# Impact of Entrepreneurial Orientation, Marketing Orientation, and Marketing Self-efficacy on the performance of tech startups in Pakistan


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**DEDICATION**

*Dedicated to loving parents, adored siblings,*

*and dear friends.*

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I am grateful to ALLAH (SWT) for blessing me with all the bounties of the universe. For giving the ability to think, read, and comprehend so I could understand the world created by him and play my minor role in the universe.

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# ABSTRACT

**Purpose –** The study explores the mediating role of marketing self-efficacy (MSE) in the relationship between Entrepreneurial Orientation (EO) and Marketing Orientation (MO) towards startup non-financial performance (SNFP).

**Design/Methodology/Approach –** This study is based on data collected through a survey conducted various incubation stage startups of Pakistan. A conceptual framework is created and tested using SmartPLS4 software.

**Findings –** The findings indicate that EO, MO, and MSE have a positive impact on SNFP. Moreover, MSE s mediates the relationship of EO and MO with SNFP.

**Originality/Value –** This study unveils intricate dynamics and relationships between EO, MO, MSE and SNFP that previously remained underexplored in the context of the startup industry. The utilization of established scales within a novel context adds a layer of originality, as it validates and extends the applicability of these measures across diverse settings. Moreover, the study enriches the global understanding of startup performance determinants. Furthermore, the research addresses a gap in the literature regarding the intermediary role of MSE, providing valuable insights into how internal belief in marketing capabilities influences the translation of EO and MO into tangible performance outcomes.

**Practical Implications -** The findings of this study are poised to offer practical implications for startup founders, policymakers, and incubators, fostering an environment that nurtures the growth and sustainability of tech startups in emerging economies.

**Social Implications** – It is suggested that economic policymakers, especially in the developing countries makes funds available and channel investments into the training and education of entrepreneurial and marketing abilities in elementary, middle, higher, and university education levels to increase entrepreneurial and marketing capabilities and marketing self-efficacy of the population.

**Keywords: Tech Startups, Entrepreneurial Orientation, Marketing Orientation, Marketing Self-Efficacy, Non-Financial Performance**

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**Entrepreneurial Orientation (EO)**

**Marketing Orientation (MO)**

**Marketing Self-Efficacy (MSE)**

**Startup Non-Financial Performance (SNFP)**

**Critical Success Factors (CSFs)**

# CHAPTER 1: INTRODUCTION

## 1.1 Research Background

The global startup ecosystem is undergoing a transformative era, with technology startups standing at the epicenter of innovation and economic progression. These startups, recognized for their agility and innovative capabilities, are playing a pivotal role in shaping the future of industries and economies alike (Griffith, 2019). In recent years, the topic of startups has captured the attention of numerous researchers from over the world (Daradkeh & Mansoor, 2023; Hasani & O'Reilly, 2021; Shaher & Ali, 2020). But despite their efforts, the harsh truth remains that the vast majority of startups fail to realize their ambitions. Approximately 90% of startups fail in the first 5 years in countries like US and India (Kalyanasundaram, 2018). These appalling results demand continuous research to identify variables that could elevate startup performance. In the context of emerging economies, particularly Pakistan, the tech startup sector has shown promising growth, fueled by increasing internet penetration, a burgeoning young population, and supportive governmental policies (Bukhari & Syed, 2019). However, this growth also brings forth a set of challenges with lack of support and marketing problems being one of the top challenges for startups in the emerging economies like Pakistan (Waqar & Štraupaitė, 2022). A crucial step towards the growth of the startup ecosystem is to identifying these challenges first, and then come up with their solutions (Waqar & Štraupaitė, 2022).

According to Watson et al., (1998), to improve the success rate of startups, we should first try to identify the determinants of their success and failure. Rashid et al., (2018) posited that a firm's capability to achieve success (i.e. making profits) can be measured through a set of variables called "performance indicators". Due to their significant role in increasing customers, non-financial performance of business ventures is equally important to their financial performance and should not be ignored in research explorations (Anwar and Shah, 2021). According to Vincent & Zakkariya, (2021), in the case of incubators (institutes that support early stage startups), major performance indicators have been understudied in the past, as most studies take into account only the financial indicators and ignore non-financial indicators despite their significant impact on overall performance. In

the case of small businesses like startups where published is mostly not accessible, there's a huge unwillingness from respondents to provide financial data to outsiders (Simpson et al., 2012). In such a case, we can lean towards measuring startup performance with non-financial indicators as past research by Anwar and Shah, (2021) has already established that their effect on startup performance is significant. In light of this, startup non-financial performance is considered the endogenous construct for this research with EO and MO being the exogenous constructs.

The relationship between EO, MO, and firm performance has been extensively studied in the past with some researchers even performing meta-analysis on the variables (Ellis, 2006; Rauch et al., 2009). Through their meta-analysis study, Rauch et al., (2009) explored the magnitude of EO-Performance relationship and observed that EO and performance has relatively large correlations. They discovered that their relationship is robust to different operationalization of key constructs as well as the cultural contexts. They also suggest the exploration of additional moderators that could impact the EO-performance relationship. Ellis (2006) conducted a meta-analysis of MO consisting of 56 studies conducted in 28 countries to make cross-national comparisons and discovered that the host country significantly effects of managerial value of MO.

When we go through the literature, it is evident that while EO and MO may have been associated with relatively high performance, most of the studies have been conducted in the non-startup context leaving a knowledge gap in understanding how startups respond to EO and MO specifically in the context of emerging economies like Pakistan. Apart from that, past research demands exploring additional variables that can help identifying the pathways through which EO and MO translate into performance outcomes. While examining the literature, we noticed the role of MSE to have been extremely understudied in the contexts of both the startups and emerging economies and in relation to EO and MO.

Addressing this gap, this paper posits MSE as a potential mediator in the relationship between EO and MO to startup performance in the unique cultural context of an emerging economy (Pakistan). MSE refers to how strongly an individual believes that they are capable of successfully performing the roles and tasks in marketing products or services (Antoncic et al., 2016). Previous research has already established that marketing

capabilities play a crucial role in the improvement of firm performance (Absah et al., 2019; Ahmed et al., 2014) . However, to date, limited research has explored the individual's belief in their marketing capabilities (MSE) which might prove to be a key ingredient to unlocking startup success.

In addition to contributing to academic discourse, this research holds significant practical implications. For practitioners, particularly those operating in similar emerging markets, the findings of this research can serve as a guide in strategic decision-making, ensuring that their firms' orientations are effectively translated into performance outcomes. For policymakers, understanding the dynamics of EO, MO, and MSE in the context of startup performance can help in the development of supportive frameworks and initiatives, fostering a conducive environment for startup growth. Through a rigorous empirical investigation and robust analytical framework, the study aims to enrich the understanding of startup dynamics in emerging economies, providing both academic and practical insights. In addition, the timing couldn't be better for the nature of this research as the entrepreneurship culture is seeing a huge surge in recent years in the emerging economies, like Pakistan that saw 20 times increase in investments from 2018-2022 (Magnitt, 2022).

Overall, the uniqueness of this research is quite prominent as it is

1) Firm- Specific (Startups)
2) Niche-Specific (Tech startups in incubators)
3) Country-Specific (only Pakistani startups)

## 1.2 Research Purpose

The purpose of this research is to contribute to the research dedicated to determining the factors that help startups become successful.

By determining the role of 3 key factors that can play their part in the performance of startups, our intention is to support empower startups and startup organizations such as incubators and accelerators with the knowledge of how they can elevate their performance.

Here's how this research fulfils the purpose intended:

1) Providing a comprehensive understanding of the role of the key elements involved in this research will offer invaluable insights to entrepreneurs, investors, and policymakers, equipping them with the knowledge to make informed decisions and support sustainable ventures.

2) Unlocking key strategies and best practices that can significantly enhance a startup's likelihood of success, leading to greater overall economic and societal benefits.

## 1.3 Research Objectives

The objectives of this research relate to studying the impact of the three key factors in the performance enhancement considering the specific context of firm type i.e., startups and the geographic context (country of Pakistan).

The following three points summarize the key objectives of the research:

1) To assess whether EO has a positive effect on the non-financial performance of startups

2) To assess whether MO has a positive effect on the non-financial performance of startups

3) To assess whether MSE has a positive effect on the non-financial performance of startups

4) To assess whether MSE mediates the relationship of EO and MO on the non-financial performance of startups

## 1.4 Problem Statement

In the realm of entrepreneurship, startups face a daunting challenge of success with their failure rate rising as high as 90% (Kalyanasundaram, 2018) . For a developing country like Pakistan, the access to resources and information regarding non-financial performance factors is limited.  Although the interest towards entrepreneurship is being enhanced, the

most startups stay unaware of critical factors like EO, MO, and MSE that can foster long-term survival and accelerate growth of startups. With most of the research in Pakistan focusing on SMEs, startups as organization have been ignored and left on their own exist in the cut-throat market fighting tooth and nail to survive their existence. To address this critical problem, our research examines the role of three key factors in the form of EO, MO, and MSE on the performance of startups. We seek to understand whether these factors have a significant impact on startups' performance. By uncovering these dynamics, we aim to provide practical insights that can empower startups to navigate challenges effectively, ultimately contributing to their success and economic resilience.

## 1.5 Definition of Terms

**Entrepreneurial Orientation (EO):**

EO is the characteristic of a firm that engages in product market innovation, embarks on somewhat risky ventures, and takes the lead in introducing 'proactive' innovations, outperforming competitors. (Miller, 1983)

**Marketing Orientation (MO):**

MO refers to the extent to which a business focuses on understanding the needs and preferences of its customers and strives to meet those needs more effectively than its competitors (Narver & Slater, 1990).

**Marketing Self-Efficacy (MSE):**

MSE refers to how strongly an individual believes that they are capable of successfully performing the roles and tasks in marketing products or services (Antoncic et al., 2016)

**Startup Non-Financial Performance:**

Non-financial performance pertains to the initiatives and efforts undertaken by a company to enhance critical metrics related to human resources, structural capital, and customer capital (Thuda et al., 2019).

## 1.6 Thesis Structure

The following structure will be followed in this Thesis:

**Chapter 1: Introduction**

This is the current and 1st chapter of this Thesis. In this chapter, we'll set the groundwork of our problem starting with explaining the background of the research, the purpose and objectives of the research, and how briefly describing what the reader can expect from the research.

**Chapter 2: Literature Review**

In this chapter we'll go over the previous research that relates to our topic. We will segregate each key variable involved in the research and leverage past research to analyze how the variable has been studied in the past. We'll examine the impact of the variables in different industries while focusing specifically on research that relates closely to our contexts. Leveraging past research, we'll also establish our hypothesis for this research in this chapter.

**Chapter 3: Research Methodology**

In this chapter, we'll mainly go over the conceptual framework used to conduct this research. We'll describe our independent, dependent, and mediating variables. We'll also get into the nitty-gritty of our data collection approach and look over the numbers of the data collected for the research.

**Chapter 4: Results and Discussion**

In this chapter, we'll go into detail to explain the results obtained from the study. We'll describe whether our dependent variables displayed a significant positive impact on

startups non-performance and whether our mediating variable successfully mediates the relationship between our dependent and independent variable.

The discussion section of this chapter will illuminate how our hypotheses have performed based upon our contexts and what startups can learn from these results of this research. We'll highlight some the decisions that startups can make based upon the impact of variable involved in this research on startup performance.

### Chapter 5: Conclusion and Future Work

This chapter will act as a concise summary of our entire research including the details of what the background of the research was, the problem this research intended to solve, and how the research has fared towards solving that problem. Finally, this chapter will take a brief look at the future prospects that maybe of importance as a result of this research.

# CHAPTER 2: LITERATURE REVIEW

In this chapter, we discuss the previous research and related articles that pave the way for this research. We'll briefly define each variable and take a look at what has already been established in the field and how it relates to the objectives of this study.

## 2.1 Evaluation of existing body of knowledge:

A comprehensive evaluation of existing body of knowledge is key to the conduction of an appropriate research study. Evaluating the existing body of knowledge illuminates the researcher of the degree of research already performed in the domain and helps them grasp a cohesive understanding of the underlying concepts and frameworks the aspire to study. By examining the existing literature, a researcher can systematically understand the research methods appropriate for the research type. The main aim of evaluating the existing literature however is to determine the degree of overlap in the existing research studies and identify a worthwhile research gap. The research gap can be the result of inadequate attention from past researchers towards a specific topic or be a result of the new dimensions that recent research has paved the way towards.

For this research, an extensive evaluation of the existing body of knowledge was conducted. In this subsequent section, we'll provide a comprehensive review of the existing literature related to our research.

### 2.1.1 Startup Non-Financial Performance

Consistence performance is a key challenge for startups and their path to growth is full of challenges as the more the progress, the more they have to face obstacles (Vincent and Zakkariya, 2021) . The performance of startups has been the focus of research for many researchers in the past with some who evaluated the performance of startups to be consequence of factors like EO (Korpysa, 2019; Linton, 2019; Vincent & Zakkariya, 2021), some evaluated it to be a consequence of MO (Du & Kim, 2021; Hai et al., 2021; ŞahiN & Siğri, 2022). But, the results of meta-analysis of variables like EO performed by Rauch et al., (2009) and on MO performed by Ellis (2006) highlighted that these relationships can have distinct results based on the context they are studied in. To have a

meaningful understanding of the performance of a business type, researchers should conduct studies that consider the specific firm and cultural context instead of assuming general contexts.

The overall performance of a business constitutes of both the financial and non-financial indicators (Vincent & Zakkariya, 2021). To understand the mechanisms of success for startups, Watson et al., (1998) performed a research based on startups in UK. According to them, to understand why the startups in an economy perform, we should first try to identify the determinants of their success and failure. Rashid et al., (2018) posited that a firm's capability to achieve success (i.e. making profits) can be measured through a set of variables called "performance indicators". Due to their significant role in increasing customers, non-financial performance of business ventures is equally important to their financial performance and should not be ignored in research explorations (Anwar and Shah, 2021). Vincent and Zakkariya (2021) posited that major performance indicators have been understudied in the past, in case of incubators (institutes that support early stage startups), as most studies don't take into account their impact despite their significant impact on overall performance. In the case of small businesses like startups where published is mostly not accessible, there's a huge unwillingness from respondents to provide financial data to outsiders (Simpson et al., 2012). In such a case, we can lean towards measuring startup performance with non-financial indicators as past research by Anwar and Shah, (2021) has already established that their effect on startup performance is significant.

### 2.1.2 Entrepreneurial Orientation:

The fundamental aspects of EO have been established through a comprehensive examination and synthesis of the strategy-making process and entrepreneurship literature from various sources. The first prominent work related to EO goes back to that of Miller (1983) who defined EO as the characteristics of a firm that "engages in product market innovation, embarks on somewhat risky ventures, and takes the lead in introducing 'proactive' innovations, outperforming competitors". Building on Miller's concept, scholars have consistently recognized and utilized "Innovativeness", "Risk-taking", and "Proactiveness" as the three dimensions of EO. But later, Lumpkin and Dess (1996)

suggested two additional dimensions “Competitive Aggressiveness” and “Autonomy“ as crucial components of the EO construct. Since then, different studies have been conducted on EO taking into account a different combination of dimensions based on the work of Miller (1983) and Lumpkin and Dess (1996).

To understand EO and its essence, it is important to establish an understanding of its indicators i.e. risk taking, proactiveness, completive aggressiveness, innovativeness, and autonomy. The seminal word of Lumpkin and Dess (1996) is key to the understanding of EO and its indicators. According to them, the five dimensions of EO can be salient to EO but can also vary independently in a given context. Autonomy suggests the liberation of individuals from organizational constraints and allowing them to act independently in their pursuit of seeing an idea to its completion. In the context of startups, it refers to the policy of enabling an environment where individuals can exercise their will to be self-directed without being weighed down by the organizational constraints like resource availability, chain of command or following procedure.

The second indicator of EO is “innovativeness”. According to the definition of innovation by Drucker (1998), innovation is “a change that creates a new dimension of performance”. According to him, innovation is a key part of entrepreneurship and it is the means through which new wealth is generated either from existing resources or through the creation of new resources. According to Rogers (2003), innovation is “an idea or an object that is perceived as new by an adopter”. Both the definitions point to the fact that being innovative is associated with engaging in newness i.e. creating newer products, using newer technologies, and staying state-of-the-art instead of staying reliant on existing products and technologies. In essence, innovation can simply be understood as the tendency and openness to new ideas, products, technologies etc. An innovative startup supports promotes creativity in problem solving and encourages their employees to share their ideas to build new products based on their knowledge and experience of interaction with the market.

“Risk taking” is the third indicator that is associated with EO. According to , Lumpkin and Dess (1996), the term can be interpreted differently depending on the context it is used in. According to Sanders and Hambrick (2007), the technical definition of risk

focuses on three areas i.e. “probability of outcomes, magnitude of outcomes and variance in outcomes”. The fourth indicator of EO is proactiveness. According to its Webster dictionary definition, proactiveness means “acting in anticipation of future problems, needs, or change ". Being proactive means that the startups should actively seek out to take initiatives in their market and try to identify opportunities of growth before their competition does. This means investing in systems that notify them about expected trend shifts in the market and building capabilities to exploit the shift of trends. To identify as a proactive startup, they need to exhibit an active opportunity seeking behavior, build a reputation for being the first-mover startup in their market and ensure to live by this reputation consistently over time. Along with capitalizing of opportunities, being proactive also calls for anticipating the problems of future in the present and avoiding them before they can appear. For the startup CEOs and managers, this means to follow the mindset that prefers to avoid the problem before it occurs instead of solving the problem after it occurs.

Another important aspect of being entrepreneurially oriented along with proactive is “competitive aggressiveness”. Although both of them are an important part of entrepreneurially oriented startup, a distinction between the two is necessary to decisions could be made with clarity. While being proactive means the intention and ability to seek out new opportunities in the market, competitive aggressiveness means the ability to respond to the competitor actions. This could mean development of a new product to rival a product that the competitor introduced to increase their market share or going after the suppliers, distributors, or talent that the competitions could have leveraged to gain a competitive advantage. In essence, proactiveness is the act of generating new demand or introducing new products/strategies to exploit the new surge in potential demand in the market while competitive aggressiveness is the act of competing for existing demand in the market. For the sake of this research, we restricted ourselves to three dimensions of the EO namely “proactiveness”, “risk-taking” and “competitive aggressiveness” following Hughes and Morgan (2007).

Prior to this research, we examined the available literature on the topic of EO in detail and explored relationship between EO and performance in the contexts of different industries and geographies. For instance, Meekaewkunchorn et al (2021) conducted a survey on 379 SME managers in the manufacturing industry of Thailand to study the effect

of three dimensions of EO (i.e. innovativeness, proactiveness, and risk taking) on the performance of SMEs. In their study, they considered "learning orientation" and "business strategy" as mediator variables between the dimensions of EO and performance. Their results showed that all three dimensions of EO considered for the study (i.e. innovativeness, proactiveness, and risk taking) have a positive influence on the performance of SMEs and that both "learning orientation" and "business strategy" mediate the positive relationship of EO and performance. However, their research did not take into account the rest of the two dimensions of EO (i.e. autonomy and competitive aggressiveness) and they did not provide insights on the non-financial performance specifically. Moreover, their research is focused on a non-startup context and cannot be extended to startups as well because firm context play a key role in the performance.

Another study conducted by Mulyana and Hendar (2020) discovered the role of EO and MO on business performance of fashion SMEs in Indonesia with "network innovation agility" as a mediating variable. In their research, they collected data 302 owners and leaders of fashion SMEs and measured the impact of EO and MO on their performance. Their results showed both EO and MO positively associated with business performance of the fashion SMEs in Indonesia. They also discovered the network innovation agility has both a direct and indirect positive influence on fashion SMEs as it mediates the relationship of EO and MO to performance. However, their research was based on a non-startup context and their focus was performance in general as they did not consider studying the non-financial aspect specifically.

A research conducted by Vincent and Zakkariya (2021) developed and tested a model where they tried to determine how startups existing in the technology incubators can increase their EO. Their study suggested the role of "absorptive capacity" in catalyzing EO and translate its outcomes on the performance of startups in incubation environments. Using a survey-based approach, they collected data from 304 technology-based startups from different incubators in India and used statistical analysis to test their hypothesis. Their research considered both financial and non-financial indicators as the indicator of startup performance. Their results suggested that startups can only increase their EO when they combine their existing resources with their absorptive capacity.

A research by Linton (2019) proposed a novel approach to studying the EO of startups. According to the research, instead of treating EO as a unidimensional perspective, a novel way to approach it would be to study it in multidimensional view and obtain a fine-grained analysis. Instead of considering EO a reflective construct, they consider EO as a formative construct where a change in any of the dimensions can cause a change in the EO construct. They argued that the formative view allows for EO to not just be seen as a single variable but rather exhibit different profiles. This way a firm that lacked in one dimension of the EO could still be considered entrepreneurially oriented if it existed high levels in other two dimensions. For instance, a startup can engage in a proactive and risk-taking behavior but may be disinclined towards risk-taking due to journey in the survival stage as taking risks could mean its eradication form the market. Linton (2019) conducted a longitudinal qualitative research over the course of 2 years in 2 startups in Sweden that showed variation of EO between and within the firm. Their findings suggest that EO dimensions vary differently for the outcome and processes and that to study EO, a more nuanced approach is needed where process and outcome are treated as salient to EO attributes.

A research study conducted by Korpysa (2019) aimed to discover the elements of EO that lead to highest influence on the performance of startups. For their research, they conducted a survey on 382 startups in Poland and performed an analysis on the individual components of EO. Their findings suggest that startups willing to take risks, exhibiting an innovative and proactive behavior tend to outperform startups that don't exhibit such behavior.

A research conducted by Lee et al. (2019) also studied the impact of EO on performance of startups with the mediating role of technological orientation and social capital. They conducted a survey on 144 firms that resided in startup supporting institutions in Korea. They discovered that EO positively influences the performance of startups and social capital and technological orientation positively mediate the EO and performance relationship.

With several other studies (Mathafena & Msimango-Galawe, 2023; Solano Acosta et al., 2018; Uzzal et al., 2019) reporting similar results, one could assume EO predominantly has a positive influence on performance. But, Saeed et al. (2014) discovered

through a meta-analysis on 41 countries that the EO-performance relationship is dependent on national context and can have distinct results based on the cultural context of country the research is performed. Along with that, previous research from Rezaei and Ortt, (2018) has posited that different dimensions of EO are related differently to the functions like R&D, production, marketing and sales. Furthermore, a recent study conducted on a sampled dataset of 110 UK low-tech and high-tech SMEs, discovered that the scales of measurement being the same, the configurations of EO dimensions that result in high or low performance are distinct for low-tech firms as compared to high-tech firms (Huang et al., 2023).

This places firm contexts and geography as important variables when trying to gauge the EO-Performance relationship, which is why we've focused our research on one particular type of firm and country i.e., tech startups in Pakistan. Therefore, with our specifically defined context and geography, we make our first hypothesis for this research:

**H1: Entrepreneurial Orientation (EO) has a positive impact on non-financial performance of startups (SNFP).**

### 2.1.3 Marketing Orientation:

MO was initially introduced by Narver and Slater (1990) as the extent to which a firm's activities are focused on understanding customer needs and satisfying them more effectively than competitors. Kohli and Jaworski, (1990) further refined the concept and proposed three components: customer orientation, competitor orientation, and inter-functional coordination. Customer orientation emphasizes the importance of understanding and meeting customer needs (Narver and Slater, 1990). Competitor orientation focuses on monitoring and analyzing competitors' actions and strategies to identify opportunities and threats (Slater & Narver, 1994) . Inter-functional coordination emphasizes the integration of marketing activities with other functions within the organization to achieve customer-focused goals (Jaworski & Kohli, 1993). As advancements in innovations increase, and the market environment becomes more dynamic, the organization must become familiar towards how to compete in their domains to attain or maintain their competitive advantage (Zhang et al., 2020).

Recently Hai et al. (2021) conducted a study on 518 Vietnamese startups to examine the role of MO on business performance and according to their results, MO had a direct positive effect on the performance of these startups. A quantitative research study conducted on 393 SMEs in the Kingdom of Saudi Arabia also displayed both EO and MO to have significant positive effect on firm performance (Ali et al., 2020). Another recent study by Wakjira and Shashi (2023) conducted in Ethiopian banks discovered that MO plays a vital role in achieving business success and can result in higher levels of employee and customer satisfaction. Additionally, their findings suggest that companies that prioritize MO possess a superior comprehension of their customers' requirements, enabling them to create exceptional solutions and gain a competitive edge in the market. But , with most of the research done is in non-startups context and with Ellis (2006) proving that cultural context is crucial to the relationship of MO and performance, there's a clear research opportunity to understand how MO will impact the performance of startups in the unique context of emerging economies (the country of Pakistan in our case). Therefore, keeping in mind the unique context of this research, we make the following hypothesis for this research.

***H2*. Marketing Orientation will have a positive impact on the non-financial performance of startups.**

### 2.1.4 Marketing Self-Efficacy:

Drucker (2012) pointed out that two of the key competencies that a firm needs for survival are innovation and marketing. Based on his study, decades later even to this day, a lot of researchers dive deep into the topic to evaluate marketing as a key competency to a firm's sustainability and growth. For example, Jones and Rowley (2011) established through their research that SMEs lacking marketing skills and marketing have low performance levels and are quite likely to fail. They also posited that, in case of SMEs, marketing is often intertwined with other activities and understanding its different contexts can be crucial to studying its impact. Another interesting study on the topic was conducted by Krasnikov and Jayachandran (2008) where they discovered a key insight stating that the impact of

marketing capability on a firm's success is stronger than research and development (R&D) and operations capabilities.

In the past researchers have generously focused their attention on studying principles like MO, as it is considered to be a critical component in driving performance of firms (Ali et al., 2020; Hai et al. 2021; Jaworski and Kohli, 1993; Solano Acosta et al., 2018; Wakjira and Shashi Kant, 2023). But the concept of MSE is comparatively understudied and hasn't attracted the attention of researchers even though Farrell (2006) pointed out that MSE has significant important on its own contrary to most research that makes it part of entrepreneurial capabilities. According to Bandura's social cognitive theory, self-efficacy influences an individual's choice of activities, effort, persistence, and resilience in the face of challenges (Bandura, 1982). In simple words, self-efficacy of a person is their belief in their own abilities to accomplish a certain task having known the challenges they'll face.

MSE as a key component has only been studied by a handful of researchers apart from Farrell (2006) who initially realized that self-efficacy is a key indicator of human behavior and developed the MSE scale. Self-Efficacy is usually domain-specific and is being studied by other researchers in domains like entrepreneurial self-efficacy (Barinua, 2011; Chen et al., 1998; Mcgee et al., 2009), Innovation self-efficacy (Carberry et al., 2018; Mcgee et al., 2009), and leadership self-efficacy (Anderson et al., 2008; Paglis & Green, 2002). Nevertheless, although low in numbers, we do have research available that takes into account the effect of MSE as a specific variable. Kim (2019) discovered that MSE plays a role in the stimulation of new firm formation in Korean context. Antoncic et al. (2016) explored the relationship between MSE and firm creation and discovered that MSE makes a difference in the creation of a new firm. Kim (2020) explored whether MSE of future entrepreneurs has an impact on their entrepreneurial intention and found the relationship to be positive. But, to-date, the role MSE on the performance of startups has not be studied. Neither has been the role of MSE as a mediator for EO and MO towards non-financial performance of startups in the context of emerging economies. Therefore, we make the following hypothesis in the unique context of our research:

**H3. MSE has a positive impact on the non-financial performance of startups.**

**H4. MSE mediates the relationship between EO and startup performance.**

**H5. MSE mediates the relationship between MO and startup performance.**

## 2.2 Research Gap

This research uses the already established scales of EO, MO, MSE, & Non-Financial Performance, and studies them with its unique conceptual framework. Although the impact of EO and MO has been studied together by past researchers, the mediating effect of MSE on EO and MO towards non-financial performance has not been examined. Moreover, the involved variables' impact in the unique context of this research i.e., tech- startups in Pakistan has not been examined before. Our research fills this research gap and paves the way for future research to contribute towards the milestone of reducing startup failure rate in Pakistan.

The following table sums up the research gap and how this research stands unique compared to past research:

*Table 1: Research Gap*

| **Authors** | **EO** | **MO** | **MSE** | **Tech Startups** | **Pakistan Region** |
|---|---|---|---|---|---|
| (Daradkeh & Mansoor, 2023) | ✔ | ✘ | ✘ | ✘ | ✘ |
| (Shaher & Ali, 2020) | ✔ | ✔ | ✘ | ✘ | ✘ |
| (Lee & Shim, 2019) | ✔ | ✘ | ✘ | ✘ | ✘ |

| | | | | | |
|---|---|---|---|---|---|
| (Mulyana & Hendar, 2020b) | ✓ | ✓ | ✗ | ✗ | ✗ |
| (Mathafena & Msimango-Galawe, 2023) | ✓ | ✓ | ✗ | ✗ | ✗ |
| (Boso et al., 2013) | ✓ | ✓ | ✗ | ✗ | ✗ |
| (J.-R. Kim, 2020) | ✗ | ✗ | ✓ | ✗ | ✗ |
| (J. R. Kim, 2019b) | ✗ | ✗ | ✓ | ✗ | ✗ |
| This Research | ✓ | ✓ | ✓ | ✓ | ✓ |

## 2.3 Problem Statement

After carefully evaluating the literature and identifying the research gap, we come to the conclusion that that in the context of the startups in Pakistan, the prior research lack evidence of factors that can influence the performance of startups. Based on this, a clear research problem has been identified and presented as follows:

"Startups have a crucial impact on economy in emerging countries, yet they struggle with a devastating failure rate of 90%. Although exploring their critical success factors (CSFs) like EO, MO, and MSE can help their growth tremendously, researchers in the past have overlooked their impact, specifically in the context of emerging economies like Pakistan. This has resulted in aspiring and established startups forced to rely continuously on trial and error, instead of deploying best-practices approved by research that can have positive

impact on their performance. If adequate attention is not shifted towards startups and their CSFs, the startup ecosystem is going to keep on struggling."

## 2.4 Research Questions

The research questions act a guide that help the researchers stay coherent in their thoughts and follow a specific pathway in their pursuit of knowledge. The research questions are inspired from the research problem and their main problem is to find answers that help provide a solution for the research problem. The importance of research questions is fundamental to any research as they not only define the scope of the research, but also help pave the way for the methodology that needs to be followed to perform the analysis and draw conclusions. In essence, the entire research methodology centers around the research questions and as they keep the research process concise and provide purpose to the investigative journey of the research.

A well-articulated research question helps bring clarity to the investigation and steers the research away from irrelevant tangents that lie outside of the scope of the study. This helps the researcher narrow their focus on the specific research query thereby saving them the time and effort. With a carefully articulated research question, a researcher is equipped with a lens that can be used to meaningfully examine the data and identify patterns, trends, and relationships that align with the research objectives.

The research question also helps the researcher to identify the population that best suits their research purposes. Based on the research question, the researcher uses the literature and subjective reasoning to identify a population that is best equipped with the knowledge and experience of answering the research question. Without a carefully crafted research question, the researcher lacks clarity regarding who the right audience might be to answer the research queries.

For this research, a main research question and 5 derived research questions were drafted to keep the investigation concise and cohesive.

**Main Research Question:**

- How does EO, MO, and MSE influence the non-financial performance

of startups?

**Derived Research Questions:**

- To what extent does EO influence the non-financial performance of startups?
- To what extent does MO influence the non-financial performance of startups?
- To what extent does MSE influence the non-financial performance of startups?
- To what extent does MSE mediate the relationship between EO and non-financial performance of startups?
- To what extent does MSE mediate the relationship between MO and non-financial performance of startups?

## 2.5 Research Objectives

Research objectives are one of the key parts of a research investigation just like research questions. While the goal of research questions is to clarify the scope of the investigation, the goal of research objectives is to identify the specific goals and outcomes of the research. The research objectives break down the overarching research questions and convert them into smaller chunks that act as a focused target for the researcher. The research objectives make a great contribution to the understanding of the research question and help form the overall narrative of the research.

For this research, we present the following 5 research objectives that are fundamental to our investigation:

- To examine the relationship between EO and SNFP
- To explore the relationship between MO and SNFP
- To assess whether MSE has an influence on SNFP
- To assess whether MSE mediates the relationship between EO and SNFP
- To assess whether MSE mediates the relationship between EO and SNFP

### 2.6 Theoretical Framework

The conceptual model used for this study is displayed Figure 1. The independent variable EO was assessed with a scale following Hughes and Morgan (2007), MO following Narver and Slater (1990), MSE following Chen et al. (1998), and non-financial performance was measured with 3 indicators namely customer satisfaction from Narver and Slater (1990), employee satisfaction following Chi and Gursoy (2009) and employee productivity using Chen et al (1998). All the items measured on 5-point Likert scale from Strongly Disagree to Strongly Agree since this type of scale has been previously used in literature (Hughes & Morgan, 2007; Jaworski & Kohli, 1993). Some items were later on removed from the analysis to satisfy the convergent and discriminant validity thresholds.

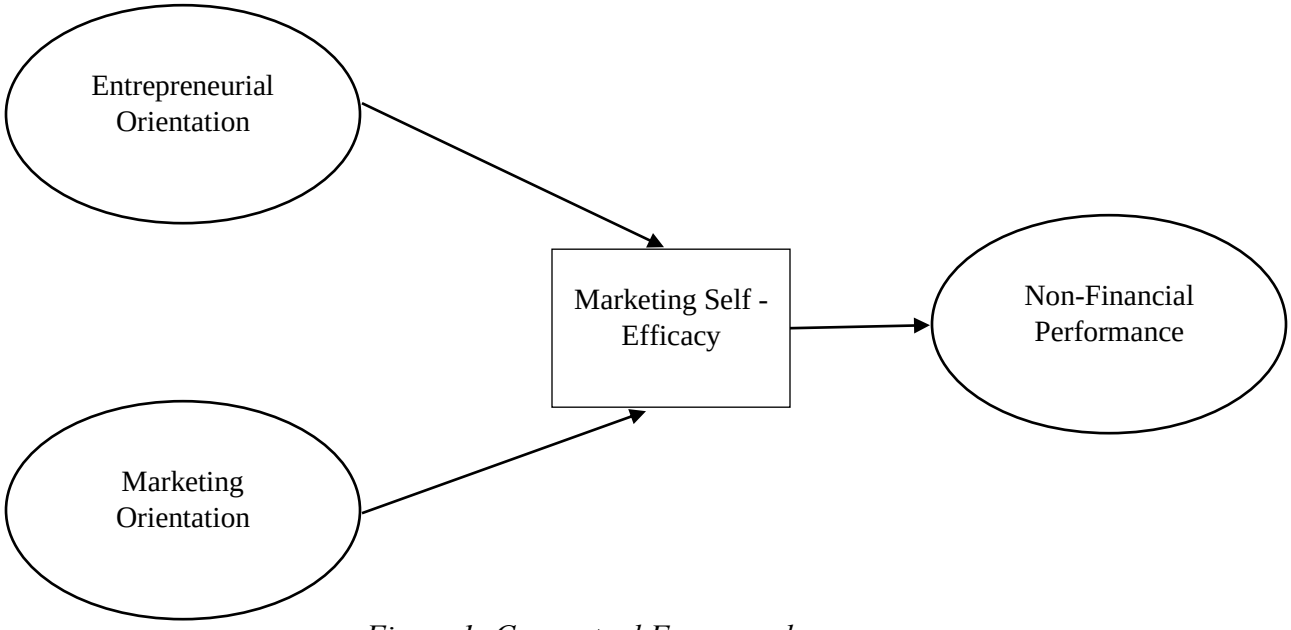


*Figure 1: Conceptual Framework*

## 2.7 Research Hypotheses

On the basis of our conceptual framework, following are the research hypotheses for this study.

**H1: EO has a positive impact on SNFP.**

**H2. MO has a positive impact SNFP.**

**H3. MSE has a positive impact on the SNFP.**

**H4. MSE mediates the relationship between EO and SNFP.**

**H5. MSE mediates the relationship between MO and SNFP.**

# CHAPTER 3: CONCEPTUAL FRAMEWORK & RESEARCH DESIGN

This chapter is dedicated to discussing the details of our complete research methodology. We'll include the details of our research design, data collection approach, sampling technique, sample size, data analysis and formulation of the questionnaire. The goal of this chapter is to communicate the step-by-step approach we undertook to formulate our research design and illuminate the process we followed to determine the outcome of our hypotheses.

## 3.1 Research Paradigm

Research in management science follows a specific research paradigm. The word paradigm is derived from the Greek word "paradigma" which means "pattern". So, the choice of a research paradigm is essentially the choice of a research pattern that the researcher follows to test the hypotheses of the research. The research paradigm paves the trajectory of the research and it influences the stance that a researcher takes to follow the methodology and the way in which the knowledge is constructed.

Since the research paradigm establishes the philosophy of knowledge and the trajectory of research, exploration of the various types of research paradigms was necessary for this research. There are multiple research paradigms that we explored for this research to choose the one that best fits the objectives of the research. Three of the main research paradigms that we explored are positivism, interpretivism, and pragmatism. A positivism paradigm is based on the belief that knowledge is objective and empirical methods are the tool that should be utilized to measure and observe the knowledge. It emphasizes that quantitative data and deductive reasoning is the way to pursuit knowledge and reach to a destination point i.e quantitative data is used to deduce patterns that lead to accurate answer to the research query. On the other hand, interpretivism paradigm suggests that the reality of knowledge is subjective and be interpreted through different perspectives. It emphasizes on the use of qualitative research methods to record different perspectives of participants and then interpret the meanings and contexts of their responses to reach to a conclusion. In comparison to positivism paradigm that emphasizes using quantitative data to reach to

conclusions, the view of interpretivism is in contrast and suggests interpretation as the best method to reach conclusions. On the other hand, pragmatism paradigm suggests that real world problems need practical solutions and that the choice of research design is best conducted based on practical solutions rather than theory and abstract principles. It suggests that a research may chose a both qualitative and quantitative research method based on what best suits the practicality of the solution to research problem.

For this research, we chose positivism as the ideal paradigm. The selection of positivism as the research paradigm aligns with the quantitative nature of the research objectives and data collection methods. Positivism emphasizes the objective measurement and analysis of data to establish empirical relationships between variables. The choice of interpretivism does not make sense for this research as no personal interviews were collected to interpret subjective opinions as they couldn't be generalized. The pragmatism paradigm also wouldn't make sense for the research given that the research was purely quantitative. The primary data collection method involved structured Likert-scale questionnaire responses and subsequent quantitative analysis using SmartPLS4, so positivism is the most suitable paradigm for this research.

There are three crucial parts of a research paradigm as illustrated by the following Figure 2.

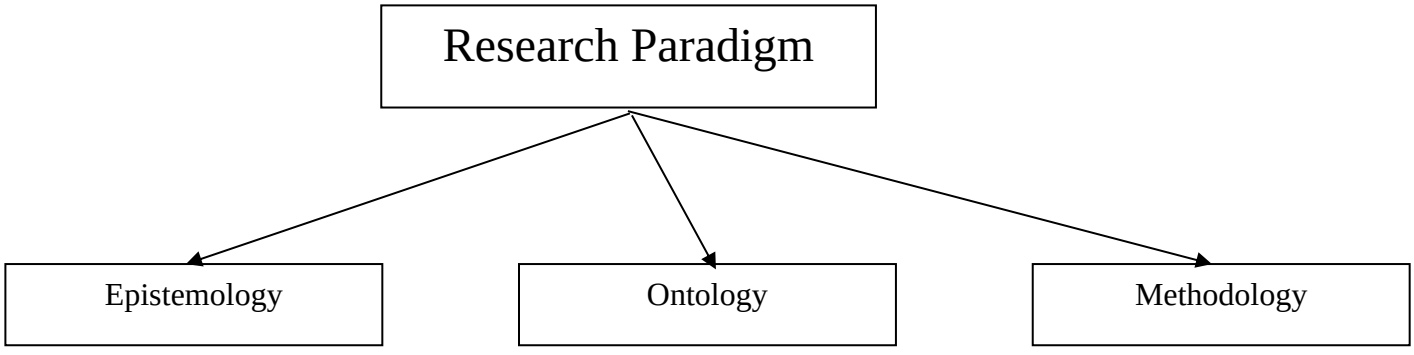


*Figure 2: Parts of research paradigm*

Epistemologically, this research adheres to a positivist perspective. It posits that knowledge is objective and can be acquired through systematic observation, measurement, and analysis of empirical data. The research aims to establish objective relationships between variables through quantitative methods.

Ontologically, the research adopts a realist stance. It recognizes that there is an objective reality, and the research seeks to uncover and understand this reality by examining the relationships between entrepreneurial orientation, marketing orientation, marketing self-efficacy, and startup non-financial performance.

The methodology for this research is descriptive-correlational type. It involves the use of a structured questionnaire with Likert-scale questions to collect quantitative data from respondents. The collected data is then subjected to statistical analysis using SmartPLS4 to test hypotheses, establish empirical relationships, and draw quantitative conclusions. We used PLS-SEM technique to test the relationships as it is preferred for this type of research, specifically with slightly smaller sample size (Hair et al., 2019).

## 3.2 Research Settings

For any research, the research settings significantly determine its direction and outcomes. Based on our research objectives, the ideal environment for this research was one where tech startups were vibrant and active, in view of its objective to delve into the impact of EO, MO, MSE, and their non-financial performance. Pakistan's tech ecosystem, particularly within incubators, provided the perfect setting. These incubators, with their nurturing environments and emphasis on fostering innovation, are breeding grounds for tech startups at various stages of their life cycles. Navigating this landscape, these startups often grapple with different orientations and self-efficacies, making it an apt environment to draw insights from for this study.

### 3.2.1 Qualitative VS Quantitative Data

Research data can broadly be categorized into qualitative and quantitative. Qualitative data revolves around descriptive, non-numerical information, often rich in depth and context.

Quantitative data, on the other hand, is numerical and focuses on quantifying phenomena. For this study, quantitative data was preferred, specifically because the research questions aimed to investigate relationships between variables, best explained through numeric representations. Quantitative data, with its structured format, allows for clear statistical analysis, making it suitable to answer this study's objectives.

### 3.2.2 E-surveys or Web-Based Surveys

In the digital age, e-surveys or web-based surveys have revolutionized data collection. They offer researchers the flexibility to reach a wide audience without geographical constraints, ensuring anonymity and often resulting in increased response rates. Beyond convenience, e-surveys offer quicker data compilation, paving the way for real-time analysis. Their significance in contemporary research cannot be overstated, particularly in scenarios where large datasets are required, or the target audience is digitally active, as was the case with the tech-savvy respondents in this study.

## 3.3 Research Design

The research design serves as the blueprint guiding the entire investigative process of a research, and is central to any empirical study. It provides the structure and strategy for addressing the research question efficiently so that a useful conclusion can be drawn. In this study, we embraced a non-experimental quantitative design based on the observatory/investigative nature of our research.

In a non-experimental quantitative design, the researcher observes variables without controlling the experimental environment. It's crucial to note that this design is purely observational. Here, the goal is to understand relationships between variables without manipulating any factors. We chose this design for our research because we aimed to comprehend the intricate interplay between EO, MO, MSE, and the non-financial performance of tech startups. In such a context, exerting control over experimental conditions would have been both impractical and potentially detrimental to the study's authenticity.

## 3.4 Instrument Development

An instrument in survey-based research is simply the questionnaire which is used to collect responses. In quantitative research, the reliability and validity of the instrument holds paramount importance as it determines the quality and credibility of the collected data. If a researcher is to create their own instrument for research, they have to justify its validity through statistical analysis. However, it is a common practice for researchers to leverage already established instruments the validity of which has been proven by past researchers. This research also follows the same strategy as all the items in the questionnaire were adapted from past research.

For this study, the primary instrument consisted of a carefully constructed questionnaire comprising 32 questions. These questions were formulated as closed-ended queries, utilizing a 5-point Likert scale. The scale ranged from 1, indicating 'Strongly Disagree', to 5, denoting 'Strongly Agree'. Such a scale facilitates quantifiable responses, streamlining subsequent analysis.

Given the crucial nature of the variables under investigation, it was imperative that the scales used demonstrated both validity and reliability. To ensure this, we utilized established scales from previous research. The scales for EO were adopted from Hughes & Morgan (2007), those for MO from Narver & Slater (1990), and those for MSE from Chen et al. (1998). Additionally, non-financial performance was assessed by drawing upon scales for sub-variables like Customer Satisfaction from Narver & Slater (1990), Employee Satisfaction from Chi & Gursoy (2009), and Employee Productivity from Lee & Brand (2010). Following is a detailed breakdown of each variable and scales used to measure.

### 3.4.1 Research Strategy

A research strategy provides a framework for the investigative process, delineating the methodology and tools to deploy. In this study, a survey-based strategy is selected. Surveys, as a data collection tool, offer both breadth and depth. They facilitate gathering vast amounts of data from a significant subset of the population while enabling researchers

to delve deep into specific constructs, behaviors, and perceptions. The strategic choice stems from the need to understand and quantify the relationships between multiple variables within the tech startup domain.

### 3.4.2 Time Horizon

The study adheres to a cross-sectional time horizon. Cross-sectional studies provide a snapshot of the variables of interest at a specific point or over a concise period. Data collection spans from February 2023 to October 2023, capturing insights and perspectives pertinent to this time frame. This approach stands in contrast to longitudinal designs, which track changes and evolutions over more extended periods.

### 3.4.3 Research Approach

Quantitative research is the chosen approach for this study. Quantitative methodologies prioritize objective measurements and numerical analysis of data collected through questionnaires, surveys, or manipulating pre-existing statistical data. In this research, the approach is underpinned by the desire to comprehend the discernible relationships between the study's variables.

### 3.4.4 Population

The focal population for this study revolves around tech startups in Pakistan, predominantly those operating within incubators. Pakistan's tech sector is burgeoning, marked by innovation and entrepreneurial spirit. This vibrancy offers a rich ground for academic inquiry, particularly regarding how orientations and self-efficacies influence non-financial performance metrics. Incubators, as nurturing environments for startups, form an integral part of this ecosystem, making them indispensable to this study.

### 3.4.5 Unit of Analysis

In any research, the unit of analysis signifies the primary entity under investigation. In this study, the overarching theme focuses on tech startups, but the granular focus centers on the

employees within these startups. Their perceptions, experiences, and feedback form the empirical backbone, designating them as the primary unit of analysis.

### 3.4.6 Measuring Scale

Data complexity is captured using a 5-point Likert scale. Such scales are invaluable tools for gauging the intensity or frequency of respondents' feelings or perceptions. Respondents express their agreement or disagreement across a spectrum, from 'Strongly Disagree' (1) to 'Strongly Agree' (5). The scale's granularity provides nuanced insights while maintaining clarity vital for quantitative analysis.

## 3.5 Instrument Distribution

The instrument was distributed collect and analyze the data in two phases. In the first phase, the measurement model analysis was performed on 54 responses to check the reliability and validity of the instrument through the PLS-SEM algorithm in smartPLS4. In phase 2, the structural model analysis was performed on 175 responses via bootstrapping in smartPLS4.

## **3.6 Data Collection**

The success of research depends on collecting data systematically and efficiently, as it forms the foundation for analysis and conclusions. In today's information age, various options are available for data collection like emails, social media, direct mail etc. with each data collection method having its own pros and cons. In this study, we followed a thorough and precise data collection process in line with the commonly accepted practices in research.

### 3.6.1 Method of Data Collection

For this research, we used a combination of electronic and physical methods to maximize our outreach. An online questionnaire was meticulously crafted with the intention be dispatched via emails and LinkedIn. With both emails and LinkedIn, we had predicted two

big challenges to be the acquisition of email addresses as they weren't publicly available and persuading the intended respondents to actually fill out the questionnaire. As our targeted audience were employees of startups, it was natural that they prefer spending their time on their job tasks rather than filling out a survey questionnaire. To address this challenge, we created a customized short link to the questionnaire and personally visited various incubators where we verbally shared the questionnaire link allowing potential respondents to access the questionnaire instantly. This mixed-method approach of data collection ensured wider coverage and increased the odds of securing comprehensive feedback.

### 3.6.2 Types of Sampling Techniques

The selection of appropriate sampling technique is crucial in research methodology, as it significantly influences the reliability and generalizability of study outcomes. There are several sampling techniques that are used in research method and are chosen based on the nature of the research. The choice of the sampling technique is usually made based upon the main research question of the research. Usually a specific target audience is selected based on the unit of analysis established in the research. A research article by Taherdoost (2016) is dedicated specifically to type of sampling techniques. According to him, in terms of research, the target audience capable of answering the main research question is termed as "population". Naturally, a researcher is not capable of analyzing the entire population due to the limitations of time and resources, which is where the sampling techniques help them choose a smaller portion of the population termed as a "sample".

Following are different types of sampling techniques usually adopted in the research method pertaining management sciences:

1. Simple Random Sampling:

Simple random sampling is a foundational method in the field of research design and it holds paramount importance. This is because it adheres to the principle of equal probability of selection for every case within the target population. This sampling technique ensures that each element or unit has an unbiased and independent chance of being included in the sample, making it a fundamental tool for achieving representative results. Despite its

conceptual simplicity and theoretical elegance, there are some challenges and considerations when it comes to choosing this type of sampling technique. Ghauri, & Grønhaug, (2005) elucidate certain drawbacks associated with this method. Firstly, the requirement for a complete frame — a comprehensive listing of all units comprising the entire population—is a notable constraint. Acquiring or constructing such a frame is a prerequisite for the application of simple random sampling and can pose logistical challenges, particularly in situations where a precise and up-to-date population listing is not readily available.

Moreover, the costs associated with obtaining a sample can be substantial in certain study scenarios, especially when dealing with geographically dispersed units. Surveys conducted through personal interviews, for instance, may incur higher costs due to the need to reach widely scattered elements within the population. This is an important consideration because it directly impacts the decision to undertake simple random sampling in terms of feasibility and practicality. Another noteworthy concern lies in the potential for elevated standard errors of estimators when utilizing simple random sampling. The randomness inherent in the selection process can lead to greater variability in the composition of the sample, consequently influencing the precision of estimates derived from that sample. This is why, when the precision and reliability of the research are stake, research need to make sure that the high variability in the composition of their sample does not affect the outcomes of their research as questions could be raised about its reliability.

So, while in theory it is quite favored that the research sample represents the populations fairly, in practice, it is quite hard to achieve because it’s quite a challenge to have access to the whole population and would require an extraordinarily significant amount in terms of cost and time, especially if the population is dispersed in different geographical regions. The justification for the expanses of such sources can only be made when the research objectives are mission critical. Additionally, the increase in variability is likely to be followed by a potential increase in the standard errors once again raising concerns upon the reliability and generalizability of the research. Nevertheless, simple random sampling is still a popular sampling technique that is widely utilized in research design by researchers

around the world and serves as a foundation of a few more nuanced sampling techniques that are derived from it.

For this research, simplified random sampling was not the ideal choice because the research is neither funded, nor the researcher has access to the population due to logistics cost associated. Therefore, a more nuanced sampling technique is needed which is more practical.

2. Stratified Sampling:

Stratified sampling is a more nuanced and cost-effective method of sampling in research design as compared to simple random sampling. In of choosing a random sample from an entire population, it suggests dividing the population different “stratums” or “subgroups”. It follows the rationale that different from an entire population, we can segregate groups that have the same characteristics and are likely to exhibit a similar behavior. According to Ackoff (1953), the main purpose of choosing the stratified sampling technique is that every stratum of the population is adequately represented. Once the population has been divided into different subgroups, then a sample can be drawn out randomly from each subgroup under the impression that a the randomly drawn out sample from that group represents the entire subgroup adequately. This way, the time and cost associated with random sampling can be efficiently reduced as much lesser participants of a population will need to observed and their behavior can be claimed to represent the entire population. Along with that, this approach is also more favorable compared to simple random sampling because its likely to result in less variability and standard errors. As the participants of subgroups possess common traits, they are likely to respond in a common behavior thus decreasing the variability and in return resulting in higher precisions which increases the reliability and generalizability of research.

To undertake a stratified sampling, a researcher needs to follow a step-by-step approach. The first step would be identifying the common traits and attributes of the population based on subjective knowledge. These traits or attributes could be decided based on various demographic, social, or organizational variables. For instance, gender is a common trait among different species in a population is often utilized in management research to study how gender influences a specific construct. Similar attributes to gender like educational

level, social status, income level, ethnicity are all attributes that can be used to divide the population intro different stratums. The selection of the attributes is subjective to the researcher and based strictly on the objectives of the study.

The second step would entail the division of the population into different subgroups based on their shared traits or attributes. Once the subgroups have been defined, then the third step is to draw out a random sample independently from each subgroup to make sure that each subgroup is adequately represented in the final research sample.

There are several advantages associated to the employment of stratified sampling due to which it is widely utilized in research methods. It offers a really nuanced way to recognize and incorporate the diversity that is present in the entire population. Since the population is divided into different subgroups before analysis, the researcher can precisely identify the interferences in each subgroup which allows for a targeted observation of the behavioral patterns in the particular subgroup. In addition, this approach is beneficial especially when a certain subgroup is underrepresented in a population. By intentionally selecting the samples from the underrepresented subgroups, the researchers can reduce the imbalances and ensure a fair representation of each subgroup in the population.

But, with all its advantages, there are also some disadvantages that come with the deployment of stratified sampling in the research design. For instance, it can be a real challenge to fulfil the primary requirement of access to accurate information and characteristics of the population so that the subgroups can be segregated accurately. And in cases where accurate data isn't available, or is partially available, or is inaccurate, then the application of stratified sampling becomes entirely questionable as the accuracy of data is compromised. In addition, the creation of subgroups requires careful consideration on the researcher's part as if it is not executed properly, it can introduce and biases and oversights once again raising questions of the reliability and generalizability of the research. One more challenge in the implementation of stratified sampling is its complexity when dealing with a very large or very small population. For small population, it is extremely difficult to divide them into different subgroups and for larger population, the logistics cost of managing multiple subgroups and ensuring representative sample for each becomes a major challenge.

For this research, the stratified did not make sense as our target population (tech startups) is niched and dispersed and there's no way for to acquire accurate data about the population. Moreover, our research intends to present findings that are generalizable to the whole population and does not intend to offer insights into the variability of behavior in different subgroups. Therefore, based on the research objectives, further exploration is needed to chooses a sampling technique.

3. Systematic Sampling:

Systematic sampling is a type of 'mixed' sampling design within research methodology. According to Kumar (2018), systematic sampling is a method that offers an efficient means of selecting a sample that represent the population because it follows a specific system. The method involves the deliberate selection of every nth element from the population, commencing with a randomly determined starting point. The systematic progression ensures a structured and evenly distributed pattern of sample selection, contributing to the reliability of outcomes. Initiating the systematic sampling process involves the identification of a random starting point within the population. This initial point is pivotal for minimizing bias, ensuring that the sample is reflective of the entire population. Subsequent elements are then chosen at regular intervals, adhering to the predetermined pattern. For instance, if the decision is made to select every fifth element, the systematic sampling proceeds by choosing the 5th, 10th, 15th, and so forth, until the desired sample size is attained. An evident advantage of systematic sampling lies in its simplicity. This method is straightforward to implement and does not necessitate an exhaustive listing of the complete population, rendering it particularly suitable for extensive populations. The simplicity inherent in systematic sampling streamlines the data collection process, offering cost-effectiveness, especially in contrast to methods requiring a comprehensive population frame. Furthermore, systematic sampling exhibits efficacy when the elements in the population follow a discernible order or pattern. In instances where the elements exhibit systematic or periodic arrangements, systematic sampling can capitalize on this structure, fostering an equitable distribution of characteristics within the sample. This distinguishes it from random sampling, where chance occurrences might introduce patterns, potentially leading to a less representative sample.

However, despite its advantages, systematic sampling is not immune to limitations. Notably, there exists a vulnerability to bias when an underlying pattern or periodicity in the population aligns with the sampling interval. Should the periodicity coincide with the sampling interval, the resultant sample may lack representativeness. For example, if a factory operates on two shifts and the sampling interval aligns with the shift change, the sample may disproportionately represent workers from one shift. Moreover, systematic sampling presupposes a degree of homogeneity within the population, implying that elements should not exhibit conspicuous patterns or considerable variations. In the presence of pronounced heterogeneity, systematic sampling may yield a less representative sample. Consequently, researchers must exercise prudence and evaluate the population's characteristics before opting for systematic sampling. Systematic sampling strikes a balance between simplicity and representativeness, making it a pragmatic choice when conducting studies or surveys involving extensive populations where exhaustive listing is impractical. Furthermore, systematic sampling proves advantageous in situations characterized by a certain degree of periodicity or order within the population. This assumes significance provided researchers judiciously select a sampling interval that does not align with the underlying pattern. Such strategic interval selection mandates a comprehensive understanding of population characteristics to mitigate the risk of biased outcomes.

4. Cluster Sampling:

Cluster sampling is a sophisticated method employed in research design, offering a strategic approach to selecting a representative sample from a larger population. According to Kumar, (2018), cluster sampling relies on the researcher's capacity to categorize a sampling population into clusters, delineated by discernible characteristics. These clusters are subsequently employed in the implementation of the Simple Random Sampling (SRS) technique for the selection of elements from each cluster. In contrast to simple random or systematic sampling, cluster sampling involves the division of the population into clusters or groups, with the objective of capturing the inherent heterogeneity within these clusters. This method acknowledges that certain populations naturally exhibit a clustered or group-based structure, and it leverages this structure to streamline the sampling process.

The main difference between the “stratified sampling” and “cluster sampling” is the randomness of the sample drawn. While the stratified sample is based on shared characteristics, the random sample drawn in a cluster is heterogeneous. Although similar to stratified sampling, in the first step of cluster sampling, the researcher needs to identify and create various clusters within the population. The choice of cluster is again subjective to the researcher and may be based upon the geographical region, the administrative division, or any natural occurring for that matter. After the clusters have been defined, the researcher then chooses a subset of these clusters randomly and includes them in the study. This deliberate method of choosing a sample simplifies the sampling process as instead of trying to reach every individual, a certain cluster is focused on which makes the data collection process more feasible in terms of logistics and cost-efficiency.

However, a big challenge in cluster sampling is present in terms of variability is present as the likelihood of homogeneity within clusters and heterogeneity between the clusters is increased in cluster sampling. This creates a problem in the reliability of the research as it can be argued that the sample does not adequately represent the population. So the researcher will be required to justify any conclusions drawn from the results of a research that followed cluster sampling.

5. Convenience Sampling:

Convenience sampling is a non-probability sampling technique commonly employed in research for its practicality and efficiency. According to Kumar, (2018), the two types of convenience sampling are “quota sampling” and “accidental sampling”. Both the methods are based on convenience i.e. ease of access to respondents until the quota for the number of respondents is met. Unlike probabilistic methods that aim to ensure every member of the population has an equal chance of inclusion, convenience sampling relies on the accessibility and ease of recruitment of participants. The practical considerations such as time constraints, limited resources, and ease of access take precedence in this type of sampling over the need for a representative sample.

Convenience sampling is one of the widely used sampling techniques due to its simplicity. This type of sampling focuses primarily on the convenience of the research rather than of representation of the sample to the population. With data collection being a big challenge,

and resources being scarce, researchers often prioritize convenience of sampling rather than the generalizability of the research. Research select participant that are most accessible to them, often from locations nearby to their residence's proximity, online forums and groups, or those who volunteer by themselves to be included in the study.

However, since in convenience sampling, the researcher does choose the sample based on a random or systematic process, there is a great potential for response bias which compromises the generalizability of the research. The risk is bias is even more elevated if the chosen sample of respondents contain attributes that are not present among the rest of the population. This means that the findings derived from the results of a research conducted a convenience sampling technique may lack external validity and a case can be made that the findings only represent a small part of the population and not the entire population. The homogeneity within the sample is like to be high if the sample data only consists of individuals that volunteered for research as most of them are likely to share similar traits and beliefs. To attain an adequate percentage of heterogeneity, a larger number of individuals are need to surveyed compared to other sampling techniques. In addition, a justification for the use of this sampling technique is required. Naturally, most researchers acknowledge the limitation of their research if they decide to undertake convenience sampling to test their hypotheses and justify their choice of sampling with an increase sample size as a compensation for choosing convenience over reliability. Since our goal for this research was to present findings that are generalizable to the tech startups, we did not follow convenience sampling.

6. Snowball Sampling:

Snowball sampling, also known as chain referral or network sampling, is a non-probability sampling method frequently utilized in social science research, particularly when studying populations that are challenging to reach or identify through traditional sampling techniques. This method relies on referrals from initial participants to recruit additional participants, creating a snowball effect. According to Kumar (2018), this type of sampling is useful when the researcher wants to study the patterns of communication, the decision making or the diffusion of knowledge in a particular group.

The first step in snowball sampling is to identify a small number of individuals who possess he attributes and characteristics that best fir the research objectives. Once these individuals have identified, they are approached and requested to take part in the study. From the ones that agree to participate in the study and record a response, the researcher intends to initiate a chain-like effect where each participant is asked to refer participants that possess traits similar to themselves to the researcher. In this way, a snowball effect is created where participants keep getting recruited to the study through referrals of participants prior to them. This referral of participants makes it easier for the research to recruit participants that would have been other difficult to reach and made part of the study. This type of sampling research is popular within research domains that study communities that are marginalized, hidden, or stigmatized. For instance, using traditional sampling techniques, it quite hard to identify the motivations of a drug abuse among the users of the drug since they rarely willingly participate in research studies. But since the snowball sampling technique follows a referral method, they're more likely to respond because the referral usually comes from someone, they already have a relationship with. This way the trust and rapport of the person they have a relationship acts a leverage motivating the users to comply to the research process.

Once again, the problem associated with snowball sampling is the homogeneity of the responses collected. Since, every participant in the sample is identified through a referral of someone similar who's also part of the same sample, the likelihood of shared characteristics between the overall sample becomes higher. And with increased homogeneity, the variability of the behavior is likely to be low. This means that the findings drawn from the research may represent a certain type of individuals and not necessarily the entire population. So, while snowball sampling may certainly be beneficial and the best choice for a particular set of research problems, the generalizability of the findings needs to be addressed adequately by the researcher.

Since the nature of this research is exploratory and the objective to test a correlation hypothesis, snowball sampling is not the ideal choice.

7. Purposive Sampling

Purposive sampling is an approach used in research methodology to select the participants of the research on purpose i.e. participants that fulfil a specific criterion that's relevant to the research objective and research problem. Individuals in purposive sampling are chosen based on a non-random order unlike in random sampling methods. This is because, in purposive sampling, the participants are intentionally selected based on their expertise to answer the main research question. Purposive sampling is beneficial when a researcher aspires to derive insights from a set of individuals that possess the characteristics desired by the other individuals who are part of the same population.

### 3.6.3 Choice of Sampling Technique

Purposive sampling was used for this research because it allowed us to target specific characteristics or criteria relevant to the research questions. When the researcher has a clear understanding of the specific attributes or experiences necessary to address the study's objectives, purposive sampling allows for the precise selection of participants possessing these desired qualities. This targeted approach facilitates a more focused and in-depth exploration of the phenomenon under investigation.

For our research, the individuals in incubators are ideal. According to Hughes and Morgan (2007), operating within incubators creates an environment where individuals are in the company of other individuals that share similar goals and situations, fostering a collective entrepreneurial spirit. Additionally, incubators promote the adoption of perceived best practices potentially steering a firm towards engaging in entrepreneurial activities.

Due to these facts, purposive sampling was chosen for this research.

3.6.3 Sample Collection

The quality of responses is often as crucial as the quantity of responses for any contemporary research. For this research, we initially gathered 183 responses over the course of 8 months. However, to ensure data integrity was of paramount importance for us. Hence, upon scrutiny, we eliminated some of the responses due to incomplete information, narrowing down the sample size to 175.

### 3.7 Limitations of the Research Design

Despite efforts to ensure the robustness of the study, inherent limitations exist. The research's cross-sectional nature implies capturing data at a specific time point, potentially missing evolving trends or dynamic shifts. The study's geographical focus on Pakistan might limit the generalizability of findings to broader or different tech startup ecosystems.

# CHAPTER 4: RESULTS AND DISCUSSION

This chapter is dedicated to discussing the results of analysis and the findings of this research. The outcomes of the conceptual framework introduced earlier will be presented in this chapter. First, we'll take a look at the various test results to determine whether our conceptual framework is valid and the items used to test the hypothesis are reliable. As all the items used in the research were adapted from prior studies, reliability test will shed light on the effectiveness of the scales to measure the constructs described in the conceptual framework. The convergent validity test will be conducted to determine whether the items measuring the same construct are distinct from each other. The discriminant validity test will be conducted to determine whether the items across the constructs are distinct from each other. Then a common method bias test will be conducted to determine the data collected has enough variance so that we can determine whether the responses are free of bias. The model fitness test will let us know the how well the data collected fits the conceptual framework of the research. Based on the results of the structural model analysis, we'll determine whether the hypotheses of the research are accepted or rejected, and appropriate conclusions will be drawn accordingly. Finally, a section dedicated to discussion of the results will be presented to present the findings of the hypotheses results and describe what the results mean for the startups.

SmartPLS4 software was used to conduct the analysis for research where a PLS-SEM based model was run to analyze and measurement and structural model. Data were automatically recorded in a Google Sheets spreadsheet since all our survey responses were web-based and then converted into MS Excel file for import and analysis in SmartPLS4 software.

### 4.1 Reliability and Validity

For any survey-based research in management science, reliability and validity and two of the most crucial elements of the measurement model. For the findings of the research to be deemed trustworthy, the thresholds of reliability are mandatory to be met. The validity of the model describes how accurately it measures what it was supposed to measure and the

reliability of the model describes the precision(consistency) of the model i.e. whether the model is capable of reproducing the same results if it was exposed to same conditions.

The reliability was assessed using Cronbach's alpha (α) and composite reliability (CR). According to (Hair et al, 2019), a value of 0.7 for Cronbach's alpha (α) a composite reliability (CR) signifies a reliable scale for measurement while an Average Variance Extracted (AVE) of 0.5 established convergent validity. For our research, the values for Cronbach's alpha (α) ranged from 0.78 to 0.92 while the CR values ranged from 0.84 to to 0.94 which satisfies the reliability criteria as stated by (Hair et al, 2019). The AVE for all 4 constructs ranges from 0.38 to 0.72, which is acceptable considering only 1 variable is troubling, and all the scales are previously validated by other researchers (Chen et al., 1998; Chi & Gursoy, 2009; Hughes & Morgan, 2007; Narver & Slater, 1990).

*Table 2: Chronbach's Alpha (α), Composite Reliability, and Average Variance Extracted (AVE)*

| | **Cronbach's alpha** | **Composite reliability (rho_a)** | **Composite reliability (rho_c)** | **Average variance extracted (AVE)** |
|---|---|---|---|---|
| **EO** | 0.827 | 0.850 | 0.870 | 0.494 |
| **MO** | 0.824 | 0.885 | 0.877 | 0.565 |
| **MSE** | 0.922 | 0.922 | 0.939 | 0.719 |
| **SNFP** | 0.781 | 0.845 | 0.809 | 0.372 |

The discriminant validity was assessed with Heterotrait-Monotrait (HTRT) ratio, as HTRT is a relatively better method of evaluating discriminant validity where values lower than 0.9 for HTMT would indicate that discriminant validity is established (Hair et al, 2019).

The HTMT values of all the constructs range from 0.62 to 0.85, so the discriminant validity is also acceptable (Fornell & Larcker, 1981).

Table 3: Discriminat Validity Measures (HTMT Ratios)

| | **EO** | **MO** | **MSE** | **SNFP** |
|---|---|---|---|---|
| **EO** | 0.703 | | | |
| **MO** | 0.699 | 0.752 | | |
| **MSE** | 0.796 | 0.725 | 0.848 | |
| **SNFP** | 0.695 | 0.762 | 0.673 | 0.610 |

### 4.2 Common Method Bias

Before assessing the structural model, the collinearity of the model needs to be checked (Hair et al, 2019). The common method bias was assessed using the Variance Inflation Factor (VIF) for the inner model (Hair et al, 2019). According to Kock (2015), a value lower than 3.33 for the inner model signifies the model to be free of common-method bias. The values for VIF for our model are all below 3.33, so the model is free of any common-method bias.

*Table 4: Collinearity Statistics (VIF of inner model)*

| **LV** | **VIF** | **Threshold** | **Source** |
|---|---|---|---|
| **EO -> MSE** | 1.967 | VIF <3.33<br>VIF<5 | (Kock, 2015)<br>(Hair et al, 2019) |
| **EO -> SNFP** | 2.922 | | |
| **MO -> MSE** | 1.967 | | |
| **MO -> SNFP** | 2.311 | | |
| **MSE -> SNFP** | 3.104 | | |

### 4.3 Normality Test

Normality test is a crucial statistical analysis test used to determine whether the responses collected from the questionnaire are distributed normally. Since our sample size is 175, we preferred to determine the normality of the data using the skewness and kurtosis of the variables instead of Shapiro Wilk test, Anderson Darling test, and Kolmogorov-Smirnov for sample size (n<300), the skewness and kurtosis are appropriate measures of normality H.-Y. Kim, 2013; Mishra et al., 2019). Skewness is a statistical variable that is used to quantify the asymmetry of the probability distribution. The skewness can be observed as left-tailed or right-tailed depending upon the data distribution. A positive skew indicates the spread of data points towards the right side and negative towards the left side. Kurtosis measures what is termed as the flatness of the curve in a normal distribution. It measures the "tailedness" of the data distribution in terms of "heavily-tailed" and "light-tailed" distribution. To determine the skewness and kurtosis of the data distribution, the threshold values i.e. (-3<skewness<+3 and -7<kurtosis<+7) are used (Curran et al., 1996; H.-Y. Kim, 2013). Based on these thresholds, our data is normally distributed as evident from the following table that showcases the exact values for each variable.

Table 5: Normality Distribution Test

| | **N (Sample Size)** | **Skewness** | | **Kurtosis** | |
|---|---|---|---|---|---|
| | | Statistic | Std. Error | Statistic | Std. Error |
| **EO** | 175 | -1.506 | 0.184 | 4.972 | 0.365 |
| **MO** | 175 | -1.365 | 0.184 | 3.422 | 0.365 |
| **MSE** | 175 | -1.458 | 0.184 | 3.333 | 0.365 |
| **SNFP** | 175 | -0.992 | 0.184 | 3.561 | 0.365 |

### 4.4 Structural Model Measurement

Based on the insights provided by (Hair et al, 2019), in the absence of any collinearity issues within the model, the next step is to analyze the structural model, beginning with the evaluation of the $R^2$ value associated with the endogenous construct(s). Shmueli and Koppius (2011) highlight that as $R^2$ quantifies the extent of variance explained in each endogenous construct, it essentially serves as a measure of the model's explanatory power. Following established guidelines, $R^2$ values can be interpreted , with values at 0.75 deemed as substantial, those at 0.50 viewed as moderate, and values at 0.25 considered weak (Hair et al, 2019). The values for $R^2$ can easily be considered substantial. The predictive relevance of the structural model was verified through the evaluation of Stone-Geisser's $Q^2$ value (Hair et al, 2019). It is essential for the $Q^2$ values to surpass zero to confirm the model's predictive accuracy as per (Hair et al, 2019)., a criterion that the variables in our research successfully met. After verifying the predictive relevance of the structural model, we proceeded to assess the impact magnitude ($f^2$) of each independent variable on the $R^2$ values associated with the dependent variable. In the context of structural models, the ($f^2$) value indicates the extent of change in the $R^2$ values due to the influence of independent variables (Hair et al., 2017). According to the guidelines set by Hair et al. (2017) the effect sizes ($f^2$) are categorized based on their strength: small (0.02), medium (0.15), and large (0.35).

*Table 6: R2 and Q2 Stone-Geissers's*

| LV | R-square | R-square adjusted | $Q^2$ Predict | Threshold | Source |
|---|---|---|---|---|---|
| **MSE** | 0.689 | 0.685 | 0.659 | 0.25; 0.5; 0.75 | (Hair et al, 2019) |
| **SNFP** | 0.453 | 0.450 | 0.547 | | |

The Standardized Root Mean Square Residual (SRMR) serves as a model fit measure, gauging the average discrepancy between the observed correlations and those implied by the model. For CB-SEM, the SRMR values less than 0.8 are considered to indicate a good model fit, but for PLS-SEM, no threshold value can be established (Hair et al., 2017). However, Henseler et al., (2015) considered it to be a suitable criterion for PLS-SEM, with Hu and Bentler (1998) arguing that in a conservative mode, an SRMR value of less than 0.1 can be considered for a good model fit. The SRMR value calculated for this study is 0.1, which is acceptable for a model fit.

*Table 7: f2 values of conceptual framework*

| | **f-square value** | **Threshold** | **Source** |
|---|---|---|---|
| EO-> MSE | 0.525 | 0.02; 0.15; 0.35 | Hair et al. (2017) |
| MO->MSE | 0.180 | | |
| MSE->SNFP | 0.828 | | |

### 4.5 Hypotheses Results

The hypothesis 1 posited that EO has a positive direct effect on SNFP. The results of the hypothesis can be determined based on the beta values and p values of the relationship where, for a positive effect, the beta values should be greater than 1.96 for a two-tailed relationship and the p-values should be less than 0.05 (Hair et al., 2017). The results of the structural model have been presented in the table 7 below.

*Table 8: Hypotheses Results of the research*

| Relationships | Beta Values | t-statistics | p-values | Threshold Values | Source | Hypothesis Decision |
|---|---|---|---|---|---|---|
| EO -> SNFP | 0.380 | 4.795 | 0.000 | P<0.05 | (Hair et al., 2017) | Supported |
| MO -> SNFP | 0.222 | 2.261 | 0.024 | | | Supported |
| MSE -> SNFP | 0.673 | 11.090 | 0.000 | | | Supported |
| MO -> MSE -> SNFP | 0.222 | 2.261 | 0.024 | | | Supported |
| EO -> MSE -> SNFP | 0.380 | 4.795 | 0.000 | | | Supported |

Hypothesis 1 Results

In the first hypothesis, we posited that EO will have a positive effect on SNFP. The results of the analysis can help us determine the outcome of this hypothesis. The results can be interpreted using all three of the metrics i.e. beta values, t-statistics, or the p-values. In statistical analysis, the beta values represent the path coefficients i.e. they represent the strength a direction of relationship between two variables. The co-efficient value of beta represents the extent of change that takes place in the dependent variable when there is an increase of one unit in the independent variable.

From the results shown in table 7, the beta value in the relationship between EO and SNFP is 0.380. This means that an increase of one unit in the EO will result in a change of 0.380 units in SNFP. And since the beta value is positive, we can determine that this change will be positive. So, using the beta value as an indicator of the relationship between EO and SNFP, we can deduce that the relationship is positive, so the hypothesis 1 stands to be true.

But although beta values do shed lights on the strength and direction of the relationship, they don't say enough about the significance of the relationship. So, determine the significance of the relationship, t-values are used. The t-values are calculated by dividing the beta values by their standard error. In general, the higher the t-statistic, the significant is the relationship between the variables. But a standard value is needed to establish the minimum threshold for a relationship to count as significant. According to Hair et al. (2019), a t-statistic of value higher than 1.96 is indicative of a significant positive relationship between the variables. As presented in table 7, the t-statistic for the relationship between EO and SNFP is 4.795 which indicates the relationship between EO and SNFP is indeed significant. The p-values, also often described as the "probability values" are associated with the t-statistic and quantify the probability of attaining the observed results by chance alone. In research, the p-values are used to determine whether the observed results are the likely to occur because of a real effect or whether they are the result of a random chance. Usually, a lower p-value is indicative of high statistical probability i.e. the chances of the observed results to be a cause of a real effect are higher as compared to a random chance. In research, two threshold values of p-value are established. If the p-value is less than 0.05 (i.e. $p<0.05$), the relationship is thought to have a 95% chance of being the result of a real effect. The 95% chance is considered significant in the practice of research. If the p-value is less than 0.001 (i.e. $p<0.001$), the relationship is thought to have a 99.9% chance of being the result of a real effect. The 99.9% chance is considered extremely significant in the practice of research. In the table 7, the p-value of the relationship between EO and SNFP has been presented as 0.000. This means that there is a 100% chance that the observed result is the cause of a real effect and its not the result of a random chance.

In view of all the metrics (i.e. beta value, t-statistic, and p-value), it can be established that the relationship between EO and SNFP is statistically significant and positive, and the Hypothesis 1 is true.

### Hypothesis 2 Results

In the 2nd hypothesis, we posited that MO will have a positive effect on SNFP. The results of the analysis can help us determine the outcome of this hypothesis. The results can be interpreted using all three of the metrics i.e. beta values, t-statistics, or the p-values. In the

table 7, the values for all 3 metrics have been presented. First, we'll look at the beta values of the relationship. The beta value will help us determine the strength and direction of relationship between MO and SNFP. Then the t-statistic will let us know the significance of the co-efficient. The p-value will help us determine the statistical significance of the chance that the observed relationship is the result of a real effect and is not the result of a random chance.

From the results shown in table 7, the beta value in the relationship between MO and SNFP is 0.222. This means that an increase of one unit in the MO will result in a change of 0.222 units in SNFP. And since the beta value is positive, we can determine that this change will be positive. So, using the beta value as an indicator of the relationship between MO and SNFP, we can deduce that the relationship is positive, so the hypothesis 2 appears to be true.

To determine the significance of the relationship, t-values are used. As presented in table 7, the t-statistic for the relationship between MO and SNFP is 2.261. This indicates the relationship between MO and SNFP is significant even after accounting for the standard error that may have impacted their relationship. It is important to note however, that the t-statistic is only slightly higher than the threshold value of 1.96. Nevertheless, the relationship between MO and SNFP is considered significant. The p-values will be used to determine whether the observed results are the likely to occur because of a real effect or whether they are the result of a random chance. In the table 7, the p-value of the relationship between MO and SNFP has been presented as 0.024. This value appears to pass the first threshold value of 95% significance ($p<0.05$) but does not pass the second threshold value of 99.9% significance ($p<0.001$). This means that the probability of the observed result between MO and SNFP has a 95% chance of being the result of real effect compared to a 5% chance of being the result of a random chance. In management science research, the 95% significance is widely accepted as a high significance value. In view of all the metrics (i.e. beta value, t-statistic, and p-value), it can be established that the relationship between MO and SNFP is statistically significant and positive, and the Hypothesis 2 is true.

Hypothesis 3 Results

In the 3rd hypothesis, we posited that MSE will have a positive effect on SNFP. The results of the analysis can help us determine the outcome of this hypothesis. The results can be interpreted using all three of the metrics i.e. beta values, t-statistics, or the p-values. In the table 7, the values for all 3 metrics have been presented. First, we'll look at the beta values of the relationship. The beta value will help us determine the strength and direction of relationship between MSE and SNFP. Then the t-statistic will let us know the significance of the co-efficient. The p-value will help us determine the statistical significance of the chance that the observed relationship is the result of a real effect and is not the result of a random chance.

From the results shown in table 7, the beta value in the relationship between MSE and SNFP is 0.673. This means that an increase of one unit in the MSE will result in a change of 0.673 units in SNFP. And since the beta value is positive, we can determine that this change will be positive. So, using the beta value as an indicator of the relationship between MSE and SNFP, we can deduce that the relationship is positive, so the hypothesis 3 appears to be true.

To determine the significance of the relationship, t-values are used. As presented in table 7, the t-statistic for the relationship between MSE and SNFP is 11.090. This indicates the relationship between MSE and SNFP is significant even after accounting for the standard error that may have impacted their relationship. It is important to note that the t-statistic is only significantly higher than the threshold value of 1.96 which signifies an extremely strong relationship between MSE and SNFP. The p-values will be used to determine whether the observed results are the likely to occur because of a real effect or whether they are the result of a random chance. In the table 7, the p-value of the relationship between MSE and SNFP has been presented as 0.000. This means that the probability of the observed result between MO and SNFP has a 100% chance of being the result of real effect compared to a 0% chance of being the result of a random chance. In view of all the metrics (i.e. beta value, t-statistic, and p-value), it can be established that the relationship between EO and SNFP is statistically significant and positive, and the Hypothesis 3 is true.

Hypothesis 4 Results

The hypothesis 4 posited that MSE positively mediates the relationship between EO and SNFP. The purpose of a mediator variable is to determine the means through which an independent variable effect the dependent variable. When a direct relationship between two variables is present but is unclear, a mediator variable is hypothesized to indirectly link the effect of one variable on another. In contrast to a direct relationship, the mediation analysis determines the indirect effect of one variable on another.

In table 7, all three metrics i.e. beta values, t-statistics, or the p-values for the indirect relationship (EO→MSE→SNFP) have been presented. The results of the analysis can help us determine the outcome of this hypothesis. In the case of mediation, the beta value indicates the strength and direction of EO and SNFP in the presence of MSE. From table 7, we can see that the beta value for the EO→MSE→SNFP relationship is 0.380. This means that with MSE acting as the indirect link between EO and SNFP, a change of one unit in EO results in a change of 0.380 units in the SNFP. Since the beta value is positive, the relationship between EO and SNFP with MSE linking them to each other is positive. In simple words, the beta value indicates that MSE successfully mediates the relationship between EO and SNFP. So, the hypothesis 4 appears to be true.

To determine the significance of the relationship, t-values are used. As presented in table 7, the t-statistic for the relationship between EO and SNFP with MSE as a mediator between them is 4.795. This indicates that the relationship between EO and SNFP is significant in the presence of a mediator variable in the for MSE even after accounting for the standard errors that may have impacted the overall relationship. The p-values will be used to determine whether the observed results are the likely to occur because of a real effect or whether they are the result of a random chance. In the table 7, the p-value of the relationship between EO→MSE→SNFP has been presented as 0.000. This value appears to pass the first threshold value of 95% significance ($p<0.05$) and also the second threshold value of 99.9% significance ($p<0.001$). This means that the probability of the observed result for the EO→MSE→SNFP relationship has a 100% chance of being the result of real effect compared to a 0% chance of being the result of a random chance. In view of all the

metrics (i.e. beta value, t-statistic, and p-value), it can be established that MSE successfully mediates the EO-SNFP relationship the hypothesis 4 is true.

Hypothesis 5 Results

The hypothesis 5 posited that MSE positively mediates the relationship between MO and SNFP. In table 7, all three metrics i.e. beta values, t-statistics, or the p-values for the indirect relationship (MO→MSE→SNFP) have been presented. The results of the analysis can help us determine the outcome of this hypothesis. In the case of mediation, the beta value indicates the strength and direction of MO and SNFP in the presence of MSE. From table 7, we can see that the beta value for the MO→MSE→SNFP relationship is 0.222. This means that with MSE acting as the indirect link between MO and SNFP, a change of one unit in MO results in a change of 0.222 units in the SNFP. Since the beta value is positive, the relationship between MO and SNFP with MSE linking them to each other is positive. In simple words, the beta value indicates that MSE successfully mediates the relationship between MO and SNFP. So, the hypothesis 5 appears to be true.

To determine the significance of the relationship, t-values are used. As presented in table 7, the t-statistic for the relationship between MO and SNFP with MSE as a mediator between them is 2.261. This indicates that the relationship between EO and SNFP is significant in the presence of a mediator variable in the form of MSE even after accounting for the standard errors that may have impacted the overall relationship. The p-values will be used to determine whether the observed results are the likely to occur because of a real effect or whether they are the result of a random chance. In the table 7, the p-value of the relationship between EO→MSE→SNFP has been presented as 0.024. This value appears to pass the first threshold value of 95% significance ($p<0.05$) but does not pass the second threshold value of 99.9% significance ($p<0.001$). This means that the probability of the observed result for the EO→MSE→SNFP relationship has a 95% chance of being the result of real effect compared to a 5% chance of being the result of a random chance. In view of all the metrics (i.e. beta value, t-statistic, and p-value), it can be established that MSE successfully mediates the EO-SNFP relationship the hypothesis 5 is true.

### 4.6 Impact of Demographics

To determine whether the demographics can influence the structural model, we performed t-test on each 3 demographic variables i.e Gender, Startup Type, and Startup Tenure. For a variable to have a significant impact, the t-value should be greater than 1.96 (Hair et al., 2017). The results show that none of the demographic variable influence the relationship. The exact values can be seen in the following table.

Table 9: Results of t-statistics for demographics

| **Type** | **t-statistics** | **p-values** | **Conclusions** |
|---|---|---|---|
| **Gender → SNFP** | 0.334 | 0.738 | **Not Significant** |
| **Startup_Tenure → SNFP** | 1.275 | 0.203 | **Not Significant** |
| **Startup Type → SNFP** | 0.317 | 0.752 | **Not Significant** |

### 4.7 Discussion of Results and Theoretical Contribution

Since startups are organization that depend hugely on external investments and venture funds for their survival in their early years instead of self-generated cash-flow, the threat they face is more critical than that of an established business, where an established business is fighting for market share, a startup is fighting an uphill battle against its own existence. Alternatively, without the right guidance and decision-making, startups are quite prone to failure, and as it stands, only 10% of them survive currently, while 90% fail (Kalyanasundaram, 2018). The overall understanding of the CSFs of startups prior to this

research is weak as most research focuses on non-startups contexts. Past research has already identified some of the critical success factors (CSFs) for startups like business environment/surroundings (Davidsson et al., 1994), level of competence (Arruda et al., 2015), and the entrepreneur's management experience (Vu et al., 2012). To explore more CSFs, contemporary research is required that garners insights specifically from startup contexts.

In this research, three CSFs for startups in EO, MO, and MSE were discovered. Utilizing the analytic capabilities of SmartPLS4 software, we examined the structural interdependencies of these constructs, revealing noteworthy implications for both theory and practice. The analysis confirmed a strong, affirmative correlation between entrepreneurial orientation and the sustainable performance of new firms. This underscores the significance of entrepreneurial traits such as innovation, proactive initiatives, and a willingness to take calculated risks as essential contributors to a firm's success, particularly within the context of sustainable business practices. Moreover, the observed positive influence of market orientation on firm performance reinforces the concept that a thorough comprehension of market dynamics and customer needs is fundamental to achieving a competitive edge and ensuring the sustainable growth of a firm. One of the key contributions of the study is determining the role of MSE in the performance of startups. The study emphasizes MSE as a key mediator between both EO and MO, and the firm's performance, suggesting that an individual's confidence in their marketing capabilities is a decisive factor in the success of their firm. This insight is in harmony with theoretical perspectives that view self-efficacy as an integral component of successful entrepreneurial activity.

The research makes key contributions to the understanding of the constructs that help startups become successful, specifically in the context of the emerging economies. Although all of the hypotheses in the research are true, distinctions can be made upon the importance of each construct over the other. Based on the beta value in the EO-SNFP and Mo-SNFP relationship, it can be established EO appears to have a stronger impact on the SNFP in the given contexts because the beta value representing EO→SNFP relationship is higher than that of the beta value representing MO→SNFP relationship. The same trend is

also visible when we compare the t-statistics of the two. The t-statistic for the EO→SNFP is 4.795 which is almost twice as high compared to the MO→SNFP relationship which is 2.261. This helps us determine that the influence of the indicators of EO i.e. “proactiveness”, “risk-taking” and “competitive aggressive” is higher on SNFP compared to the influence of the indicators of MO i.e. “customer orientation”, “competitor orientation” and “inter-functional orientation”. These insights are important because let us know exactly how the startups should behave in order to realize the positive impacts of high non-financial performance.

Equipped with the knowledge that EO positively impacts the SNFP, startups can actively seek to take calculated risks as risk-taking is one of the indicators of the non-financial performance and is associated with an increase in non-financial performance. Along with that, startups should try to be proactive in their decision making as proactiveness is also one of the indicators of EO which has been associated with an increase in the non-financial performance for startups.

The research extends existing academic discourse by empirically validating the intermediary role of MSE in the entrepreneurial ecosystem. It broadens the scope of knowledge on the interplay between personal skills and organizational strategies, and how these affect outcomes related to firm performance. In addition, by integrating the aspect of MSE, the research offers a more intricate understanding of how entrepreneurial orientation influences firm success, especially in sustainable ventures. On a practical level, the findings advocate for the inclusion of MSE development in entrepreneurial education programs. Such an approach promises to better prepare future entrepreneurs to face the marketing challenges of the modern business environment. From a social point of view, investment and funding in the education of entrepreneurial and marketing capabilities at all levels of education can improve the startup ecosystem and bolster the economy.

The insights garnered from this study bear significant practical ramifications for a spectrum of stakeholders in the entrepreneurial landscape. For startup founders, the study illuminates the critical role of marketing self-efficacy in steering their ventures towards success and sustainability. This calls for a conscientious effort on their part to cultivate marketing competencies and build confidence in these abilities. Founders should actively

seek out training opportunities, mentorship programs, and collaborative experiences that bolster their marketing skillset and self-assurance in these competencies. Policymakers are urged to pay attention to these insights and create policies that support the development of marketing proficiencies within tech startups.

The research also sheds light on how MO helps increase the non-financial performance for startups. The indicators of MO are "customer orientation", "competitor orientation" and "inter-functional orientation". This means that startups that focus on their customers' problems and create products that actually solve those problems are associated with a high non-financial performance. Along with that, startups take into account the activity of their competitors and respond to their activity in the market are likely to have a better non-financial performance than the ones that don't pay attention to their competitors. Additionally, startups that believe in a collaborative culture and are inter-functionally connected are able to achieve higher non-financial performance than the ones that work in silos. The inter-functional connectedness appears to help startups understand their market's needs effectively resulting in the development of a product that gets accepted by the market faster.

The positive association of MSE will SNFP provides crucial insights into how the belief of individuals in their abilities to perform their tasks impacts the overall performance of their organization. This means startups comprised of teams having superior belief in their abilities tend to outperform startups whose individuals don't believe in their abilities to perform their tasks. Based on this insight, the implication for startups is to recruit individuals with high MSE. Along with that, the insights identifies a need for skill training, confidence boosting, and mindset training of startup teams so their belief in their abilities can be reinforced with positive thinking. Additionally, for CEOs and managers of the startup, this insight suggests taking initiatives that reinforce the belief of their teams in their abilities and avoid behavior that that diminishes their belief in their abilities.

Combining the knowledge of these studies with our research that highlights the importance of EO, MO, and MSE for startups, a set of best-practices can be established that startups can use to propel themselves to success. For instance, based on the result of MSE mediating the relationship between EO and MO to the non-financial performance of

startups, we can establish that startups can benefit greatly by adopting the best-practice of prioritizing individuals with elevated levels of EO, MO, and MSE to work in their teams. This is in alignment with (Keating & Olivares, 2007) who discovered addressing the human resource needs to be the most crucial factor in startup firms. Another best practice that startups can adopt is to organize skill-based confidence building trainings to increase the EO, MO, and MSE levels of their current teams. This is in alignment with Twomey and Harris (2000) who posited that supporting the human resource needs of employees leads to increase in their career development and entrepreneurial behavior. One more best practice that startups can adopt is what can be termed as "the carrot is better than the stick", which implies that rewarding startup teams for their ideas and performance is better than threatening them of the consequences of lack of performance, as (Stirin Tzur et al., 2016) have proved through 3 experiments that rewards positively moderate the relationship between self-efficacy and performance. To establish more best practices, future research is going to play a key role in this research domain.

# CHAPTER 6: FUTURE RESEARCH AND LIMITATIONS

With the positive effects of EO, MO, and MSE having been established in this research, exploring their antecedents can of critical importance for future research. Exploring the antecedents will help identify the key areas that lead to the increase of EO, MO, and MSE, ultimately resulting in performance of startups. For instance, based on the definition of MSE that posits MSE to be an individual's belief in their marketing capabilities, a strong hypothesis could be made that the knowledge sharing between startup employees increases the MSE across the startups resulting in overall growth of startup. Another hypothesis positing that marketing book reading enhances an individual's MSE. If proven correct, startup can adopt additional best-practices where they arrange weekly knowledge sharing sessions and book review sessions between their teams. Similarly, additional antecedents to EO and MO could also be explored and resulting best-practices can be documented for startups to use.

Despite significant theoretical and practical contribution, the current study has some limitations that can be eliminated in the future research. Firstly, the data collected only comprised of startups from Pakistan, mainly from startups in incubators, which limits the generalizability of the research. Secondly, this research is primarily cross-sectional in nature spanning data collection in only the major cities over 8 months. Longitudinal studies could provider deeper insights for the same conceptual framework. The study utilized a purposive sampling technique which restricts the randomness of the research.

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## ANNEX A

### Section A: Entrepreneurial Orientation (EO)

| Sr no. | Statement | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| 1 | The term 'risk taker' is considered a positive attribute for people in our business. | | | | | |
| 2 | People in our business are encouraged to take calculated risks with new ideas. | | | | | |
| 3 | Our business emphasizes both exploration and experimentation for opportunities. | | | | | |
| 4 | We always try to take the initiative in every situation (e.g., against competitors, in projects and when working with others) | | | | | |
| 5 | We excel at identifying opportunities. | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| 6 | We initiate actions to which other organizations respond | | | | | |
| 7 | Our business is intensely competitive. | | | | | |
| 8 | In general, our business takes a bold or aggressive approach when competing. | | | | | |
| 9 | We try to undo and out-maneuver the competition as best as we can. | | | | | |

**SECTION B: Market Orientation (MO)**

| Sr no. | Statement | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| 10 | Our business objectives are driven primarily by customer satisfaction. | | | | | |
| 11 | We constantly monitor our level of commitment and orientation to serving customers' needs. | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| 12 | Our strategy for competitive advantage is based on our understanding of customers' needs. | | | | | |
| 13 | We rapidly respond to competitive actions that threaten us. | | | | | |
| 14 | Top management regularly discusses competitors' strengths and strategies. | | | | | |
| 15 | We target customers where we have an opportunity for competitive advantage. | | | | | |
| 16 | All of our business functions are integrated into serving the needs of our target markets | | | | | |
| 17 | All of our managers understand how everyone in our business can contribute to creating customer value. | | | | | |

**SECTION C: Marketing Self-Efficacy (MSE)**

We are confident in our abilities to achieve the following:

| Sr no. | Statement | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| 18 | Set and meet market share goals. | | | | | |
| 19 | Set and meet sales goals | | | | | |
| 20 | Set and attain profit goals | | | | | |
| 21 | Establish position in product market | | | | | |
| 22 | Conduct market analysis | | | | | |
| 23 | Expand business | | | | | |

**SECTION D: Startup Non-Financial Performance (SNFP)**

| Sr no. | | Statement | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
|---|---|---|---|---|---|---|---|
| 24 | **Customer Satisfaction** | We have been able to create value for our customers. | | | | | |
| 25 | | We have been able to retain our customers. | | | | | |
| 26 | | We have been able to keep our customers satisfied. | | | | | |
| 27 | **Employee Satisfaction** | Overall, I am satisfied with my job at my current company. | | | | | |
| 28 | | I intend to keep working at the company long into the future. | | | | | |
| 29 | | I often think about quitting my job. | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 30 | | As soon as I can find another job I am going to leave | | | | | |
| 31 | **Employee Productivity** | I do a large amount of work each day. | | | | | |
| 32 | | I accomplish tasks quickly and efficiently. | | | | | |
| 33 | | I have a high standard of task accomplishment. | | | | | |
| 34 | | My work outcomes are of high quality. | | | | | |
| 35 | | I always beat our team targets. | | | | | |