot deck replacement and regression analysis are recommended. For SEM data with missing values in this range, the model-based imputation method is also suggested as a suitable approach.

This study comprises 128 feedback respondents, and all of them have participated in and provided responses to the questionnaire. It is essential for the researcher to analyze missing values to ensure the data's completeness and to maintain the reliability and validity of the measurements. Missing values are analyzed based on percentages, and the results are presented in Table 4.2.1 below. The results indicate that there is no missing value (Demographic (0%), Neuro (0%), Extrv (0%), Consc (0%), Open (0%), Agree (0%), DC (0%) and Inno Per (0%) for each variable in the study. This means that respondents have provided complete responses to every question in the questionnaire. No imputation techniques were employed because the data is complete.

4.2.1 Percentage of Missing Value for each Variable

Variable	Missing Value (%)
DEMOGRAPHIC	
NEURO	0
EXTRV	0
CONSC	0
OPEN	0
AGREE	0
DC	0
INNO PERF	0

4.2.2. Outliers

In the field of statistics, an outlier is defined as an observation that significantly deviates from the other data points within a dataset, as outlined by Sürücü & Maslakci (2020). These specific data points are typically positioned far away from the main cluster of observations and do not adhere to the established data pattern. Outliers can be a result of various factors, including measurement errors, inaccuracies in data entry, or they may even represent genuine yet uncommon events or phenomena. Outliers can be broadly categorized into two main types: univariate outliers and multivariate outliers. The following section provides a comprehensive exploration of the results pertaining to both univariate and multivariate outliers.

4.2.3. Univariate Outliers

Leys et al. (2019) stated that univariate outliers refer to individual data points that display extreme or uncommon values within the distribution of a single variable, without considering the distribution of other variables in the dataset. In simpler terms, these outliers are identified by examining a single variable in isolation. In this research, univariate outliers were identified using the Z-score. According to the criteria established by Sürücü and Maslakci (2020), data is considered to contain outliers when the Z-score falls outside the range of -3.29 to +3.29. In the context of this study, outliers were detected as the Z-scores fell within the range of -3.29 to +3.29. Referring to Table 4.2.4, it is observed that the lowest Z-score for the variable (prcsinov4) is -3.704, and the highest Z-score for the same variable is 1.021. Given these values, it is evident that the Z-scores do not fall within the range of -3.29 to +3.29. Consequently, this indicates the presence of outliers.

Table 4.2.3 Minimum and Maximum Zscore Result

Zscore	Minimum	Maximum
Zscore(neuro1)	-0.921	1.077
Zscore(neuro2)	-0.936	1.060
Zscore(neuro3)	-1.148	0.865
Zscore(neuro4)	-1.061	2.820
Zscore(neuro5)	-0.997	2.870
Zscore(neuro6)	-0.941	2.071
Zscore(extrv1)	-0.981	1.012
Zscore(extrv2)	-2.844	1.029
Zscore(extrv3)	-2.033	1.028
Zscore(extrv4)	-2.844	1.029
Zscore(consc1)	-2.857	1.013
Zscore(consc2)	-0.965	1.028
Zscore(consc3)	-2.673	0.891
Zscore(consc4)	-0.837	1.185
Zscore(open1)	-2.757	1.186
Zscore(open2)	-0.798	1.244
Zscore(open3)	-1.084	3.439
Zscore(open4)	-0.811	1.224
Zscore(open5)	-2.741	1.100
Zscore(agree1)	-1.651	1.148
Zscore(agree2)	-2.142	0.991
Zscore(sens1)	-2.849	1.021
Zscore(sens2)	-2.884	0.982
Zscore(sens3)	-2.692	1.115
Zscore(sens4)	-3.022	0.866
Zscore(sens5)	-2.789	1.113

Zscore(Sens)	-3.182	2.331
Zscore(seiz1)	-0.936	1.060
Zscore(seiz2)	-1.112	0.892
Zscore(seiz3)	-0.907	1.094
Zscore(seiz4)	-2.899	0.966
Zscore(Seiz)	-1.918	1.963
Zscore(reconf1)	-2.709	1.081
Zscore(reconf2)	-2.190	1.523
Zscore(reconf3)	-1.129	0.878
Zscore(reconf4)	-2.699	0.791
Zscore(reconf5)	-2.784	1.727
Zscore(reconf6)	-0.921	1.077
Zscore(Reconf)	-2.942	2.228
Zscore(prdinov1)	-2.667	0.816
Zscore(prdinov2)	-2.214	0.801
Zscore(prdinov3)	-2.456	0.961
Zscore(prdinov4)	-2.251	0.986
Zscore(prcsinov1)	-2.610	0.963
Zscore(prcsinov2)	-1.892	0.974
Zscore(prcsinov3)	-2.259	0.972
Zscore(prcsinov4)	-3.704	1.021

4.2.4. Multivariate Outliers

Multivariate outlier analysis is a technique used to identify outliers in datasets that involve multiple variables. It focuses on identifying unusual observations based on their values across all variables, as explained by Leys et al. (2019). This approach differs from univariate outlier analysis, which considers outliers in each variable independently. Mahalanobis distance is a commonly used method in multivariate outlier analysis. It calculates the distance between a data point and the center of the dataset while taking into account the correlations between variables. This distance measure, introduced by Ghorbani (2019), is valuable for identifying multivariate outliers. When dealing with outliers in a dataset, there are several strategies to consider. One option is to remove outliers from the dataset.

However, this may not always be the best choice, especially if the outliers represent valid data points that provide valuable insights, as noted by Smiti (2020). An alternative approach is to transform the data or employ robust statistical methods that are less sensitive to outliers. These techniques can effectively manage the impact of outliers while retaining essential information in the dataset. For data analysts working with datasets that encompass multiple variables or dimensions, multivariate outlier analysis is an essential tool, as highlighted by Thudumu, Branch, Jin, & Singh (2020). It enables the detection and management of outliers in a comprehensive and informative manner. As such, this study employed Mahalanobis Distance, and the results are presented in Table 4.2.5. The presence of multivariate outliers in the data is indicated if the p-value for Mahalanobis Distance is below 0.001. The results indicate that the Mahalanobis Distance is within acceptable limits for all respondents, except for respondent number 56, whose value is 0.31929, and the associated p-value is 0.0006 (p-value<0.001). This suggests that respondent 56 exhibits multivariate outlier characteristics in the data.

Table 4.2.4 Mahalanobis Distance Results

ID	Mahalanobis distance	pvalue
56	0.31929	0.0006
92	1.29815	0.02824
118	1.33318	0.0302
69	1.36926	0.0323
64	1.47089	0.0386
109	1.51375	0.04142
116	1.55478	0.04423
71	1.66611	0.05229
85	1.77951	0.06118
18	1.80854	0.06356
50	1.82714	0.06511
41	1.85575	0.06752
60	2.17055	0.09664
66	2.38591	0.11899
105	2.47844	0.12913
2	2.48409	0.12976
117	2.48703	0.13008
31	2.71975	0.15689
123	2.73279	0.15844
93	2.78211	0.16434
72	2.90222	0.17898
99	2.92612	0.18194
30	2.99584	0.19063
95	2.99773	0.19087
23	3.03084	0.19503

89	3.25809	0.22417
128	3.32007	0.23227
46	3.36967	0.23878
17	3.44383	0.24857
76	3.47163	0.25226
104	3.50133	0.25621
25	3.52049	0.25876
70	3.64534	0.27546
67	3.66666	0.27832
49	3.76016	0.2909
120	3.79872	0.29611
7	3.80486	0.29694
36	3.92892	0.31371
59	3.94042	0.31526
16	4.14373	0.34277
57	4.28379	0.36167
108	4.29857	0.36366
94	4.48551	0.38873
39	4.51366	0.39248
4	4.52418	0.39388
96	4.5588	0.39849
90	4.59287	0.40302
83	4.61845	0.40641
55	4.67679	0.41412
100	4.77984	0.42766
82	4.80059	0.43037
102	4.83841	0.4353
48	4.88727	0.44165
88	4.92369	0.44636
65	4.9374	0.44813
110	4.97074	0.45243
14	5.1036	0.4694
52	5.13993	0.474
40	5.38027	0.50396
10	5.47391	0.51538
77	5.59253	0.52966
51	5.66985	0.53883
11	5.68353	0.54044
111	5.73641	0.54664
103	5.73838	0.54687
81	5.77672	0.55134
91	5.82254	0.55664

79	5.85414	0.56027
28	5.94685	0.57083
127	5.98652	0.5753
53	5.99703	0.57648
126	6.13381	0.59163
121	6.13855	0.59215
62	6.1518	0.5936
45	6.40483	0.6206
35	6.47641	0.62801
114	6.5035	0.63079
26	6.50451	0.63089
21	6.51117	0.63158
68	6.67846	0.64839
84	6.76231	0.65661
115	6.86992	0.66695
9	6.99266	0.67847
78	7.03314	0.68221
42	7.13885	0.6918
22	7.31415	0.70723
119	7.31741	0.70751
27	7.32155	0.70787
86	7.3583	0.71102
38	7.54624	0.72673
33	7.62352	0.733
54	7.67531	0.73713
98	7.73106	0.74152
12	7.84596	0.75039
74	7.84933	0.75065
106	7.86402	0.75176
15	7.89284	0.75394
3	7.91298	0.75545
29	7.93412	0.75703
101	8.22912	0.77821
122	8.33823	0.78564
125	8.42066	0.79112
47	8.60378	0.80288
37	8.68616	0.80799
34	8.90407	0.82095
97	8.91178	0.8214
44	9.17203	0.83587
113	9.19562	0.83713
63	9.19829	0.83727

124	9.28366	0.84176
58	9.43173	0.84929
24	9.6629	0.86042
80	10.06173	0.87792
5	10.12718	0.8806
112	10.19943	0.8835
73	10.33695	0.88884
107	11.05547	0.91332
75	11.16645	0.91663
20	11.29983	0.92046
87	11.59256	0.9283
43	11.81602	0.9338
61	11.88388	0.93539
8	12.00739	0.9382
6	12.51232	0.94853
13	15.8334	0.98532
1	22.59856	0.99906

4.3. Normality Assumption

Normality tests are conducted to assess whether the data collected from a sample follows a normal distribution. While Partial Least Squares Structural Equation Modeling (PLS-SEM) is known for its flexibility and doesn't strictly require normally distributed data, as indicated by Hair et al. (2019), it can be sensitive to significant departures from normality, potentially leading to inflated standard error values, as noted by Sarstedt et al. (2019). Consequently, the inclusion of normality testing remains a crucial step, even in studies utilizing PLS-SEM for data analysis.

In this study, two statistical metrics, skewness, and kurtosis, were calculated to characterize the distribution of the data. Skewness quantifies the degree of asymmetry in the distribution, while kurtosis measures the distribution's peakedness or flatness, as explained by Pandey & Pandey (2021). Skewness and kurtosis, were computed to describe the data's distribution and presented in Table 4.3. As per Thelwall (2022), data is typically considered to follow a normal distribution when the values of skewness and kurtosis fall within the range of -2 to +2. In this study, the results indicated that the skewness values ranged from -1.788 to 0.127 and the kurtosis values ranged between -0.366 to 7.888. Result shown the data for Inno Perf (Skewness=-1.788, Kurtosis=7.888) was not normally distributed.

Table 4.3 Skewness and Kurtosis Result

Variable	Skewness	Kurtosis
NEURO	0.103	0.253
EXTRV	-0.054	-0.197
CONSC	0.006	-0.366
OPEN	-0.150	-0.136
AGREE	-0.371	-0.069
DC	0.127	-0.144
INNO PER	-1.788	7.888

4.4. Demographic Profile

4.4.1. Gender of Respondents

In this dataset, there are 127 respondents in total (after dropping observation number 56, which was an outlier). Among them, 87 respondents, or 68.5% of the total sample, are male, while 40 respondents, comprising 31.5% of the total, are female. This information provides a breakdown of the gender distribution within the sample, showing that the majority are male respondents, with a smaller but significant proportion being female respondents, making up the complete dataset of 127 individuals.

Table 4.4.1 Gender

	Frequency	Percent
Male	87	68.5
Female	40	31.5
Total	127	100.0

4.4.2. Marital Status

As can be seen in Table 4.4.2, the results indicate that 50 individuals, accounting for 39.4% of the total sample, are classified as single, while 59 respondents, constituting 46.5% of the total, are categorized as married. Additionally, there are 18 individuals, representing 14.2% of the total, who fall into the other (e.g., divorced or widowed) category.

Table 4.4.2 Marital Status

Status	Frequency	Percent
Single	50	39.4
Married	59	46.5
Others	18	14.2
Total	127	100.0

4.4.3. Age of Respondents

The results indicate that 47 individuals, which accounts for 37.0% of the total sample, fall into the less than 25 years old, while 41 respondents, making up 32.3% of the total, belong to the 26-35 age group. Additionally, there are 39 individuals, representing 30.7% of the total, in the 36-50 age group. This statistical breakdown provides a clear distribution of age groups within the sample, with a fairly even representation across these three age categories.

Table 4.4.3 Distribution of Age

Age	Frequency	Percent
25 or below	47	37.0
26-35	41	32.3
36-50	39	30.7
Total	127	100.0

4.4.4. Managerial Experience

In this dataset, the variable represents the frequency distribution of managerial experience characteristic, and it's categorized into four groups based on the occurrences. The results show that 14 respondents, equivalent to 11.0% of the total sample, fall within the 0-1 years category. A much larger proportion, with 66 occurrences, which constitutes 52.0% of the total, is in the 2-5 years category. There are 45 respondents, making up 35.4% of the total, found in the 6-10 years category. Lastly, a very small number, only 2 respondents or 1.6% of the total, are placed in the 11-15 years category. This distribution provides insights into the frequency of this specific characteristic within the sample, with the majority of occurrences falling within the 2-5 category. Refer Table 4.4.4.

Table 4.4.4 Distribution of Managerial Experience

	Frequency	Percent
0-1 years	14	11.0
2-5 years	66	52.0
6-10 years	45	35.4
11-15 years	2	1.6
Total	127	100.0

4.4.5. Level of Education

Table 4.4.5 revealed that most of respondents (50 respondents, or 30.7%) hold an associate degree. The results indicate that 38 individuals, constituting 29.9% of the total sample, hold an associate degree, Additionally, 39 respondents, making up 30.7% of the total, possess a master's degree.

Table 4.4.5 Level of Education

Education Level	Frequency	Percent
Associate degree	38	29.9
Bachelor’s degree	50	39.4
Master’s degree	39	30.7
Total	127	100.0

4.4.6. Startup Age

Table 4.4.6 shows that 41 startups (32.3%) are 2-3 years old. A slightly larger group, consisting of 47 startups (37.0%), represents startups with 4-5 years old. Furthermore, 39 startups (30.7%) are either 5 years old or more than 5 years old. This distribution provides insights into the range of startup age within the sample, with a substantial number of startups falling into the 4-5 years category, followed by 2-3 years and 5 years categories.

Table 4.4.6. Distribution of Startup Age

	Frequency	Percent
2-3 years	41	32.3
4-5 years	47	37.0
5 years	39	30.7
Total	127	100.0

4.4.7. Startup Size

Table 4.4.7 shows the distribution of the number of employees (i.e., size of the startups in the sample). The table reveals that 77 startups, which makes up 60.6% of the total sample, have less than 10 employees. A sizeable group, with 44 employees or 34.6% of the total, falls into the category between 11 and 19 employees. Additionally, 6 startups, representing 4.7% of the total, have more than 20 employees. This distribution provides insights into the distribution of startup's size or number of employees within the sample, with a majority having less than 10 employees, followed by a significant number with 11-19 employees, and a smaller group having more than 20 employees.

Table 4.4.7 Distribution of Startup Size

Years	Frequency	Percent
Less than 10 employees	77	60.6
Between 11 and 19 employees	44	34.6
More than 20 employees	6	4.7
Total	127	100.0

4.5. Descriptive Statistics and Correlation Table

Table 4.5.1 shows the descriptive statistics. The table indicates that, the mean of Neuro is approximately 1.531 with a standard deviation of about 0.217. Extrv has a mean of approximately 4.439 and a standard deviation of 0.286. Similarly, Consc has a mean of about 4.472 and a standard deviation of 0.240. Open has a mean of around 3.808 and a standard deviation of 0.250. Agree exhibits a mean of roughly 4.280 with a standard deviation of 0.474. DynCap has a mean of approximately 4.458 and a standard deviation of 0.136. Lastly, InnovPerf has a mean of about

4.431 and a standard deviation of 0.278. These statistics provide insights into the central tendencies and variabilities of these variables within the dataset.

Table 4.5.1 Means and Standard Deviations

Variable	Mean	Std. Deviation
NEURO	1.531	0.217
EXTRV	4.439	0.286
CONSC	4.472	0.240
OPEN	3.808	0.250
AGREE	4.280	0.474
DC	4.458	0.136
INNO PER	4.431	0.278

Table 4.5.2 displays the correlations between study's variables. Noteworthy are significant correlations, denoted by p-values less than 0.05. Based on these results, the majority of variable pairs do not exhibit significant correlations except for two pairs of variables. There is a significant correlation between "NEURO" and "OPEN" ($r = 0.234$, p-value < 0.05). Additionally, "CONSC" and "INNOVPERF" also show a significant correlation ($r = -0.232$, p-value < 0.05).

See next page for Table 4.5.2.

Table 4.5.2. Correlation Table

		NEURO	EXTRV	CONSC	OPEN	AGREE	DC	INNO PERF
NEURO	Pearson Correlation	1	0.010	-0.009	.234**	-0.106	-0.039	0.105
	Sig. (2-tailed)		0.912	0.924	0.008	0.238	0.662	0.242
EXTRV	Pearson Correlation		1	0.148	-0.043	.207*	0.007	-0.016
	Sig. (2-tailed)			0.096	0.630	0.020	0.934	0.860
CONSC	Pearson Correlation			1	0.103	0.129	0.007	-.232**
	Sig. (2-tailed)				0.250	0.148	0.937	0.009
OPEN	Pearson Correlation				1	-0.012	0.007	-0.149
	Sig. (2-tailed)					0.893	0.938	0.095
	N					127	127	127
AGREE	Pearson Correlation					1	0.022	-0.169
	Sig. (2-tailed)						0.806	0.058
DC	Pearson Correlation						1	-0.004
	Sig. (2-tailed)							0.967
INNO PER	Pearson Correlation							1
	Sig. (2-tailed)							

4.6. Reliability and Validity Assessments

Measurement scales were assessed gor their reliability and validity by using Partial Least Square-Structural Equation Modelling (PLS-SEM) with the help of Smart-PLS 4 statistical software package. In this research, the evaluation of the PLS-SEM model was carried out in two distinct phases: the assessment of the measurement model and the evaluation of the structural model. The initial phase focused on assessing the measurement model and involved two primary criteria. The first criterion aimed to measure construct reliability, which was accomplished by utilizing two key metrics: Cronbach's alpha and composite reliability. These reliability metrics are essential for examining the consistency and internal reliability of the constructs within the model.

The second criterion in the measurement model assessment involved assessing construct validity, which was further divided into two components: convergence validity and discriminant validity. Convergence validity was assessed by scrutinizing indicator loading and the average variance extracted (AVE), which serve as indicators of how well the measures of the constructs align with each other. Additionally, discriminant validity was evaluated using various criteria, including the heterotrait-monotrait ratio (HTMT), cross-loading, and the Fornell-Larcker criterion. These criteria collectively ensure that the constructs are distinct from one another and do not significantly overlap.

Moving on to the third phase, the assessment of the structural model encompassed a comprehensive evaluation, including the examination of several crucial metrics such as Variance Inflation Factor (VIF), R-squared (R^2), F-squared (F^2), Q-squared (Q^2), and path coefficients, which also included mediator and moderator effects. These metrics collectively provide insights into the model's explanatory capability, the presence of multicollinearity, its predictive accuracy, and the strength and significance of relationships among variables within the structural model.

4.6.1. Construct Reliability

In the realm of Partial Least Squares Structural Equation Modeling (PLS-SEM), construct reliability plays a pivotal role in assessing the stability and consistency of a measurement instrument or test, as emphasized by Hair et al. (2019). It essentially measures the degree to which a measure consistently produces reliable results across different samples of individuals and across time, ensuring that it consistently captures the same underlying construct or trait under various circumstances, as noted by Clark & Watson (2019). The evaluation of construct reliability in PLS-SEM typically involves two fundamental metrics: Cronbach's alpha and composite reliability. Cronbach's alpha quantifies the internal consistency of a set of items, with higher values signifying greater reliability, as highlighted by Sürücü & Maslakçi (2020). On the other hand, composite reliability assesses the extent to which the latent variable accounts for the variance in the indicators, with higher values indicating stronger construct reliability. Researchers often aim for Cronbach's alpha values exceeding 0.7 and composite reliability values exceeding 0.8, although these thresholds may vary depending on the specific context of the study, as discussed by Purwanto & Sudargini (2021).

Table 4.6.1 presents the results of the construct reliability assessment within the model, providing insights into the reliability of the constructs considered in the research. The finding demonstrated every construct in the model shows the satisfactory value of Cronbach alpha and composite reliability which are greater than 0.70 (Hair et al, 2021). The results of Cronbach's alpha and composite reliability indicate that all values are less than 0.70. This signifies that the construct reliability in PLS-SEM has not been achieved.

Table 4.6.1. Cronbach's Alpha and Composite Reliability Results

Variable	Cronbach's alpha	Composite reliability
DC	0.139	0.196
Inno Per	0.555	0.108
agree	-0.015	-0.021
consc	0.027	-0.192
extrv	0.198	0.195
neuro	0.023	0.197
open	-0.281	0.46

4.6.2. Construct Validity

Construct reliability serves as a statistical metric used to assess the consistency and stability of a measurement instrument or test, as emphasized by Sarstedt et al. (2019). This assessment focuses on the extent to which a measurement tool produces consistent results over different time periods and among diverse groups of individuals. It essentially evaluates how effectively a test or scale captures the same underlying concept or trait across multiple administrations or various groups, as explained by Clark and Watson (2019). One common method for evaluating construct reliability is the test-retest approach, which involves administering the same assessment to the same individuals on two separate occasions and calculating the correlation between the scores obtained during each instance, as outlined by Reynolds, Altmann, and Allen (2021). Alternatively, the split-half method entails dividing a test or scale into two segments and computing the correlation between the scores obtained from each segment, as described by Pourmehdi (2021). Additional techniques for estimating construct reliability include inter-rater reliability, internal consistency, and parallel-form reliability, as detailed by Yan and Fan (2021).

In the context of this study, convergent validity is a critical concept. Convergent validity examines whether constructs that are theoretically expected to be related indeed exhibit observable relationships. After estimating construct reliability, the researcher reports the results through essential statistical indicators such as the average variance extracted (AVE) and indicator loading (IL). These metrics facilitate the assessment of the quality of the measurement instrument, ensuring consistent and reliable results across various contexts and over time, benefiting both researchers and practitioners. This section analyzes Indicator Loading (IL), which should exceed 0.70, and Average Variance Extracted (AVE), which should exceed 0.50. If the IL does not exceed 0.70, researchers can continue the investigation by ensuring that the IL value exceeds the AVE. If it is less than the AVE value as well, the item should be removed from the measurement, following the guidance of Amora (2021).

Indicator loading reflects the strength of the relationship between each variable and its corresponding construct in a structural equation model. Table 4.7 furnishes an in-depth analysis of the convergent validity evaluation pertaining to the Agree construct. The Agree construct, which is assessed using two indicators, is observed to exhibit a unidimensional nature. The outcomes reveal that the indicator loadings span from 0.394 to 0.916. Only agree1 exceeding the 0.70 threshold while agree2 below than 0.70. Furthermore, the Average Variance Extracted (AVE) attains a value of 0.497, which not surpasses the prescribed minimum requirement of >0.50.

Consc1 and Consc2 have indicator loading values of 0.997 and 0.057, respectively. Consc2 does not meet the validity criteria, as it needs to exceed 0.70. The AVE for these constructs is 0.499, which is almost 0.50 as per the specified criteria. Thhe table 4.7 displays indicator loading values for variables extrv2, extrv3, and extrv4. For extrv2, the high indicator loading of 0.912 suggests a strong association with its underlying construct. On the other hand, extrv3 and extrv4 have loading values of -0.284 and 0.407, respectively. While extrv4 exhibits a reasonably strong relationship, extrv3 shows a weaker, negative relationship. Only extrv2 have indicator loading more than 0.70. The Average Variance Extracted (AVE) value for extrv is 0.36, indicating that it captures 36% of the variance in its construct, and it should ideally exceed 0.50 for better validity.

The table presents neuro4 has an indicator loading of -0.562, suggesting a negative association with its underlying construct. Neuro6 exhibits a high indicator loading of 0.877, indicating a strong positive relationship with its construct. However, Neuro5 has an indicator loading of 0.065, implying a relatively weak relationship. The indicator loading value for Neuro6 satisfies the requirement of 0.70. The AVE value for neuro construct is 0.363, indicating that it captures 36.3% of the variance in its construct.

Open1 has a high indicator loading of -0.955, indicating a strong association with its underlying construct. Open3 exhibits a moderate indicator loading of 0.442, suggesting a reasonable relationship. However, Open5 has a low indicator loading of -0.078, indicating a relatively weak relationship. However, the Open constructs do not meet the researcher's desired criteria, which should ideally exceed 0.70. The AVE value for open1 is 0.371 (less than 0.50), meaning it captures 37.1% of the variance in its construct.

Indicator loading for prcsinov1 and prcsinov2 both have negative indicator loading values of -0.561 and -0.632, respectively, indicating a negative association with their underlying constructs. prcsinov3 has a positive loading of 0.279, suggesting a moderate positive relationship, while prcsinov4 has a negative loading of -0.233, implying a negative relationship. While prdinov1 and prdinov2 also exhibit negative indicator loading values of -0.216 and -0.357, respectively, indicating negative associations with their constructs. Prdinov3 has a positive loading of 0.117, suggesting a weak positive relationship, while prdinov4 has a negative loading of -0.441, indicating a negative relationship. However, none of the prcsinov constructs meet the Indicator Loading (IL) requirement, which should ideally exceed 0.70. The AVE values of prcsinov construct are 0.154, indicating that it captures 15.4% of the variance in its construct. AVE is less than 0.50.

The indicator loading values for reconf1, reconf2, reconf4, reconf5, seiz4, sens1, sens2, sens3, sens4, and sens5 do not exceed the threshold of 0.70 as required. Similarly, the AVE value is 0.122, which falls below the desired threshold of 0.50.

Table 4.6.2. Indicator Loading (IL) and Average Variance Extracted (AVE) Results

Items	DC	Inno Per	agree	consc	extrv	neuro	open	AVE
agree1			0.916					0.497
agree2			0.394					
consc1				0.997				0.499
consc3				-0.057				
extrv2					0.912			0.36
extrv3					-0.284			
extrv4					0.407			
neuro4						-0.562		0.363
neuro5						0.065		
neuro6						0.877		
open1							-0.955	0.371
open3							0.442	
open5							-0.078	
prcsinov1		-0.561						0.154
prcsinov2		-0.632						
prcsinov3		0.279						
prcsinov4		-0.233						
prdinov1		-0.216						
prdinov2		-0.357						
prdinov3		0.117						
prdinov4		-0.441						
reconf1	0.062							0.122
reconf2	-0.431							
reconf4	0.62							
reconf5	-0.036							
seiz4	0.424							
sens1	0.521							
sens2	-0.208							
sens3	0.248							
sens4	-0.144							
sens5	0.265							

4.6.3. Discriminant Validity

Discriminant validity pertains to how effectively a construct can be distinguished from other constructs in empirical terms (Roemer, Schuberth, & Henseler, 2021). Establishing discriminant validity signifies that a construct possesses distinct attributes that are not overlapping with those of other constructs in the model (Cheung et al., 2023). In this study, the researcher utilized three approaches to evaluate discriminant validity: the Fornell-Larcker method, the Heteroit Monotrait (HTMT) criterion, and cross-loading analysis.

4.6.3.1. Fornell Lacker Table

The assessment of discriminant validity was carried out using the Fornell-Larcker (1981) criterion, which involves comparing the square root of the Average Variance Extracted (AVE) with the correlations between constructs. All diagonal values representing the square roots of AVE should be greater than the correlation coefficients between the constructs. Cross-loading, on the other hand, refers to a situation where an indicator variable loads significantly on more than one latent construct in the model (Mohajan, 2020; Mat Roni & Djajadikerta, 2021). If each indicator's loading is higher for its designated construct compared to other constructs, it indicates that the indicators of different constructs are not interchangeable (Chin, 1998; Pandey & Pandey, 2021). Assessment within the construct, particularly focusing on off-diagonal values, which confirms the adequacy of discriminant validity based on the Fornell-Larcker criterion established in 1981 (Cheung et al., 2023).

Table 4.8.1 provides an overview of the Fornell-Larcker criterion results. The values in the Fornell-Larcker matrix for the constructs are not consistently smaller than the diagonal values. It indicates the discriminant validity was not establish using Fornell Lacker.

Table 4.6.3.1. Fornell-Lacker Table

	DC	Inno Per	agree	consc	extrv	neuro	open
DC	0.35						
Inno Per	0.37	0.392					
agree	0.259	0.16	0.705				
consc	-0.056	0.123	-0.016	0.706			
extrv	-0.23	-0.07	0.02	0.12	0.6		
neuro	-0.307	-0.106	-0.141	0.048	0.305	0.602	
open	-0.076	-0.049	-0.158	-0.028	0.08	0.073	0.609

4.6.3.2. Heteroit Monotrait (HTMT) Results For Each Construct

HTMT (Heterotrait-Monotrait Ratio) is a measure used to evaluate the discriminant validity of a construct by comparing the correlations between different constructs (heterotrait correlations) with the correlations between items measuring the same construct (monotrait correlations), as described by Sarstedt et al. (2019). A HTMT ratio below 0.9 indicates strong discriminant validity, implying that the construct being measured is effectively distinguishable from other related constructs (Roemer et al., 2021). According to Hair et al. (2021), it is recommended that the HTMT value be below 0.85 for robust discriminant validity. The results show that the Heterotrait-Monotrait Ratio (HTMT) falls within the range of 0.607 to 5.189, providing evidence of the not establishment of discriminant validity. Table 4.8.2 offers a detailed assessment of the HTMT values.

Table 4.6.3.2. HTMT Result for Each Construct

	DC	Inno Per	Agree	Consc	Extrv	Neuro	Open
DC							
Inno Per	0.724						
Agree	3.767	2.311					
Consc	1.976	1.267	5.189				
Extrv	1.122	0.607	3.743	1.56			
Neuro	1.05	0.735	3.897	2.554	1.095		
Open	1.118	0.686	3.365	2.319	0.937	1.133	

4.6.3.3. Cross Loadings

This section addresses cross-loading, which occurs when an indicator variable (or manifest variable) shows significant loadings on more than one latent construct (or factor) within a model, as explained by Mohajan (2020) and Mat Roni & Djajadikerta (2021). If each indicator's loading is higher for its designated construct compared to other constructs, it indicates that the indicators of different constructs cannot be used interchangeably, in line with the insights of Chin (1998) and Pandey & Pandey (2021). For a detailed analysis of cross-loading in the context of this study, please refer to Table 4.8.3 The cross-loading for the constructs in this study does not meet the criteria.

Table 4.6.3.3. Cross-Loading Results

	DC	Inno Per	agree	consc	extrv	neuro	open
agree1	0.237	0.149	**0.916**	0.021	0.07	-0.089	-0.123
agree2	0.103	0.056	**0.394**	-0.088	-0.11	-0.147	-0.113
consc1	-0.056	0.127	-0.012	**0.997**	0.123	0.059	-0.024
consc3	0.004	0.043	0.049	**-0.057**	0.034	0.148	0.057
extrv2	-0.213	-0.06	0.025	0.098	**0.912**	0.284	0.003
extrv3	0.074	0.05	0.087	-0.048	**-0.284**	-0.102	-0.205
extrv4	-0.077	-0.009	0.081	0.067	**0.407**	0.094	0.05
neuro4	0.161	0.061	0.03	0.078	-0.254	**-0.562**	0.043
neuro5	-0.035	0.068	-0.244	0.051	-0.021	**0.065**	0.03
neuro6	-0.273	-0.101	-0.122	0.098	0.224	**0.877**	0.11
open1	0.075	0.126	0.108	0.028	-0.058	-0.062	**-0.955**
open3	-0.023	0.177	-0.204	0.057	0.036	0.073	**0.442**
open5	0.009	-0.148	0.025	0.163	-0.15	0.038	**-0.078**
prcsinov1	-0.155	**-0.561**	0.011	-0.08	-0.001	0.079	0.154
prcsinov2	-0.202	**-0.632**	-0.172	-0.011	0.026	0.016	0
prcsinov3	0.162	**0.279**	0.057	0.115	0.044	0.15	-0.033
prcsinov4	-0.045	**-0.233**	0.034	-0.112	0.032	0.086	0.091
prdinov1	-0.035	**-0.216**	0.084	-0.088	-0.034	-0.029	-0.043
prdinov2	-0.144	**-0.357**	-0.149	0.037	0.154	0.203	-0.025
prdinov3	0.123	**0.117**	-0.022	0.064	0.007	-0.082	0.016
prdinov4	-0.142	**-0.441**	-0.059	-0.043	0.064	0.067	-0.046
reconf1	**0.062**	0.198	0.066	0.139	0.107	0.176	-0.1
reconf2	**-0.431**	-0.303	-0.13	-0.026	-0.016	0.055	-0.001
reconf4	**0.62**	0.199	0.141	0.02	-0.287	-0.213	-0.17
reconf5	**-0.036**	0.09	-0.226	0.031	-0.106	-0.007	0.187
seiz4	**0.424**	0.171	0.073	-0.044	-0.071	-0.135	0.047
sens1	**0.521**	0.037	0.177	-0.058	-0.125	-0.306	0.018
sens2	**-0.208**	-0.055	-0.027	0.198	-0.067	0.068	0.11
sens3	**0.248**	0.034	-0.016	-0.032	-0.083	-0.061	0.121
sens4	**-0.144**	-0.092	-0.046	0.012	0.029	0.052	0.002
sens5	**0.265**	0.115	0.089	-0.185	-0.027	0.091	0.04

4.6.4. Assessment of Structural Model

Structural Equation Modeling (SEM) is a statistical analysis method used to uncover and understand the relationships between different variables, as explained by Hair et al. (2021). SEM allows researchers to explore theoretical connections between latent variables, which are underlying constructs or dimensions, and the individual indicators or items that make up each construct. Additionally, SEM is a versatile modeling tool that includes factor analysis, regression analysis, and path analysis in complex multivariate models, as described by Zhang (2022). As Partial Least Squares Structural Equation Modeling (PLS-SEM) gains popularity among researchers in various fields, the focus of research has shifted toward more dynamic and intricate research models. In this study, the assessment of the structural model involved the evaluation of several criteria, including Variance Inflation Factor (VIF), R-squared, F-squared,and Q-squared.

4.6.4.1. Variance Inflation Factor

The Variance Inflation Factor (VIF) is a valuable tool for detecting multicollinearity, a situation where two or more predictor variables exhibit high correlations with each other, as discussed by Thompson, Laible, Padilla-Walker, and Carlo (2019) and Senaviratna & Cooray (2019). In cases of multicollinearity, it becomes challenging to determine the individual influence of each variable on the dependent variable, as pointed out by Zhang (2020). VIF quantifies how much the variance of the estimated regression coefficient for a predictor variable is inflated due to multicollinearity, according to Bayman & Dexter (2021). Therefore, VIF is calculated by comparing the variance of the estimated regression coefficient to the actual regression coefficient variance, assuming all other predictor variables are included in the model. As suggested by Ramayah et al. (2018), it is advisable for the VIF value to be below 3.3.

Table 4.9.1 displays the VIF values for the paths: DC -> Inno Per (VIF=1.00), agree -> DC (VIF=1.05), consc -> DC (VIF=1.02), extrv -> DC (VIF=1.13), neuro -> DC (1.13), and open -> DC (VIF=1.04). The results show that the VIF values are below 3.3, as required by the criteria.

Table 4.6.4.1. Assessment of Variance Inflation Factor (VIF)

Path	VIF
DC -> Inno Per	1.00
agree -> DC	1.05
consc -> DC	1.02
extrv -> DC	1.13
neuro -> DC	1.13
open -> DC	1.04

4.6.4.2. Coefficient of Determination (r^2)

The term coefficient of determination explains how independent factors contribute to the latent dependent variables. R-squared, or R^2, serves as an indicator of the model's predictive accuracy and signifies the collective impact of exogenous variables on endogenous variables. In simpler terms, R-squared represents the proportion of variance in the endogenous construct that can be explained by all the connected exogenous constructs. This effect is measured on a scale from 0 to 1, with higher values indicating a higher level of predictive accuracy. According to Pandey and Pandey (2021), values of 0.75, 0.50, and 0.25 are interpreted as substantial, moderate, and weak, respectively. The results in Table 4.9.2 revealed that the Coefficient of Determination (R^2) for DC and Inno Per are 0.167 (weak) and 0.137 (weak), respectively.

Table 4.6.4.2. Assessment of Coefficient of Determination (r^2) for DC and Inno Per

Constructs	R-square
DC	0.167
Inno Per	0.137

4.6.4.3. Effect Size (f2)

Effect size (f^2) is evaluated at this stage using Smart-PLS 4 to measure the relative impact of predictor constructs on endogenous constructs. Liu and Yuan (2021) recommend considering both practical significance (effect size) and statistical significance (p-value) when assessing effect size. The calculation of effect size follows a formula developed by Cohen (1988), where effect sizes of 0.02, 0.15, and 0.35 represent small, medium, and large impacts, respectively.

Table 4.9.3 presents the Effect Size (f2) for the research paths in this study. As indicated in the table, the effect size for the relationship between DC and Inno Per was 0.159 (Small). The values indicate the relative impact of the predictor constructs (agree, consc, extrv, neuro, open) on the endogenous constructs (Inno Per and DC). The values listed (0.060, 0.001, 0.029, 0.053, 0.000) represent the weak effect sizes of each predictor construct on the endogenous constructs, although without specific units or scale information, it's challenging to interpret the exact meaning of these values.

Table 4.6.4.3. Effect Size (f^2) Result

	DC	Inno Per
DC		0.159
Inno Per		
agree	0.060	
consc	0.001	
extrv	0.029	
neuro	0.053	
open	0.000	

4.6.4.4. Stone Geisser (q2) Predictive Relevance

Q-squared is a measure used to assess the predictive capability of a model and is sometimes referred to as cross-validated redundancy, according to Bayaga (2021). When the Q-squared value is greater than 0, it indicates that the exogenous (independent) constructs have predictive relevance for the endogenous (dependent) constructs, as discussed by Hair et al. (2019). The results present Q-square values for various constructs: DC (-0.033) and Inno Per (-0.016) is NOT relevance as predictor variable.

Table 4.6.4.4 Stone Geisser (q^2) Predictive Relevance Result

	SSO	SSE	Q² (=1-SSE/SSO)
DC	1280	1321.791	-0.033
Inno Per	1024	1040.703	-0.016

4.7. Hypothesis Testing

As the results in the above section revealed, the reliability and validity assessments indicated that the measurement scales were neither reliable nor valid. In other words, the measurement items did not form a scale. Therefore, conducting hypothesis testing through formal procedures (i.e., by using regression or PLS-SEM) was not meaningful. Instead, correlation table (Table 4.5.2.) was used to assess H1 – H6, which posit direct relationships between the relevant variables.

The correlation table indicates that none of the personality traits is significantly related to dynamic capability. The table further shows that dynamic capability is not significantly correlated to innovation performance. (Even though the table shows a significant correlation between CONSC and INNO PERF (r =-0.232), this pair of variables is not related to the study's hypotheses). Taken together, these results suggest that the first six hypotheses are not supported. Similarly, the lack of significant correlations between dynamic capability and innovation performance in Table 4.5.2. suggests that the mediating hypotheses (i.e., H7 – H11) was also not supported. (These hypotheses were also assessed in Smart-PLS 4. The results, which are not reported here, confirm that none of the hypothesis was supported.)

4.8. Summary

This chapter provides a thorough examination of the analyses conducted on both the measurement and structural models. Initially, the measurement model assesses the accuracy and precision of the measurement instruments. The loadings for all indicators did not exceed 0.7, the Average Variance Extracted (AVE) values did not surpass 0.5, and all constructs did not meet the threshold of 0.7 for both Cronbach's alpha and composite reliability. These results did not confirm the reliability and validity of the measurement scales. Subsequently, the chapter delves into the testing of hypotheses by correlation table. The table shows lack of correlations between the pair of variables posited in H1 – H11, suggests that none of the hypothesis was supported.

5. DISCUSSION AND CONCLUSION

5.1. Discussion

The present study aimed to investigate the influence of the Big Five personality traits on the innovation performance of startups in the context of Saudi Arabia, with a particular focus on the mediating role of dynamic capabilities. The research hypotheses were built on the assumption that the Big Five personality traits would impact dynamic capabilities, which in turn would affect innovation performance. However, the results of the data analyses indicated that the measurement scales were not reliable and valid. Therefore, the correlation table was used to examine the study's hypotheses. The lack of correlations between the pair of variables posited in H1 – H11 suggests that none of the hypothesis was supported

One of the key factors that may have contributed to the lack of significant results in this study is related to the measurement scales. The measurement scales employed to assess the Big Five personality traits, dynamic capabilities, and innovation performance exhibited several issues. Neither Cronbach's alpha nor composite reliability met the recommended threshold of 0.70 for all constructs. This implies that the measurement items may not be consistently measuring the underlying constructs, suggesting low or lack of reliability.

Similarly, the loadings for all indicators did not exceed 0.70, indicating a weakness in the relationships between the indicators and their respective latent constructs. Further, the Average Variance Extracted (AVE) values did not surpass 0.50 for any of the constructs, which is below the recommended threshold of 0.50 for convergent validity. This indicates that the shared variance among the items was low. These results collectively suggest that the measurement items do not adequately capture the latent constructs they were intended to measure, suggesting the lack of validity of the scales.

It's important also to mention that the scales used in this research may not be suitable for cross-cultural research. In other words, they may not necessarily consider cultural adaptation or localization, which involves tailoring questions, examples, and scales to be more culturally relevant while still achieving the research goals that take place of Saudi Arabia. Additionally, the possibility of poor-quality respondents may introduce the potential for response bias, which could further compromise the validity of the findings. These suggest a need for more robust data collection techniques (e.g., conducting pilot study, assessing the construct equivalence) in future research.

When using scales that lack cultural adaptation or localization, we risk overlooking cultural factors that might influence participants' responses. For example, questions and examples in these scales might not resonate with individuals from different cultural backgrounds, potentially leading to misinterpretations or biased responses. such as: I often feel helpless and I need someone to help me. I often feel worse than others. I sometimes feel so ashamed that I would rather not see myself. I sometimes feel completely worthless. Such questions may trigger psychological sensitivity, leading to biased responses. In other words, response bias occurs when respondents provide answers that do not accurately reflect their true beliefs, attitudes, or experiences. Such biases can distort the data and compromise the validity of our findings.

In the context of research conducted in Saudi Arabia or any similar culturally distinct setting, it's important to be aware that some respondents may not be adequately engaged, motivated, or knowledgeable about the subject matter. They might provide careless or inaccurate responses, potentially due to factors like social desirability (responding in a way they perceive as socially acceptable). Addressing these issues may requires a combination of culturally sensitive research design, rigorous data collection techniques, and effective quality control measures to ensure the reliability and validity of the research outcomes.

It’s worth mentioning that this study used "Concise survey measures for the Big Five personality traits" by Smith et al. (2021) as the measurement scale for the Big 5 personality traits. However, other measurement scales exist in the literature, which have been employed in various contexts. One measurement scale conducted a meta-analysis to investigate the relationship between the Big Five personality dimensions and job performance across different occupational groups (Barrick & Mount, 1991). Similarly, other scales explored the relationships between team composition in terms of team members' Big Five personality traits and individual satisfaction with the team (Peeters et al., 2006). These studies provide valuable insights into the practical applications of the Big Five personality traits in different settings. Such scales could have worked in our sample.

Moreover, other scales used in the GCC countries could also work in our sample. The development and validation of a cross-culturally applicable scale for measuring the Big Five personality traits have been explored and to demonstrate the need for culturally sensitive measurement tools (Kutlu, 2022). Additionally, another study focused on examining the reliability and validity of the Arabic version of the Personality Inventory for DSM-5 (PID-5) to measure maladaptive personality traits in the Emirati population of the United Arab Emirates, indicating the relevance of culturally adapted measurement instruments for personality assessment in the Arab context (Coelho et al., 2020). Furthermore, other studies emphasized the importance of considering cultural variations in the measurement of personality traits, highlighting the need for a comprehensive understanding of the emic and etic aspects of personality assessment across cultures (Jiang, 2021). This underscores the significance of developing measurement scales that are sensitive to cultural nuances and variations in the Arab context.

Moreover, Wang et al., (2023) indicated the use of Big-Five Personality Traits Scale as a popular instrument for classifying personality traits, suggesting its potential applicability in the Arab context as well. Additionally, the research on the Mini-IPIP Scales provided insights into the development of concise and effective measures of the Big Five factors of personality, which could be valuable in cross-cultural research on personality traits, including in the Arab context (Donnellan et al., 2006).

To sum up, the measurement scale for the big five personality traits in the Arab context requires culturally adapted and validated instruments. Those studies collectively emphasize the importance of developing cross-culturally applicable measurement scales and considering cultural variations in the assessment of personality traits in the Arab context.

In light of these issues with the measurement instruments, it is reasonable to question the validity and reliability of the data collected in this study. Consequently, the lack of significant findings in this analysis may be attributed to these measurement problems rather than an absence of relationships in reality. Future research should place greater emphasis on the development and validation of measurement tools to better capture the constructs of interest.

In conclusion, the present study sought to examine the influence of the Big Five personality traits on the innovation performance of startups in Saudi Arabia with dynamic capabilities as a mediator. However, the measurement scales lacked reliability and validity. This highlights the importance of robust measurement tools and data collection procedures (e.g., pilot testing, assessing the construct equivalence) in research, and future investigations should address these issues to provide a more accurate understanding of the relationships among these variables in the context of Saudi Arabian startups.

5.2. Limitations

Some limitations of this study can be identified as follow:

Cultural Context: A prominent limitation lies in the cultural specificity of the study's findings. The reliance on Big Five personality trait assessments primarily formulated within Western cultural contexts may poses a substantial constraint. The lack of culturally adapted measurement tools for personality assessment within the GCC context may be a significant hindrance. This limitation challenges the validity and reliability of the findings, highlighting the necessity for culturally sensitive measurement instruments tailored to the Saudi Arabian context.

Measurement Accuracy: The study's reliance on self-reported assessments of personality traits and innovation performance may introduce potential biases, including social desirability bias or individual interpretation of questionnaire items, which may lead to the lack of reliability and validity in the measurement scales.

Sample Representativeness: Since this study implemented non-probability sampling, some units in the population may have no chance of being included in the sample. Moreover, since the selection of the startups included in the sample is often based on ease of access, sampling bias may also be an issue. With a different sample, the scales might have been reliable and valid.

5.3. Conclusion

The study sought to investigate the relationship between the Big Five personality traits among executives in startups and their innovation performance in Saudi Arabia, with a focus on the mediating role of dynamic capabilities. The results indicated that the measurements scales lacked reliability and validity, making hypothesis testing through formal procedures (e.g., regression analysis or PLS-SEM) not meaningful. Examination of the correlation table did not support the posited hypotheses.

The lack of reliability and validity in the measurement scales highlight a critical need for employing culturally sensitive and contextually adapted measurement scales to evaluate personality traits, specifically in Saudi Arabia or culturally similar contexts [(e.g., in the Gulf Cooperation Council (GCC) countries)]. The lack of reliability and validity in the current study underscores the necessity for refined measurement scales, particularly when assessing the Big Five personality traits within the Arab context. Recognizing and accommodating diverse cultural nuances is imperative for accurate assessment and a deeper understanding of human behavior across varying cultural landscapes.

The lack of significant correlations in the correlation table may also suggest that the relationship between personality traits and innovation performance might not be as portrayed in this current study; that is, may be more complicated, especially in the unique business environment of Saudi Arabian startups. Cultural and societal factors, including Saudi Arabia's distinct cultural norms impacting risk-taking propensity, alongside regulatory and geopolitical influences, can significantly shape innovation performance within the startup ecosystem.

In conclusion, this research highlights the need for a more nuanced, context-specific approach to understanding factors influencing innovation within Saudi Arabian startups. It emphasizes the importance of avoiding direct application of Western-context scales to GCC countries, especially in the Saudi Arabian context. Instead, it advocates for tailored research approaches that consider and integrate local cultural and contextual intricacies.

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APPENDICES

Appendix 1: Survey Items

Big-Five Personality Traits Scale Items

Neuroticism:

*I sometimes feel completely worthless

*I often feel helpless and I need someone to help me.

*I often feel worse than others

*I often feel anxious and nervous

* I sometimes feel so ashamed that I would rather not see myself

*If things do not work out, I get discouraged.

Extraversion:

* I like talking to other people

* I prefer being alone to being in company

*I like to be around a lot of people

* I am glad if things are happening around me

Conscientiousness:

* I can organize my time to arrange everything

* If I promise something I will do it

* Sometimes, I am not reliable as I could be

*I try to fill my duties consciously

Openness:

***** I often play with abstract theories

* I am fascinated by motives I see in the nature and art

* I am not interested in the existential problems

* I desire knowledge

* When reading poetry, I get goose bumps

Agreeableness:

* Some people think I am an egoist

*Some people think I am cold

Dynamic Capability Scale Items

Sensing:

*Our company knows the best practices in the market.

*Our company is up-to-date on the current market situation.

*Our company systematically searches for information on the current market situation.

*As a company, we know how to access new information.

*Our company always has an eye on our competitors' activities.

Sensing:

*Our company can quickly relate to new knowledge from the outside.

*We recognize what new information can be utilized in our company.

*Our company is capable of turning new technological knowledge into process and product innovation.

*Current information leads to the development of new products or services.

Reconfiguration:

*By defining clear responsibilities, we successfully implement plans for changes in our company.

*Even when unforeseen interruptions occur, change projects are seen through consistently in our company.

*Decisions on planned changes are pursued consistently in our company.

*In the past, we have demonstrated our strengths in implementing changes.

*In our company, change projects can be put into practice alongside the daily business.

*In our company, plans for change can be flexibly adapted to the current situation.

Innovation Performance Scale items:

Product Innovation:

*The level of newness (novelty) of our firm's new products.

*The use of latest technological innovations in our new products.

*The speed of our new product development.

*The number of new products our firm has introduced to the market

Process innovation:

*The technological competitiveness of our company.

*The speed with which we adopt the latest technological innovations in our processes.

*The up-datedness or novelty of the technology used in our processes.

* The rate of change in our processes, techniques and technology.

Appendix 2: Informed Consent Document and Questionnaire

INFORMED CONSENT DOCUMENT

This study titled The Influence of the Big Five Personality Traits on the Innovation Performance of Startups: The Mediating Role of Dynamic Capabilities: Evidence from Saudi Arabia aims to i) examine the impact of Big Five personality traits on dynamic capabilities of startup businesses in the context of Saudi Arabia and ii) investigate if startups' dynamic capabilities influence their performance. The study is conducted by MOHAMMED ABDULLAH SALEM BA GUBAIR and the results are expected to help startup managers understand how to better manage their firms.

- This research is being carried out by MOHAMMED ABDULLAH SALEM BA GUBAIR, who is enrolled in the Master's Program in Business Administration at the Social Sciences University of Ankara, Turkey, as his Master's Thesis.

- Your participation in this research is completely on a voluntary basis.

- If you agree to participate in this research, data will be collected from you by the attached survey instrument, which contain some questions about yourself and your company, which are designed in accordance with the purpose of the study.

- You do not have to indicate your name or provide any information that will reveal your identity. If provided, the names of participants in this research will be kept confidential.

- Data collected within the scope of this research will only be used for scientific purpose. Your responses will be aggregated with the responses of other participants to examine the hypothesized patterns in the study and will not be used outside the purpose of this research or in any other research, and, will not be shared with others without your (written) permission.

- You have the right to review the data collected from you if you wish.

- The data collected from you will be protected with a password on the researcher's computer and will be archived or destroyed at the end of the research.

- There will be no questions or requests that may make you feel uncomfortable. However, if you experience any discomfort while participating, you will be able to leave the study at any time. If you leave the study, your data will be removed from the study and destroyed.

I agree that the information I have provided to this study will be used for scientific purposes, with my own consent, knowing that I can withdraw from the study if I wish. ☐

Thank you for taking the time to read and evaluate the informed consent form.

Researcher's Name, Surname: MOHAMMED ABDULLAH SALEM BA GUBAIR

Part I: Please circle the options below that are correct for you.

Gender: 1) Male 2) Female

Marital Status: 1) Single 2) Married 3) Others

Age: 1) 25 or below 2) 26-35 3) 36-50 4) 51 or above

Years of managerial experience:

1) 0 – 1 year 2) 2 – 5 years 3) 6 – 10 years
4) 11 – 15 years 5) More than 15 years

Educational Qualification:
1) High school degree 2) Associate degree 3) Bachelor's degree
4) Master's degree 5) PhD and above

Startup age:
1) 0 – 1 year 2) 2-3 years 3) 4-5 years 5) More than 5 years

Number of employees:
1) Less than 10 2) Between 11 and 19 3) More than 20

Part 2: Please indicate your agreement with the following statements.

Question Items		Strongly agree	Agree	Neutral	Disagree	Strongly disagree
1	I sometimes feel completely worthless.					
2	I often feel helpless and I need someone to help me.					
3	I often feel worse than others.					
4	I often feel anxious and nervous					
5	I sometimes feel so ashamed that I would rather not see myself.					

6	If things do not work out, I get discouraged.					
7	I like talking to other people.					
8	I prefer being alone to being in company.					
9	I like to be around a lot of people.					
10	I am glad if things are happening around me.					
11	I can organize my time to arrange everything.					
12	If I promise something I will do it.					
13	Sometimes, I am not reliable as I could be.					
14	I try to fill my duties consciously.					
15	I often play with abstract theories.					
16	I am fascinated by motives I see in the nature and art.					
17	I am not interested in the existential problems.					
18	I desire knowledge.					
19	When reading poetry, I get goose bumps					

20	Some people think I am an egoist.					
21	Some people think I am cold.					

Part 3: Please indicate your agreement with the following statements.

Question Items		Strongly agree	Agree	Neutral	Disagree	Strongly disagree
22	Our company knows the best practices in the market.					
23	Our company is up-to-date on the current market situation.					
24	Our company systematically searches for information on the current market situation.					
25	As a company, we know how to access new information.					
26	Our company always has an eye on our competitors' activities.					
27	Our company can quickly relate to new knowledge from the outside.					
28	We recognize what new information can be utilized in our company.					
29	Our company is capable of turning new technological knowledge into process and product innovation.					
30	Current information leads to the development of new products or services.					
31	By defining clear responsibilities, we successfully implement plans for changes in our company.					
32	Even when unforeseen interruptions occur, change projects are seen through consistently in our company.					

33	Decisions on planned changes are pursued consistently in our company.					
34	In the past, we have demonstrated our strengths in implementing changes.					
35	In our company, change projects can be put into practice alongside the daily business.					
36	In our company, plans for change can be flexibly adapted to the current situation.					

Part 4: Please evaluate your company's innovation performance against your major competitors in your industry.

Question Items		Strongly agree	Agree	Neutral	Disagree	Strongly disagree
37	The level of newness (novelty) of our firm's new products.					
38	The use of the latest technological innovations in our new products.					
39	The speed of our new product development.					
40	The number of new products our firm has introduced to the market.					
41	The technological competitiveness of our company.					
42	The speed with which we adopt the latest technological innovations in our processes.					
43	The up-datedness or novelty of the technology used in our processes.					
44	The rate of change in our processes, techniques and technology.					

------------- Thank you for participating in this research -------------