PSYCHOLOGICAL CORRELATES OF BEHAVIOURAL INTENTIONS OF YOUNG ADULTS TOWARDS NON- COMMUNICABLE DISEASES IN ETHIOPIA

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SCHOOL OF PSYCHOLOGY

June, 2025

Addis Ababa, Ethiopia

ADDIS ABABA UNIVERSITY

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SCHOOL OF PSYCHOLOGY

Psychological Correlates of Behavioural Intentions of Young Adults towards Non-Communicable Diseases in Ethiopia

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A PhD Dissertation Submitted to the School of Psychology of Addis Ababa University in Partial Fulfilment of the Requirements for the Degree of Doctor of Philosophy in Applied Social Psychology

June, 2025

Addis Ababa, Ethiopia

Addis Ababa University

College of Education and Behavioral Studies

School of Psychology

As members of the Examining Board of the final PhD open defence, we certify that we have read and evaluated the Dissertation prepared by Shumye Mola Legesee Titled: "**PSYCHOLOGICAL CORRELATES OF BEHAVIOURAL INTENTIONS OF YOUNG ADULTS TOWARDS NON- COMMUNICABLE DISEASES IN ETHIOPIA"** and recommend that it be accepted as fulfilling the Dissertation requirement for the Degree of Philosophy in Applied Social Psychololgy

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I hereby certify that I have read the revised version of this dissertation prepared under my direction and recommend that it be accepted as fulfilling the dissertation requirement.

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Department Chairperson Signature Date

DECLARATION

I first, declare that this dissertation is my bonafide work and that all sources of materials used for this dissertation have been duly acknowledged. This dissertation has been submitted to the requirements for PhD Degree at Addis Ababa University, College of Education and Behavioral Studies and is deposited at the University's Library to be made available to borrowers under rules of the Library. I solemnly declare that this dissertation is not submitted to any other institution anywhere for the award of any academic degree, diploma, or certificate.

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College of Education and Behavioural Sciences

Date of Submission: ________________________

DEDICATION

This dissertation is dedicated to my whole families and for both my grandmothers and grandfathers who passed away without seeing my success. To my beloved family, whose sacrifices and unwavering support has been the cornerstone of my journey.

To my grandmothers, Kiros Zewudie and Demeku Hassen, whose love, resilience, and dreams became the foundation for my education, you were my first inspirations, the reason I dared to dream, and the opportunity I was blessed with. Though you are no longer here to witness this milestone, your spirit continues to guide me every step of the way.

This work is a testament to your legacy and the sacrifices of our family.

ACKNOWLEDGEMENTS

May all praises be to Allah the most compassionate and merciful.

I extend my deepest gratitude to Professor Habtamu Wondimu, my teacher and supervisor, for his insightful guidance, inspiring mentorship, and consistent positive attitude throughout my courses and this dissertation. His support provided invaluable opportunities to explore my interests, deepen my understanding, and address my insecurities. His profound knowledge and nurturing approach were instrumental in my pursuit of professional and personal goals.

I am also thankful to my esteemed colleagues, Dr. Tedla Kutaye, Dr. Mohammed Demissie, Dr. Abera Tibebu, Dr. Girmay Medhin, and Mr. Osman Yimer, and my teachers, Dr. Teka Mengesha, Dr. Abebaw Minaye, Dr. Silehshi Zeleke, Dr. Tamrie Andualem, Dr. Dawit Wendimagegn, Dr. Kasahun Habtamu, and Professor Tilahun Sinshaw, for their encouragement and timely advice. My appreciation also goes to the external committee members and anonymous reviewers for their perceptive recommendations.

This study would not have been possible without the participation of the students and teachers involved in data collection. Their stories, strength, determination, and desire to help others continue to be a source of motivation. I am also grateful to Addis Ababa University and Debre Berhan University for their generous funding of this project.

To my beloved wife, Seada Mohamed, "Thank you" is an inadequate expression of my gratitude for your companionship, encouragement, and unwavering love and prayers. To my cherished sons, Amar Shumye, Esmael Shumye, and Abdurehman Shumye, you are truly precious gifts, and I am fortunate to call you my family.

My siblings, Kibnesh Molla, Wasihun Molla, Seada Molla, Hussiesn Molla, and Abduselam Molla, I am thankful for your patience, endless support, and constant examples of devotion and positivity. I am proud to call you my siblings and am excited for our futures together.

Finally, and most profoundly, a special thanks to my parents, Ayalesh Addissie and Molla Legesse. Though my educational journey has been long and challenging, your unwavering support, selfless sacrifices, and boundless love have allowed me to freely pursue my dreams and develop my skills. You provided a cherished, unwavering, and affectionate family home for which I am endlessly indebted.

ABSTRACT

Non-communicable diseases (NCDs) are a significant threat in Ethiopia and globally, largely influenced by psychological factors affecting preventive behaviors. This study investigated the relationships between knowledge of NCDs, self-efficacy, outcome expectancy, personal risk perception, and behavioral intentions to prevent NCDs among young Ethiopian adults. Using a quantitative approach with data from 420 university students, the study found that knowledge, perceived severity, self-efficacy, and outcome expectancy significantly predict behavioral intentions, accounting for 73% of the variance. However, perceived vulnerability did not significantly contribute. Gender, age, and academic year moderated some relationships. The findings emphasize the importance of boosting knowledge and self-efficacy in NCD prevention programs, while also considering gender and age in interventions.

Keywords: Non-Communicable Diseases, Self-efficacy, Risk Perception, Outcome Expectancy, and Behavioural Intention

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List of Abbreviations and Acronyms

ADD = Attention Deficit Disorder

BI= Behavioural Intension

BMI = Body Mass Index

BP = Blood Pressure

CSA = Central Statistics Agency

CVDs = Cardiovascular Diseases

DALYs = Disability Adjusted Life Years

ED = Erectile Dysfunction

FPC = Finite Population Correction

FMOH = Federal Ministry of Health

HBP = Health Behaviour Practice

KON = Knowledge of NCDs

NCDs = Non-communicable Diseases

OE = Outcome Expectancy

PMDD = Premenstrual Disorder

PMT = Protection Motivation Theory

RP = Risk perception

SEF = Self-efficacy

SEM= Structural Equation Modelling

SPSS = Statistical Packages for Social Sciences

SSA = Sub – Saharan Africa

UN = United Nations

WHO = World Health Organization

.

CHAPTER ONE

1. Introduction

Non-communicable diseases (NCDs)—such as heart disease, cancer, diabetes, and chronic respiratory illnesses—are a growing global health crisis. They account for a significant portion of illness and death worldwide, with a particularly heavy impact on low- and middle-income countries like Ethiopia (World Health Organization, 2019). In Ethiopia, NCDs are responsible for a substantial percentage of annual deaths (Ministry of Health, 2021). This alarming trend highlights the urgent need for effective prevention, especially among young adults, a crucial demographic for establishing lifelong healthy habits.

The development of NCDs is complex, influenced by genetics, environment, and modifiable behaviors like unhealthy diets, physical inactivity, tobacco use, and harmful alcohol consumption (Global Burden of Disease Study, 2019). While public health efforts often focus on raising awareness, simply knowing the risks isn't always enough to change behavior. This gap underscores the vital role of psychological factors that shape individuals' intentions and actions regarding prevention (Alizadeh et al., 2024).

Psychological theories like the Health Belief Model, Protection Motivation Theory, and the Theory of Planned Behavior offer strong frameworks for understanding what drives health behaviors (Ajzen, 1991; Rosenstock, 1974; Rogers, 1983). These theories suggest that behavioral intentions—the immediate precursors to actual behavior—are influenced by beliefs about susceptibility to disease, its severity, the benefits and barriers of preventive actions, expected outcomes, and self-efficacy (one's confidence in performing a behavior). For NCD prevention, understanding how these psychological factors interact with behavioral intentions in young Ethiopian adults is essential for creating effective public health interventions. Despite the increasing burden of NCDs in Ethiopia, there's limited understanding of the specific psychological factors influencing preventive behavioral intentions in this key age group (Ayele, 2023). This study aims to fill that gap, providing valuable insights for future health promotion initiatives.

1.1. Background of the Study

How we are living our lives is shifting. In our country, many aspects of daily life—how we learn, work, travel, and even spend our leisure time—are increasingly becoming sedentary. At the same time, our eating habits are shifting away from traditional, nutrient-rich foods toward a diet filled with processed meals, snacks, and beverages that are often high in unhealthy fats, salt, and sugar. Compounding this, the environments where we live, both indoors and outdoors, are becoming more polluted. Indoor air quality is deteriorating, largely due to emissions from cooking and heating, while outdoor pollution is driven by industrial activity and motor vehicle emissions (World Health Organization [WHO], 2023). Demographic changes including urbanisation and aging are occurring most rapidly (Birley & Iaia, 2015). These facts are indicative of the notion that people are more prone to non-communicable diseases. Our lifestyle is becoming more and more at the risk of NCDs.

Around the world, non-communicable diseases (NCDs) account for two-thirds of the 38 million deaths that occur annually. Alarmingly, 42% of these are premature, happening before the age of 70, and the vast majority—about 80%—take place in low- and middle-income countries (World Health Organization [WHO], 2023). In developing countries like ours, the situation is even more concerning, with non-communicable diseases (NCDs) leading to sudden and often unexplained deaths at much younger ages compared to Western countries. For example, in Sub-Saharan Africa (SSA), NCDs are responsible for more than half of all adult deaths in countries such as Mauritius, Namibia, and Seychelles. Alarmingly, the burden of NCDs in SSA is projected to rise by 27% over the next decade, signaling a growing public health crisis in the region (Gouda et al., 2019).

Non-communicable diseases (NCDs) encompass a wide range of conditions, but four major illnesses—cardiovascular diseases, cancer, diabetes, and chronic obstructive pulmonary diseases—account for 82% of all NCD-related deaths, drawing the most global attention. These four conditions are especially significant in public health due to their shared risk factors: tobacco use, unhealthy diets, harmful alcohol consumption, and physical inactivity (World Health Organization [WHO], 2023). In many developing countries, including Ethiopia, these risk factors are becoming increasingly common among young adults. The growing prevalence of behaviors such as tobacco use, unhealthy eating, harmful alcohol consumption, and physical inactivity is putting Ethiopia's youth at greater risk of developing non-communicable diseases (NCDs) (Tesfaye et al., 2021).

Ethiopia, a large country in East Africa with over 110 million people, had 83% of its population living in rural communities as of 2019 (Central Statistics Agency [CSA], 2019). Like many other developing nations, Ethiopia faces a dual burden of diseases—both communicable and non-communicable. Many of these health burdens could be prevented if individuals had a better understanding of their personal health risks. According to the World

Health Organization (2014), non-communicable diseases (NCDs) were responsible for 42% of deaths in Ethiopia. NCDs are often caused by a combination of factors, which interact with other conditions, including infectious diseases like Streptococcal infections. Addressing these challenges will require integrating NCD prevention and treatment into existing health programs, especially at the community level (World Health Organization [WHO], 2014).

In Ethiopia, non-communicable diseases (NCDs) are responsible for an estimated 42% of all deaths, with 27% of these being premature, occurring before the age of 50. This is 20 years younger than the reported age for premature deaths in Western countries. Disability Adjusted Life Years (DALYs) lost due to NCDs in Ethiopia increased dramatically, from 20% in 1990 to 69% in 2015, more than double that of communicable, maternal, neonatal, and nutritional issues combined (Misganaw et al., 2017; Weldearegawi et al., 2013). Despite this sharp rise in NCD-related DALYs and deaths, the per capita health spending on NCDs remains minimal (Misganaw et al., 2017). A review of the different approaches to tackling NCDs versus communicable diseases, based on factors such as disease acuity, potential for control or cure, cost, and social stigmas, reveals little ethical or logical justification for the continued neglect of NCDs (Luna & Luyckx, 2020).

The issue of non-communicable diseases (NCDs) among young adults in Ethiopia is compounded by multiple challenges that require a comprehensive understanding to develop effective interventions. According to Tesfaye et.al, (2021) despite young adults' vulnerability to NCDs due to a mix of lifestyle, environmental, and psychological factors, their awareness of these diseases remains low. This lack of understanding is often tied to limited health literacy, which affects young people's ability to comprehend the risks associated with certain behaviors and the benefits of preventive measures (Tesfaye et al., 2021). When young adults are unaware of these risks, they are less likely to prioritize healthy behaviors, making it crucial to bridge health literacy gaps.

Moreover, cultural beliefs and societal norms in Ethiopia strongly influence perceptions of health and disease. Traditional views about health often focus on infectious diseases, with less emphasis on chronic, non-communicable conditions like cardiovascular disease, diabetes, or mental health disorders. Such cultural perspectives may lead to a lower sense of urgency among young people to adopt preventive behaviors against NCDs, and in some cases, may even contribute to stigma. For example, mental health issues and related psychological conditions, which are significant risk factors for NCDs, often carry stigma, further discouraging young adults from seeking mental health support or discussing their struggles openly (Tesfaye et al., 2021). Acknowledging and addressing these cultural beliefs is critical to creating interventions that resonate with young adults and encourage healthy choices.

Socioeconomic factors also play a substantial role in young adults' NCD risk. Many young people in Ethiopia face economic barriers that limit their access to healthcare services, including preventive care and mental health resources. Socioeconomic disparities also reduce opportunities for healthier lifestyle choices, as individuals from lower-income backgrounds may lack access to nutritious food options or safe environments for physical activity. Consequently, these disparities impact the behavioral intentions of young adults toward NCD prevention, with limited resources contributing to a cycle of vulnerability to NCDs (Tesfaye et al., 2021).

The influence of social networks and peer dynamics adds another layer of complexity to NCD prevention efforts among young adults. Peer influence can either reinforce healthy behaviors or contribute to riskier ones, such as smoking or physical inactivity, depending on the social context. Interventions that effectively leverage positive peer support could be key in promoting healthier lifestyle choices among Ethiopian youth.

Lastly, existing NCD prevention programs often fall short of addressing the unique psychological needs and preferences of young adults in Ethiopia. Current interventions may not consider the critical role of psychological factors—such as stress, anxiety, or depression—that contribute to unhealthy behaviors linked to NCD risk (Misganaw et al., 2017). Tailoring interventions to account for these psychological influences is essential, as ignoring them could lead to limited success and may even exacerbate long-term health consequences for the youth. Addressing these challenges holistically is essential to reduce the growing burden of NCDs in Ethiopia and to foster a healthier future generation.

According to Heller et.al., (2019) risk perception, both at the individual and community levels, does not necessarily dictate the behavioural and decision-making roles undertaken by individuals. This observation highlights the presence of a cohesive policy community and its leaders, although their influence is largely confined to the health sector. The roles of guiding institutions and civil society have only recently begun to gain traction. Moreover, research has shown that framing non-communicable diseases (NCDs) as being driven by four risk factors and four specific diseases does not fully resonate with experts within the broader policy community. Instead, the economic argument surrounding these issues appears to have garnered some level of authority. Ultimately, despite numerous opportunities for policy change, the studies indicate that institutional constraints have limited their effectiveness.

While credible indicators and effective interventions are available, their applicability in low- and middle-income countries remains uncertain (Heller et al., 2019).

Psychological models used to explain, predict, and encourage health behaviors often consist of a range of different components. While some elements are specific to individual models, many share similarities or overlap, having evolved from common theoretical foundations through a gradual process of development (Armitage & Christian, 2003; Noar & Zimmerman, 2005). Narrative reviews suggest that the success of health behavior change interventions, particularly those based on models such as the Theory of Planned Behavior (TPB) and the Transtheoretical Model (TTM), could be improved with more structured and targeted approaches to refining these models and their components (Armitage & Conner, 2000; Weinstein & Rothman, 2005). Such efforts should focus specifically on improving health outcomes.

In the realm of psychological explanations for health behavior, numerous theories have been developed. Some, like the Health Belief Model (Rosenstock, Strecher, & Becker, 1994) and the Transtheoretical Model (Velicer et al., 2005), are general frameworks aimed at explaining the determinants behind a wide range of health behaviors. Other models, such as the AIDS Risk Reduction Model by Catania, Kegeles, & Coates, (1990), are specifically designed to address and modify particular health behaviors. Additionally, social-psychological models such as the Theory of Reasoned by Action Ajzen & Fishbein, (2004), the Theory of Planned Behavior of Ajzen, (2011), and Social-Cognitive Theory of Bandura, (1990), while originally formulated outside the context of health, have been widely applied to understand and influence various health-related actions.

Based on the aforementioned theories and various research findings, it becomes clear that multiple factors influence the likelihood of engaging in specific health behaviors. These determinants can generally be grouped into internal factors, such as knowledge, and external factors, such as social support, both of which play crucial roles in shaping behavior. Important internal factors that contribute to promoting health-related behaviors include knowledge about risk factors and risk reduction, attitudes, beliefs, and core values (ABCs), social and life adaptation skills, psychological factors like self-efficacy, and physiological aspects. On the other hand, key external factors encompass social support, media influences (such as public service announcements), socio-cultural, economic, and political conditions, biological influences, the healthcare system, environmental stressors, and societal laws and regulations (Cole et al., 1992).

The presence or absence of these factors can either encourage or hinder the adoption of healthy behaviors. For instance, an individual's perceived personal susceptibility to a specific disease—an internal factor tied to their attitudes, beliefs, and core values (ABCs)—increases the likelihood that they will engage in health-promoting behaviors. Conversely, if an individual does not perceive a health threat as serious, which is also related to their ABCs, they are less likely to feel motivated to change risky behaviors.

Contemporary social psychological literature highlights several key factors in explaining behavior. Bandura, for instance, stresses the significance of knowledge, arguing that heightened awareness and understanding of health risks are crucial preconditions for self-directed behavioral change. However, he also acknowledges that information alone may not have a strong impact on deeply ingrained, harmful habits (Bandura, 1990). For change to occur, people must possess sufficient knowledge of potential risks to feel compelled to take action. Similarly, raising awareness about the serious threat of illness is essential for creating the conditions necessary for behavioral change.

In contrast to Bandura's perspective, Becker & Maiman (1975) contends that there is limited evidence to suggest that patient education consistently influences health behavior. Similarly, Rosenstock et al., (1994) argued that efforts to promote compliance with health-related behaviors must involve more than simply providing information. Supporting Becker's view, Catania points out that understanding the risk factors associated with a disease is essential for accurately assessing personal risk and developing a sense of susceptibility to infection. However, she acknowledges that this knowledge may not directly predict behavioral change processes (Catania et al., 1990). Catania also clarifies her stance by indicating that if health education includes specific guidance on the most effective forms of assistance and how to access them, it can significantly impact the "taking action" phase of the behavioral change process.

Additionally, Bandura highlights another crucial factor in health behavior: self-efficacy. He asserts that perceived self-efficacy can influence whether individuals consider changing their health habits, the effort they put into making changes, the extent of those changes, and their ability to maintain them. The belief that one can self-motivate and regulate behavior is vital in determining whether individuals take steps to alter harmful habits (Bandura, 1990). Becker further supports Bandura's emphasis on self-efficacy, noting that the performance of a behavior is determined by the strength of an individual's effort and their level of control over factors that may hinder the behavior. The more effort a person exerts and the greater their control over internal and external influences, the more likely they are to successfully engage in the behavior (Stuifbergen et al., 1990).

Becker also points out that perceived self-efficacy affects various aspects of behavior, including the acquisition of new behaviors, the inhibition of existing ones, and the disinhibition of certain actions. It influences individuals' choices of environments, the effort they are willing to invest in tasks, and their persistence in overcoming challenges. Self-efficacy can also impact emotional responses, such as anxiety and distress, as well as thought patterns (Allen et al., 1990). Catania supports this idea by indicating that perceived susceptibility is significantly related to risk behaviors, independent of knowledge (Catania et al., 1990).

Research has examined the role of outcome expectancy in understanding behavior across various domains. For instance, the anticipation of positive outcomes has been linked to increased peer aggression (Pornari & Wood, 2010) and heightened levels of physical activity (Williams et al., 2005). Additionally, outcome expectancy has been positively correlated with academic performance (Zimmerman, 2002) and behaviors that promote better health (Gao et al., 2014). Beyond its influence on individual behaviors, evidence suggests that outcome expectancy can also moderate the relationship between behavioral predictors and actual engagement in those behaviors (e.g., Stewart et al., 2009). Thus, the impact of different predictors on performance can be amplified or diminished by a person's beliefs regarding the effectiveness of their actions.

Despite official health organizations highlighting non-communicable diseases (NCDs) as a significant threat to public health—essentially sounding the alarm as Slovic (1987) put it, "risk does not exist independent of our minds and culture" (p. 690)—it is crucial to recognize that risk perception is a subjective psychological construct. Extensive research over the past two decades has demonstrated that risk perception is shaped by cognitive, emotional, social, cultural, and individual factors, varying both among individuals and across different countries (Ferrer & Klein, 2015; Hanoch, Rolison, & Freund, 2018; Loewenstein, Hsee, Weber, & Welch, 2001; Leiserowitz, 2006; Slovic, 2010). Therefore, this study aims to explore the effects of knowledge, risk perception, self-efficacy, and outcome expectancy on the behavioral intentions of young adults concerning non-communicable diseases.

1.2. Problem Statement

The rise of non-communicable diseases (NCDs) is becoming a pressing concern in developing nations like Ethiopia, largely attributed to lifestyle changes (Shiferaw et al., 2018). Mortality rates from these diseases can vary significantly across Ethiopia's diverse regions, reflecting the socio-economic disparities that exist (Getachew et al., 2015; Tesfaye, 2008; Shurin, 2015). Interestingly, while the mortality rates from NCDs tend to be similar in rural areas, the underlying causes can differ from one region to another (Gebremariam et al., 2018; Melaku et al., 2016). Both low-income and affluent communities are affected by these diseases, as they transcend economic boundaries (Abebe et al., 2017; Weldearegawi et al., 2013). Particularly, urban populations who are economically disadvantaged face heightened risks for NCDs due to unhealthy dietary practices, smoking, alcohol consumption, and sedentary lifestyles (Prevett, 2012). These risk factors have been identified as critical contributors to the increasing incidence of NCDs, which pose a significant threat for developing metabolic syndrome, characterized by the clustering of conditions such as abdominal obesity, high blood pressure, and elevated blood sugar levels (Mohammed et al., 2014).

In observing the ongoing rise of non-communicable diseases (NCDs) in Ethiopia, I am increasingly struck by the ways in which socio-economic and cultural factors compound the challenges young adults face. While young adulthood is an optimal stage for instilling lifelong healthy habits, the prevailing environmental, social, and psychological factors make it exceedingly difficult for young people to access or prioritize health-promoting behaviors. From a public health perspective, there is an urgent need to bridge this gap, especially as the

NCD burden strains Ethiopia's healthcare infrastructure, a challenge further complicated by economic constraints that limit healthcare access for many young people.

My personal encounters and observations within various communities reveal a common gap in health literacy and awareness about NCDs. For instance, the concept of preventive health remains unfamiliar to many young adults, particularly in rural and low-income urban areas where the emphasis is often on addressing immediate needs rather than adopting preventive lifestyle measures. Moreover, the lack of dialogue around mental health and its connection to chronic diseases like hypertension or diabetes often leads to stigma, which is especially detrimental for young people who may already be grappling with stress, anxiety, or other mental health issues that elevate NCD risk. These insights underscore the pressing need to integrate culturally sensitive mental health education within NCD prevention efforts, as mental and physical health are intrinsically linked.

Another observation noteworthy is the variation in dietary practices and physical activity levels influenced by Ethiopia’s diverse cultural landscape. Traditional diets and physical activity levels often differ significantly across regions, yet rapid urbanization is altering these patterns and introducing new, often unhealthy, dietary practices. It is clear that strategies to prevent NCDs need to account for these regional and cultural differences to be effective. Additionally, witnessing the influence of peer networks on behavior, I see potential in leveraging positive peer influence to promote healthier behaviors among young adults.

In Ethiopia, adults who exhibit high levels of inactivity, as well as those who are overweight or experience abdominal obesity, are particularly vulnerable to chronic lifestyle-related diseases (Tesfaye et al., 2009; Dagne et al., 2019). Addressing the risk factors associated with NCDs is essential to reducing this disease burden (Action & Guidance, 2017). International organizations, including the World Health Organization (WHO), have identified these risk factors as significant modifiable contributors to NCDs (WHO, 2013).

Promoting positive health behaviors and ensuring access to preventive healthcare services can significantly reduce the incidence and mortality rates associated with NCDs. Research strongly supports the idea that changing dietary habits and increasing physical activity can have a beneficial impact on various NCD risk factors within populations (Derman et al., 2009; Helelo et al., 2014; Makamu, 2015). The WHO recommends that adults aged 18 to 64 should engage in at least 150 minutes of moderate-intensity aerobic activity each week or a minimum of 75 minutes of vigorous-intensity activity, or a combination of both (WHO, 2010). Regular physical activity is not only beneficial for health but can also serve as a vital intervention, akin to medication (Uchima et al., 2019). Despite this understanding, many people do not take proactive steps to protect themselves from NCDs. This study suggests that individuals must be aware of the risks, possess knowledge about these diseases, believe in their ability to make changes (self-efficacy), and hold positive expectations about the outcomes of their behaviors to initiate meaningful changes.

For individuals to lead active lifestyles and make healthier choices, it is crucial for them to view physical activity, a balanced diet, and reduced substance abuse as essential components of a healthy lifestyle (Derman et al., 2009; Dishman et al., 1985; Makamu, 2015). A key aspect of behavioral intentions related to personal health is the recognition that maintaining healthy behaviors benefits both individuals and society at large. While indulging in unhealthy foods occasionally may not pose significant problems, regular consumption can lead to serious health issues. Unfortunately, much of the existing research has focused on the psychological factors influencing short-term health behaviors (Maio et al., 2007), often overlooking the importance of training and coaching young people on maintaining a healthy lifestyle. Emphasizing the need for sustainable healthy behaviors is crucial, particularly during young adulthood, as this stage is pivotal for establishing lasting habits.

In the Ethiopian context, there is a scarcity of studies examining the risk factors and burdens associated with NCDs across various regions, frequently focusing on a single type of NCD. Furthermore, research on the interplay between risk perception, self-efficacy, outcome expectancy, and knowledge of NCDs as factors influencing behavioral intentions remains limited. Nonetheless, current literature indicates a significant burden from NCDs and widespread distribution of their risk factors (Misganaw et al., 2017; Misganaw et al., 2014). Many community health workers lack adequate knowledge about conditions like hypertension and diabetes, alongside misconceptions regarding their causes, treatments, and general risk factors for NCDs (Mamo et al., 2007). Economic challenges, cultural beliefs, and practices that affect food choices and physical activity levels have also been identified as key risk factors in previous studies (Suhrcke et al., 2011).

To respond effectively to these research questions and achieve the study's objectives, this investigation builds on existing approaches in both local and global contexts, exploring knowledge of NCDs, self-efficacy, outcome expectancy, risk perception, and behavioral intentions among young adults. Recent studies have started to delve deeper into these aspects (Giday & Weldeyes, 2015; Helelo et al., 2014; Misganaw et al., 2017; Muluneh et al., 2012; Nigatu, 2012). While these contributions are significant, they often fail to address the psychological and social factors that can influence behavioral intentions regarding NCDs, which are crucial in helping individuals recognize their risks and adopt healthier behaviors.

Reflecting on the current gaps in literature and practice, it’s apparent that there is a need to delve deeper into the psychological and social determinants of health behaviors. While research highlights the impact of risk perception, self-efficacy, and knowledge on health outcomes, there remains limited insight into how these factors interact to shape young adults' behavioral intentions in the Ethiopian context. By addressing these gaps, I hope this study will contribute valuable data that can inform the development of comprehensive, psychologically informed interventions to reduce the NCD burden. This study intends to explore not only the awareness of NCD risks but also the attitudes and beliefs young people hold towards preventive measures. Only by understanding these aspects can we hope to foster a sustainable shift towards healthier lifestyles among Ethiopian youth. Additionally, few studies have utilized validated measurement tools to assess the psychological constructs relevant to these intentions. This study is designed to address these gaps with clear objectives.

1.3.Objectives

1.3.1. The general objective of this study

The main objective of this study was to investigate the interconnection among knowledge, self-efficacy, outcome expectancy, risk perception and behavioural intension of young adults towards non-communicable diseases in Ethiopia.

1.3.2. Specific Objectives

The specific objectives of this study are:

1. Investigate the effects of Risk Perception (RP), Self- Efficacy (SE) and Outcome Expectancy (OE) on Behavioural Intention (BI);
2. Examine the direct and indirect effect of knowledge of NCDs (KONCDs), on Behavioural Intention (BI);
3. Analyse the mediation roles of Risk Perception (RP), self-efficacy (SE), and Outcome Expectancy (OE) on the relationship between knowledge of NCDs and Behavioural Intention (BI);
4. Examine the effect of knowledge of NCDs on Risk Perception (RP): (perceived vulnerability and seniority); Self-Efficacy (SE) and Outcome Expectancy (OE);

5. Identify the strongest psychological determinant of behavioural intention of young adults.
6. Examine the moderating role of back ground (demographic) characteristics of respondents on the relationship between and among knowledge of NCDs on Risk Perception (RP): (perceived vulnerability and seniority); Self-Efficacy (SE) and Outcome Expectancy (OE).

1.3. Significances of the Study

This study aims to contribute to the scientific understanding of how young adults in Ethiopia experience non-communicable diseases (NCDs) by examining their risk perceptions, motivations for prevention, and behavioral practices related to these diseases. The researcher anticipates that the findings will have both theoretical and practical implications. Given that the concept of NCDs is still relatively new in Ethiopia, there appears to be a significant gap in research focused on the risk perceptions, prevention motivations, and behavioral practices of young adults in this context, as indicated by searches conducted through platforms like Google Scholar and the main library.

By delving into risk perception and prevention motivation theories, this research will help enhance the knowledge and understanding of these constructs, particularly in the context of developing effective prevention programs for young adults in universities. The insights garnered from this study will be valuable for policymakers and curriculum designers, highlighting the importance of integrating NCD prevention strategies into the Ethiopian education system.

The outcomes of this research will yield both practical and theoretical advancements, particularly in the area of training young adults in universities to prevent NCDs. The findings will provide essential data for designing intercultural training programs that promote teamwork and foster interpersonal relationships for organizational effectiveness. The study seeks to provide empirical evidence that underscores the necessity of prioritizing NCD training for university students. Ultimately, this research aims to deliver actionable insights for university administrators and the Ministry of Education in Ethiopia, encouraging measures that enhance the health and well-being of young adults in the academic setting.

1.4. Delimitation of the Study

The delimitation of this study is discussed based on the variables, participants and instruments included in the study as follows:

1.4.1. Variable

For this study, the measurement instruments for the variables risk perception (RP), self-efficacy (SE), outcome expectancies (OE), Knowledge of NCDs (KON) and Behaviour Intentions (BI) were considered after being piloted.

1.4.2. Participants

The pilot study was confined to young adults in taking classes in Debre Berhan University during the second semester of the 2021. This study was conducted on Debre Birhan University students who were attending regular class in the first semester of the academic year 2022.

1.4.3. Instruments

The target instruments of this study were all self-reported questionnaires of perception of severity, perception of vulnerability, self-efficacy, outcome expectancy and behavioural intention scales. To reduce the risk of inconsistency, respondents were given precise instructions for the administration of the instrument and then an inter-item consistency of the questionnaires was calculated.

1.5. Conceptualization and Operationalization of Concepts

1.5.1. Operational definitions of terms

The researcher has keen sense that operationally defining the involved constructs is basic in a research. The only way to ensure consistent data collection is by employing a detailed operational definition that eliminates ambiguity. Thus, the variables for this study have been defined and how they were measured is presented in the following manner for the sake of this study.

1.5.1.1. Behavioral Intentions

Behavioral intentions refer to explicit decisions to engage in specific actions and reflect a person’s motivation towards achieving a goal, encompassing both direction and intensity. This study evaluates intentions primarily through dichotomous-graded items, such as, “I plan to participate in vigorous physical activity at least twice a week.” Responses are captured on a four-point Likert scale, ranging from "strongly disagree" to "strongly agree," to mitigate ceiling or floor effects that may arise in certain contexts. The total score for each scale is calculated by summing the responses across all relevant items. It’s important to distinguish behavioral intentions from behavioral expectations, the latter being an estimate of the likelihood that an individual will perform a given behavior.

1.5.1.2. Knowledge of NCDs

In this study, "knowledge of NCDs" pertains to the participants’ understanding of non-communicable diseases (NCDs), their causes, and the available preventive measures or treatments. The knowledge assessment gauges respondents’ familiarity with various aspects of NCDs, including symptoms, risk factors, fatality rates, and preventive strategies. Participants answer questions like, “Are you aware of the causes of NCDs and the protective measures one can take?” The knowledge level is evaluated using the cognitive subscale of the risk perception scale, with the total score computed by aggregating the responses.

1.5.1.3. Outcome Expectancies

Outcome expectancies involve personal beliefs about the potential outcomes linked to certain behaviors. These beliefs are assessed in terms of their perceived positivity or negativity for the individual. Generally, the more favorable or less unfavorable the anticipated consequences of a behavior change, the stronger the intention to pursue that behavior. Outcome expectancies are measured using if/then statements, where the “if” clause describes the target behavior (e.g., “If I start exercising regularly…”) and the “then” clause outlines a possible positive or negative outcome (e.g., “…then I might feel healthier” or “…then I will need to exert significant effort to maintain it”). Responses are recorded on a five-point Likert scale, ranging from (1) strongly disagree to (5) strongly agree. Scores for positive and negative outcome expectancies are derived by summing or averaging responses across the respective scales.

1.5.1.4. Risk Perception

Risk perception captures an individual's assessment of their susceptibility to health threats, typically framed within the dimensions of vulnerability and severity. Vulnerability pertains to the perceived likelihood of experiencing a health issue, such as hypertension. This should be assessed as both an absolute construct (i.e., the subjective probability of being affected) and a relative construct (i.e., comparing one's risk to that of others in the same demographic group), as recommended by Weinstein (1987). The assessment of vulnerability includes items like, "What do you think is the chance that you will develop…?" for absolute vulnerability and "Compared to an average person of your age and gender, how would you rate your risk of…?" for relative vulnerability. Responses are given on Likert scales, for example, from (1) very unlikely to (7) very likely for absolute vulnerability, and from (1) very low to (7) very high for relative vulnerability. Severity is evaluated through items such as, "How serious would the following health issues be if left untreated?" rated on a similar Likert scale. A cumulative score for absolute vulnerability, relative vulnerability, and severity is obtained by summing all item responses.

1.5.1.5. Self-Efficacy

Self-efficacy refers to an individual's belief in their capability to carry out a specific behavior. Also known as action self-efficacy (Schwarzer & Renner, 2000), this construct supports goal-setting. The self-efficacy items typically present a statement regarding the target behavior, followed by a barrier (e.g., "I am confident that I can engage in physical activity regularly… even if it's challenging"). The answers are measured using a four-point Likert scale, with responses ranging from (1) not at all true to (4) exactly true. The overall self-efficacy score is calculated by summing or averaging the responses across all items.

1.5.1.6. Conceptualization and Operationalization of Young Adults in Ethiopia

Understanding the specific demographic under study is crucial for the clarity and rigor of any research. This section conceptualizes "young adults" within the Ethiopian context and details their operational definition for the purposes of this study.

Conceptual Definition: Young Adults

Conceptually, "young adulthood" typically refers to the developmental period following adolescence, generally spanning from the late teenage years through the early thirties (e.g., 18 to 35 years). This stage is characterized by significant physiological, psychological, and social transitions. Physiologically, it marks the peak of physical health, yet it is also a critical period for the onset of behavioral patterns that contribute to long-term health outcomes, including the risk of non-communicable diseases (NCDs).

Psychologically, young adults are often engaged in identity formation, developing greater independence, establishing personal values, and navigating complex social relationships. This period is also marked by significant life events such as pursuing higher education, entering the workforce, and often, the formation of families. From a social psychological perspective, young adulthood is a pivotal time for habit formation; health behaviors adopted during these years tend to persist into later life, making it a crucial window for NCD prevention efforts.

In the Ethiopian context, the definition of young adulthood aligns with these global understandings but is also shaped by specific socio-cultural and economic factors. For many, this period involves transitioning from parental homes to independent living, often facilitated by university enrollment or early career entry. University students, in particular, represent a concentrated sub-group of young adults who are transitioning to new environments, often making independent health choices for the first time, and are influenced by peer dynamics and academic pressures. Their health behaviors during this formative period are highly susceptible to both positive and negative influences, making them a vital population for NCD prevention interventions.

Operational Definition: Young Adults in This Study

For the purpose of this dissertation, "young adults in Ethiopia" are operationally defined as:

- Age Range: Individuals aged [Specify your exact age range, e.g., 18 to 30 years or 18 to 35 year**s]** at the time of data collection. This range is chosen to capture the core developmental stage of young adulthood, aligning with common demographic classifications and ensuring a focus on the target population relevant to NCD prevention.
- Educational Status: Currently enrolled undergraduate and/or postgraduate students at Debre Berhan University. This specific setting provides a relatively homogenous and accessible population of young adults in a structured environment, allowing for a focused case study on the psychological correlates within an academic context in Ethiopia.

- Enrollment Status: Students attending regular classes during the [Specify relevant academic semester/year, e.g., First Semester of the 2022/2023 Academic Year]. This ensures that participants are active members of the university community and are readily available for participation in the study.

This operational definition ensures that the study specifically targets the intended population segment, allowing for consistent participant selection and facilitating the interpretation of findings within the specified context of Debre Berhan University

CHAPTER TWO:

Related Literature Review

2.1. Introduction

A non-communicable disease (NCD) is defined as a medical condition that is not infectious. These diseases typically have a long duration and tend to progress slowly. Examples of NCDs include heart disease, stroke, various cancers, asthma, diabetes, chronic kidney disease, arthritis, osteoporosis, and cataracts (NEVIS, 2017; MOH, 2016). While commonly referred to as "chronic diseases," NCDs are specifically characterized by their non-infectious origins.

Chronic diseases, such as heart disease, stroke, cancer, chronic respiratory illnesses, and diabetes, are the leading cause of death globally, responsible for 63% of all fatalities. According to a report by the World Health Organization (WHO) from 2010, out of the 36 million deaths attributed to chronic diseases in 2008, 29% involved individuals under the age of 60. This often-overlooked epidemic of chronic diseases poses significant challenges to economic development in many nations and exacerbates poverty. Contrary to popular belief, approximately 80% of deaths from chronic diseases occur in low- and middle-income countries (Shiferaw et al., 2018; Mohammed et al., 2014).

The increasing prevalence of non-communicable diseases presents a significant obstacle to socio-economic progress, particularly in developing nations. It is projected that deaths from NCDs will rise by an additional 17% over the next decade. The rapid escalation of these diseases disproportionately impacts poorer and disadvantaged populations, widening the health disparities both between and within countries. Given that many NCDs are largely preventable, the incidence of premature deaths from these conditions could be significantly reduced (WHO, 2013).

The World Health Organization estimates that NCDs account for 41 million deaths each year, representing 71% of all deaths worldwide (Mohammed et al., 2014). In developing countries like Ethiopia, NCDs have emerged as major public health challenges, hindering efforts to achieve sustainable development goals. The WHO also indicates that approximately 8.5 million lives are lost each year due to NCDs in East Africa (Mohammed et al., 2014). Ethiopia faces a substantial burden from NCDs and is at a high risk of increased exposure to the associated risk factors in the future (Tran et al., 2011).

Research on non-communicable diseases (NCDs) in Ethiopia indicates that over 42% of total deaths can be attributed to these conditions (Shiferaw et al., 2018). The likelihood of dying from one of the four major NCDs—cardiovascular diseases (CVDs), diabetes, cancer, and chronic respiratory diseases—stands at approximately 24% for individuals aged 30 to 70 years. This research highlights a rising concern regarding several risk factors for NCDs, particularly hypertension and overweight/obesity. Furthermore, it noted a 27% increase in premature deaths from NCD-related causes between 1990 and 2010. According to the STEP survey conducted in Ethiopia (Roba et al., 2019), among individuals aged 40 to 64 years, 12% had already experienced some form of CVD or exhibited a high (≥30%) 10-year risk for CVDs. Alarmingly, nine out of ten respondents reported having at least one risk factor for NCDs, while one in five had a combination of three to five risk factors. These findings underscore the national concern regarding the rising prevalence of NCD risk factors in Ethiopia (MOHS, 2016).

2.2. Non-Communicable Diseases and Their Risk Factors: The Ethiopian Context

2.2.1. The Burden of Non-Communicable Diseases in Ethiopia

Like many developing countries, Ethiopia is facing the consequences of epidemiological, demographic, economic, and nutritional changes that continue to promote the chronic disease epidemic (Muluneh et al., 2012; and Belachew, 2015). Current projections suggest that the proportion of individuals living into older age and in urban areas will significantly increase over the next two decades. For instance, life expectancy is expected to rise from 53 years for males and 56 years for females to 65 years for males and 68 years for females by the years 2025-2030. Additionally, the urban population is anticipated to grow from the current 15% to 23% during the same period (Desta et al., 2012).

Available data also indicate that chronic diseases and their associated risk factors in Ethiopia tend to manifest at younger age groups and result in higher mortality rates compared to developed nations. The following section summarizes the evidence highlighting the increasing significance of chronic diseases, especially among urban populations in Ethiopia (Prevett, 2012).

2.2.1.1. Cardiovascular diseases (CVD) and stroke

In Ethiopia, there is a notable lack of reliable data on mortality and morbidity related to cardiovascular diseases (CVD), largely due to the nature of these conditions (e.g., silent myocardial infarction or asymptomatic coronary artery disease) and the general neglect of chronic diseases (Giday & Weldeyes, 2015).

Clinicians and public health officials increasingly agree that the prevalence of CVD and its contributing factors, such as obesity and diabetes, has risen in recent decades (Lagiou et al., 2012). Possible explanations for this apparent increase include heightened public awareness and healthcare access, improved diagnostic capabilities in health facilities, and rapid population growth. However, these factors require careful examination to accurately determine the extent of the increase (Maru, 1989).

While undernutrition continues to be a pressing concern in much of rural Ethiopia, the transition to urban areas and the adoption of Western lifestyles may lead to low birth weight and developmental issues, which could significantly contribute to cardiovascular diseases later in life. Historical evidence from hospital-based studies dating back to 1984 indicates that cardiovascular diseases were among the top ten causes of mortality in Ethiopian hospitals (Getachew et al., 2015).

Recent studies have shown an increasing hospital burden from stroke over the past few decades, with hemorrhagic stroke being the most prevalent type. Key risk factors for stroke include hypertension, often in conjunction with heart disease. A significant portion of hypertensive patients were found to be either untreated (28.9%) or receiving inconsistent treatment (38.3%) (Gebremariam & Yang, 2016).

In contrast to the disease patterns observed in Western countries, Ethiopian patients with cerebrovascular diseases tend to be younger. Notably, research by Bekele et al. revealed that a substantial percentage of stroke patients are young adults (28%), with hypertension and rheumatic heart disease being the most common risk factors (Alemayehu & Oli, 2002).

2.2.1.2. Hypertension

Hypertension, commonly known as high blood pressure, is the most prevalent cardiovascular disease and the leading cause of stroke, as well as a significant contributor to heart attacks. A population-based study conducted in Addis Ababa in 2006 found that the prevalence of hypertension—defined as a systolic blood pressure of ≥ 140 mmHg or diastolic pressure of ≥ 90 mmHg, or reported use of antihypertensive medication—was approximately 32% among men and 29% among women. In contrast, the prevalence in rural areas was much lower, at 10% for men and 5% for women in Butajira. Among adults with high blood pressure, less than 6% in Butajira and about 33% in Addis were aware of their condition.

Furthermore, fewer than 5% in Butajira and 15% in Addis were receiving treatment for hypertension. Notably, women in Addis had better awareness and access to treatment compared to men, while the gender difference in Butajira was not assessed (Tesfaye et al., 2009).

A more recent study among working adults in Addis Ababa reported a slightly lower prevalence of hypertension, at 22% for men and 19% for women (Tran et al., 2011).

2.2.1.3. Type II diabetes mellitus

Diabetes has become a significant health issue and an increasing cause of death in Ethiopia. It represents a chronic condition that requires ongoing medical attention and continuous self-management education to prevent acute complications and reduce the risk of long-term complications.

The classification of diabetes is not always straightforward. Evidence from Ethiopia indicates that the majority of insulin-dependent diabetes cases differ from what is typically classified as type 1 diabetes in Western countries. Local studies suggest that the clinical characteristics of many insulin-dependent patients in Ethiopia resemble what has been described as malnutrition-related diabetes, a category not currently recognized in the World Health Organization (WHO) classification. Generally, insulin-dependent diabetes among Ethiopian patients occurs at an older age (peak age 25-29), with a higher prevalence among men, often against a backdrop of malnutrition and poverty. This contrasts with type 1 diabetes in the West, which typically appears at a younger age among more affluent individuals, with a similar incidence in boys and girls (Fekadu et al., 2010).

Estimates on the prevalence of diabetes in Ethiopia vary widely, ranging from 0.3% in the Gondar region to 1.9% nationally (Watkins and Alemu, 2003; Gill et al., 2009). Type 2 diabetes is increasingly common among urban residents, affecting 71% of urban dwellers compared to only 23% in rural areas, which aligns with global trends observed in many developing countries facing economic and nutritional transitions. The rise in urban populations adopting sedentary lifestyles and diets high in fats and meat products has contributed to the growing burden of disease. Additionally, increased harmful consumption of alcohol and tobacco are risk factors associated with overweight and obesity, which are key drivers of type 2 diabetes.

Anecdotal evidence from a private clinic treating diabetes patients in Addis Ababa suggests that most individuals with type 2 diabetes belong to the middle economic class, often working as merchants or office workers with sedentary jobs. Research from Gondar indicates that the median age for type 2 diabetes diagnosis is around 50 years for both genders, with women generally exhibiting a higher body mass index (BMI) than their male counterparts (mean BMI of 25.0 for females and 23.3 for males) (Alemu et al., 2009).

Existing data highlight that infections are common causes of morbidity among diabetics, with prevalence rates as high as 46.2% among hospitalized patients. Cardiovascular diseases and end-stage renal disease contribute significantly to mortality. Common infections in diabetic patients include diabetic foot infections, pulmonary tuberculosis, urinary tract infections, pneumonia, and skin and subcutaneous infections (Tesfaye et al., 2015).

Consistent with global literature, Ethiopian patients with diabetes experience significant dyslipidemia, characterized by higher triglyceride levels and low-density lipoprotein compared to non-diabetics (Siraj et al., 2006).

Beyond its substantial impact on individual health and well-being, diabetes also places a considerable economic burden on communities and healthcare systems. Studies on hospitalization costs show that diabetes patients generally incur significantly higher expenses for the treatment of both acute and chronic complications compared to non-diabetic patients. Additionally, interviews with key stakeholders at selected referral hospitals reveal that a large portion of public hospital budgets for medications is allocated for the procurement of insulin and other treatments for chronic diseases, with expenditures continuously rising (Desta et al., 2012).

2.2.1.4. Cancers

2.2.1.4.1. Burden and pattern

Most of the global cancer burden is now concentrated in low- and middle-income countries, including Ethiopia. Although there are indications that cancers are becoming significant public health challenges, there is a lack of solid evidence on the incidence and patterns of cancer in Ethiopia, primarily due to the absence of a population-based cancer registry (Weldearegawi et al., 2013).

Data from the country's leading radiotherapy center at Tikur Anbessa Specialized Referral Hospital reveal that cervical cancer is the most common type of cancer, followed by breast cancer and other head and neck tumors among patients visiting the facility (Muluneh et al., 2012). Since cervical cancer exclusively affects women, and breast cancer is significantly more prevalent among women than men, over 70% of cancer patients at Tikur Anbessa

Hospital are female. Notably, around 45% of these patients come from Addis Ababa (Desta et al., 2012).

Limited awareness and access to cancer treatment and care, particularly in rural areas, complicate efforts to determine whether the same cancer patterns exist in the broader population. Recently, initiatives have been launched to establish a population-based cancer registry in Addis Ababa as a pilot project, with the intention of gradually expanding it to the entire country (Mamo et al., 2007). Once implemented, this initiative is expected to generate reliable data on cancer incidence, prevalence, and associated risk factors, which is crucial for planning population-based prevention and control measures.

2.2.1.4.2. Awareness and treatment seeking behaviour

Studies indicate that many patients in Ethiopia have limited or no awareness of cancers, which contributes to delays in seeking healthcare and ultimately leads to higher mortality rates. In many cases, patients are unaware of the signs and symptoms of cancer and, as a result, seek medical attention only after their condition has progressed beyond effective treatment. Moreover, even when they become aware of their illness, a sense of despair and resignation often prevails, further delaying their pursuit of healthcare (Dumalaon-Canaria et al., 2014).

Without clear guidance on where to go for specific symptoms, many patients waste significant amounts of time and resources before finally reaching effective treatment centers where they can receive the care they need (Dye et al., 2010).

2.2.1.5. *Chronic kidney disease and chronic respiratory diseases*

In spite of the fact that there is restricted data about the example of ceaseless renal and respiratory ailments in the nation there is agreement among specialists that the two conditions are happening at expanding recurrence.

2.2.1.5.1. Chronic kidney disease

Contributing components to incessant renal ailment incorporate diabetes and hypertension which have become increasingly more significant lately. This is as opposed to perceptions 10 years or prior where irresistible causes (for the most part intestinal sickness and sepsis) and premature birth confusion were substantially more typical and used to cause intense renal disappointment. Such signs for dialyses for instances of intense renal disappointment are currently observed periodically. Rather, dialyses is currently ordinarily required for patients with incessant renal disappointment coming about because of hypertension or diabetes. Desta et al., (2012)

2.2.2. Risk factors of NCDs in Ethiopia

Numerous interminable non-transferable sicknesses share hazard factors that are to a great extent preventable and can be tended to through social, natural and basic approaches, programs mediations. Huge levels of NCDs are preventable through the decrease of their four fundamental social hazard factors: tobacco use, physical idleness, hurtful utilization of liquor and unfortunate diet (Bhuiyan et al., 2013).

2.2.2.1. Tobacco use and khat consumption

Available evidence indicates that smoking, regular khat chewing, and excessive alcohol consumption are significant risk factors for non-communicable diseases (NCDs), particularly among men in urban areas of Ethiopia. A population-based study conducted in Addis Ababa in 2006 found that the prevalence of daily smoking and khat chewing among adult men was 11% and 18%, respectively. In Butajira, similar figures from 2003 showed current smoking and khat chewing rates of 7% and 15%, respectively (Tesfaye, 2008).

A school-based survey of students aged 13 to 15 years in Addis Ababa reported a smoking prevalence of 4.5% among boys and 1% among girls, with the average age of smoking initiation being 20 years (Bhuiyan et al., 2013). This study also identified that being male and having one or both parents who smoke were associated with a higher likelihood of smoking. Conversely, recognizing the harmful effects of smoking served as a protective factor.

Overall, knowledge and attitudes toward smoking among youth were found to be poor; approximately 30% of boys and 25% of girls believed that smokers have more friends, while 18.6% of boys and 16% of girls thought that girls who smoke appear more attractive (Rudatsikira, Abdo, & Muula, 2007).

Furthermore, exposure to secondhand smoke is alarmingly high. Nearly 20% of students live in households where others smoke in their presence, over 40% are exposed to smoke in public places, and 10% have parents who smoke (Rudatsikira et al., 2007).

2.2.2.2. Harmful use of alcohol

In many regions of Ethiopia, drinking alcoholic beverages is a common aspect of social gatherings. However, alcohol consumption poses significant health and social risks due to its intoxicating, harmful, and addictive properties (Rudatsikira et al., 2007). Similar to trends observed in many countries, men tend to drink more frequently and in larger quantities per occasion, often leading to intoxication. A population-based study conducted in Addis Ababa and Butajira revealed that 69% of men and 57% of women in Addis Ababa reported alcohol consumption in the year prior to the study, while 23% of men and 19% of women in Butajira reported the same. Additionally, 33% of men in Addis Ababa and 17% in Butajira admitted to binge drinking at least once during the previous year. Among women, the prevalence of binge drinking was approximately 7% in Addis Ababa and 5% in Butajira (Tesfaye, 2008).

2.2.2.3. Physical Inactivity

The effects of urbanization are increasingly evident in Ethiopian cities and towns, characterized by a rising reliance on motor vehicles and sedentary occupations such as trade and office work. These changes are accompanied by shifting dietary and lifestyle patterns that have yet to be adequately described (Lancet, 2012). According to Tesfaye (2008), over a quarter of the adult population in Addis Ababa leads a sedentary lifestyle, in stark contrast to Butajira, where around 80% of the population engages in physically demanding jobs.

Currently, sports and physical activities do not play a significant role in the daily lives of urban residents, especially among women (Ephrem, 2017). Access to sports facilities, public parks, and playgrounds is limited and continues to shrink as urban land costs rise. Schools are also affected by the increasing expense of land, with newer schools often featuring taller buildings and less outdoor space compared to older institutions.

2.2.2.4. Dietary Habits

Regarding dietary habits, both the Addis Ababa and Butajira populations exhibit low intake of fruits and vegetables, with nearly universal prevalence of insufficient consumption reported in studies conducted in 2006 and 2003, respectively (Fikru, 2008). Unfortunately, there are no studies that have assessed salt consumption among the Ethiopian population. Overall, grains constitute the primary source of calories in both urban (52%) and rural (63%) Ethiopia (Haji, Gelaw, Bekele, & Tesfay, 2011).

2.3. Risk and Risk Perception

According to the Merriam-Webster Online Dictionary, **risk** is defined as the possibility of loss or injury. When faced with any task that involves taking action, individuals often assess the likelihood of such loss or injury occurring. If this probability falls within an "acceptable" range, they may choose to engage in the risky behavior (Henrion & Fischhoff, 1986; Lichtenstein, 1981). However, if the perceived risk exceeds acceptable limits, people typically refrain from taking that action. This assessment of what constitutes an acceptable risk can vary significantly depending on the context.

Risk has been examined from various perspectives, including economic, psychological, and consumption viewpoints. Economists and insurers often define risk in terms of the potential for a company, country, or investment to default—essentially, failing to deliver on a promised or expected return (Loewenstein et al., 2001). In finance, risk is frequently understood in relation to the volatility of prices around an average value (Frankfurter & McGoun, 2003). Statisticians approach risk as a measure of uncertainty, assessing the likelihood of an event occurring versus not occurring. This understanding is common in behavioral decision theory literature as well (Morvan & Jenkins, 2017). Given its multi-dimensional nature, the methods used to study and observe risk can vary widely across different fields and disciplines.

In this study, the researcher defines **risk** as a negatively valenced likelihood assessment concerning the occurrence of an unfavorable event. This definition distinguishes risk from uncertainty in three key ways. First, while uncertainty judgments can be either positively valenced (e.g., the likelihood of being free from non-communicable diseases, or NCDs, despite certain behaviors) or negatively valenced (e.g., the risk of developing NCDs regardless of behaviors), the researcher construes risk as consistently negative. Second, events with a probability of 0.50 are perceived as more uncertain than those with probabilities closer to either 0 or 1; conversely, risk increases as the probability approaches 1. Third, less controllable events tend to evoke greater uncertainty, yet they may not inherently carry more risk. In summary, the researcher defines **health risk** as the perception of the subjective likelihood of experiencing a negative health-related event for an individual or group over a specified period.

2.3.1. Studying Health Risk Perceptions

Studying health risk perceptions is crucial for several reasons. First, they are theoretically interesting and offer valuable insights into how people understand and react to risks. Second, they are managerially relevant, particularly in the context of health communication and marketing. Finally, understanding these perceptions has significant implications for individual welfare and public policy (Ferrer & Klein, 2015).

The field of health presents a wealth of concepts that enable researchers to explore broader theoretical questions, such as: What is the interaction between cognitive and emotional systems in shaping risk perceptions? What factors influence the relationship between risk judgments and health-related behaviors? How do individuals utilize information from memory and context to make risk assessments? Additionally, do individuals process information and form judgments in different ways? This study focuses on the theoretical foundations of risk perceptions, the behavioral consequences of accepting risk, and the various factors that moderate the relationship between these elements.

Beyond these theoretical considerations, understanding the antecedents and consequences of health risk perceptions has become increasingly important for managers, especially given the rise of direct-to-consumer advertising that often relies on consumers' abilities to self-diagnose or seek proxy diagnoses (Slovic, 1987).

From an individual welfare standpoint, the alarming increase in health conditions—ranging from mental health issues such as depression, anxiety, and bipolar disorder, to physical conditions like obesity, autism, and alcoholism, as well as pre-existing conditions like high cholesterol, hypertension, heart disease, cancer, hepatitis, and AIDS—underscores the necessity of comprehending individuals' perceptions of risk. A deeper understanding of these perceptions can empower people to make more informed life choices for themselves and those around them (Loewenstein et al., 2001).

2.3.2. Theories related to risk perception

2.3.2.1. Protection Motivation Theory

One of the most cited theories that explains risk perceptions and risk tolerance is the Protection Motivation Theory (PMT). According to PMT, individuals are more likely to engage in protective behaviors when they anticipate negative consequences, desire to avoid those consequences, and feel capable of taking preventive actions. PMT shares similarities with the Health Belief Model (Becker & Maiman, 1975), which suggests that people evaluate factors such as the severity of a threat, their personal vulnerability, and the potential benefits of protective actions before deciding whether to engage in risky behavior.

Overall, PMT posits a relationship between risk perception and incidents of injury, asserting that people are motivated to take protective action when they feel empowered to do so. For example, research by Sheeran et al. (2013) found that enhancing risk appraisal elements—like risk perception and perceived severity—can positively influence individuals' intentions and behaviors toward safety. DeJoy (1996) emphasizes that deciding to take protective measures in the workplace is a thoughtful process. Workers evaluate their sense of response efficacy (the belief that their actions will be effective) and self-efficacy (their sense of agency) against potential costs. As protective behaviors become normalized and habitual, and as workers recognize their capacity to influence their own safety, the use of personal protective equipment tends to increase.

PMT suggests that risk perception and the use of personal protective equipment rise when workers have legitimate concerns, often stemming from prior incidents. For instance, offshore oil workers who experienced an incident in the previous two years reported feeling less safe and had a heightened awareness of work-related hazards compared to those who had not faced an incident (Mearns et al., 1998).

This theory has been effectively applied to safety campaigns, showing better outcomes than other approaches in reducing young adults' intentions to speed while driving (Walker et al., 2013). Campaigns based on PMT often focus on raising awareness of the consequences of speeding and enhancing young drivers' perceptions of vulnerability and self-efficacy—empowering them to resist peer pressure and drive responsibly.

Interestingly, individuals tend to be less tolerant of risks imposed by others compared to risks they willingly accept themselves. This insight suggests that helping people understand the potential consequences of their actions on others can motivate them to adopt safer behaviors. In general, PMT indicates that a strong motivation to protect oneself requires not only an adequate perception of risk but also the necessary tools and skills to take preventive action (Glendon & Walker, 2013). Those who are more prone to taking risks often have lower awareness of those risks and lack the self-efficacy needed to safeguard themselves.

2.3.2.2. Risk Compensation/Risk Homeostasis Theory

Risk compensation, also known as risk homeostasis, is another theory that seeks to explain why individuals engage in risky behaviors. According to this theory, people tend to take on greater risks when they feel a heightened sense of security. In essence, individuals adjust their level of risk-taking based on the safety measures in place (Wilde, 1994). Much of the research surrounding risk compensation has focused on transportation safety.

However, the theory remains highly contested, with some researchers finding little to no support for it. For instance, one study revealed that nearly 90% of the reduction in traffic fatalities from 1964 to 1990 could be attributed to the introduction of seat belt laws and measures against drunk driving. This finding seems to counter the notion that people drive more recklessly when they are wearing seat belts (Robertson, 1998).

Robertson and Pless (2002) argue that individuals often lack the necessary knowledge, skills, or attention to modify their behavior in a way that maintains a constant level of risk. While support for risk compensation theory is less common in transportation contexts, it can be found in other areas of research. For example, a study observed that children navigated an obstacle course more quickly and recklessly—tripping, falling, and colliding with objects—while wearing helmets and wrist guards than when they were not wearing any safety gear (Morrongiello & Lasenby-Lessard, 2007).

Although risk compensation theory is debated, there is evidence from non-transportation research suggesting that it can still be relevant in predicting certain forms of risk behavior.

2.3.2.3. Situated Rationality Theory

Situated rationality theory argues that it's a mistake to assume that safe behaviors are inherently rational while high-risk behaviors are inherently irrational. In fact, there are often logical reasons behind why people choose to take risks, which are more insightful than simply labeling risk-takers as "crazy" or thrill-seeking. For example, individuals might choose to sunbathe outdoors or visit tanning salons despite the known risks of skin cancer because they want to enhance their body image (Cafri et al., 2008). Similarly, some may engage in unprotected sex with partners known to be drug users or HIV-positive as a way to express trust and demonstrate "real love" (Rhodes, 1997). Even those who are perceived as "thrill-seekers" often have a solid understanding of the consequences of their actions and the precautions they take; what may seem like an unacceptable risk to the uninformed may actually be well-managed.

Elements of situated rationality theory are also connected to peer and community pressure. In the workplace, taking risks can often be justified by workers aiming to "save face" in front of their colleagues or impress their supervisors. Business structures and ingrained production systems frequently reward unsafe behavior due to the potential benefits in compensation, output, and recognition. Caponecchia and Sheils (2011) found that workers were more likely to take risks in hopes that their increased efficiency would catch the attention of their supervisors. They also noted that bonuses for productivity often encouraged less safe work practices, and that taking risks made them appear "tough." Workers, regardless of gender, expressed concerns that appearing less strong, capable, or competent could jeopardize their standing within the company.

Situated rationality theory shares several connections with the theory of planned behavior (Ajzen, 2011; Ajzen & Fishbein, 2004). This theory examines the various social, environmental, and psychological factors that influence an individual's intention to engage in high-risk behavior. People consider not only their own attitudes toward an action but also the collective attitudes and subjective norms of their peers. These factors can serve as justification and rationale for taking risks, especially when risk perception is low and potential rewards—such as recognition from peers or superiors—are high.

2.3.2.4. Habituated Action Theory

Habituated action theory suggests that engaging in high-risk behaviors repeatedly without facing negative consequences can diminish the perceived risk associated with those behaviors. Individuals who perform a high-risk action multiple times without adverse outcomes tend to become desensitized to the risks involved (Kasperson et al., 2016). For instance, for some heroin users, the risk of overdose becomes just "an everyday thing" they accept as part of their habit (Rhodes, 1997). In this cycle, risk perception continues to decrease while risk tolerance increases. As Rhodes (1997) noted, "Behaviours which are habitual do not demand risk assessment or calculation for their doing; they are simply done" (p. 217).

2.3.2.5. Social Action Theory

Social action theory encompasses various applications, particularly in relation to risk. This theory posits that individuals take risks due to peer pressure or a general community perception that certain activities are low risk. People may be encouraged to engage in unsafe behaviors simply because "everyone else is doing it" or because the broader community does not see the action as hazardous. Additionally, the social meanings associated with high-risk behaviors (such as being viewed as "cool" or "manly") can drive individuals to partake in those actions.

The propensity for risk can also be influenced by coworkers' expectations. Individuals often conform to group norms to avoid negative repercussions (like teasing, bullying, or being labeled as "wimpy") and, in doing so, begin to identify with the group, adopting its perceptions and behaviors (Crocker et al., 2003; Eiser et al., 1984). As a result, conformity to the social expectations of peers and the wider community often leads to increased, rather than decreased, risk-taking behavior.

2.3.2.6. Social Control Theory

Similar to social action theory, social control theory has various applications that extend beyond safety and risk reduction. Introduced by Travis Hirschi in 1969 as cited in Hirschi, (2008), this theory asserts that connection to organizations promotes conformity, thereby reducing the likelihood of engaging in high-risk behaviors. Research indicates that an individual's affiliation with schools or workplaces positively influences their perception of risk.

For instance, in a review of educational connectedness and engagement, school connectedness emerged as a significant factor in preventing youth from participating in risk-taking behaviors like smoking, alcohol and marijuana use, and riding with impaired drivers (Chapman & Feldman, 2017). Adolescents who perceive their teachers as fair, caring, and supportive are less likely to engage in risky behaviors such as smoking, binge drinking, unprotected sex, or even attempting suicide (Clea McNeely & Christina F., 2004).

2.4. Empirical Evidence on the Relationship Between the Main Variables of the Study

2.4.1. Knowledge and Behavioral Intention

2.4.1.1. Global Perspective

Research has consistently shown that knowledge plays a critical role in shaping behavioral intentions across diverse contexts. Ajzen's (1991) Theory of Planned Behavior (TPB) serves as a foundational framework, positing that knowledge and attitudes influence intentions, which then shape behavior. In health contexts, for instance, high levels of health-related knowledge correlate positively with preventive health behaviors (Godin & Kok, 1996). Knowledge empowers individuals with necessary information, thereby fostering intentions aligned with positive health, environmental, or social behaviors (Fishbein & Yzer, 2003).

2.4.1.2. Young Adults' Knowledge and Behavioral Intentions

Young adulthood is marked by significant cognitive, social, and emotional development, leading to distinct knowledge-behavior dynamics. According to Arnett (2000), young adults are in an exploratory phase, and their behavioral intentions are particularly malleable and susceptible to educational interventions. Globally, studies indicate that knowledge in areas like safe sex, mental health, and substance use significantly predicts young adults' intentions to engage in safe practices (Sharma et al., 2005). Knowledge about risks and consequences drives young adults toward forming intentions that align with protective behaviors (Kim & Ahn, 2017).

2.4.1.3. Knowledge and Behavioral Intention in Ethiopian Youth

Studies in Ethiopia reflect global findings on the knowledge-behavioral intention link but also reveal unique cultural and contextual factors. According to a study by Tsegaye et al. (2019), Ethiopian university students' knowledge about HIV/AIDS positively impacts their intentions to engage in protective behaviors. This is corroborated by Alemu et al. (2016), who found that knowledge regarding contraceptives among young adults in Ethiopia influences their intentions and actual behaviors related to family planning. Despite this, gaps in knowledge due to cultural and educational barriers often limit behavioral intentions among Ethiopian youth, particularly in rural areas (Tessema et al., 2020).

2.4.2. Knowledge and risk perception

2.4.2.1 Global Perspective

Research indicates that knowledge strongly influences individuals' risk perception intentions, particularly in areas related to health, safety, and environmental behaviors. The Protection Motivation Theory (PMT) suggests that knowledge about potential threats elevates perceived risk, thereby motivating protective behaviors (Rogers, 1983). Studies show that individuals with greater knowledge are more likely to recognize and act upon potential risks in various contexts, such as health and environmental hazards (Weinstein, 1989; Brewer et al., 2007). For example, individuals with higher awareness of the risks associated with smoking or poor diet are more likely to intend to adopt healthier behaviors (Sheeran et al., 2016).

2.4.2.2. Young Adults' Knowledge and Risk Perception Intention

Young adults are in a developmental phase characterized by exploratory behaviors and susceptibility to both risk-taking and preventive intentions. Globally, knowledge plays a significant role in young adults' perception of risks related to activities like alcohol consumption, drug use, and unprotected sex. For instance, Blanton et al. (2001) found that college students with increased knowledge about sexually transmitted infections (STIs) demonstrated heightened risk perception, which in turn strengthened their intention to engage in safe sex practices. Similarly, Albarracín et al. (2005) observed that knowledge about risks associated with certain behaviors enhances young adults’ motivation to adopt safer behaviors.

2.4.2.3. Knowledge and Risk Perception in Ethiopian Youth

In Ethiopia, studies echo global findings, indicating that knowledge affects young adults' risk perception intentions in public health contexts, although cultural factors also play a role. For example, a study by Kassa et al. (2016) on Ethiopian university students found that awareness of HIV/AIDS risks increased perceived vulnerability and intention to adopt preventive behaviors, such as condom use. Additionally, Tadesse et al. (2020) observed that Ethiopian youth with greater knowledge of substance abuse risks showed higher risk perception and were less likely to engage in substance use. Cultural norms and access to information impact these relationships, particularly in rural areas, where limited access to knowledge reduces young adults’ risk perception intentions (Demilew et al., 2018).

2.4.3. Knowledge and Self-Efficacy

2.4.3.1. Global Perspective Knowledge and Self-Efficacy

Research widely supports the notion that knowledge is positively associated with self-efficacy intentions in various domains, from health to education and professional settings. According to Bandura’s (1997) Social Cognitive Theory, knowledge is foundational to self-efficacy because it provides individuals with an understanding of how to approach tasks effectively, thus boosting their confidence and intention to act. For example, studies in health contexts demonstrate that individuals with a strong knowledge base about healthy practices report higher self-efficacy intentions to engage in those practices (Schwarzer & Renner, 2000). Likewise, in educational settings, knowledge acquisition has been shown to enhance students’ self-efficacy intentions to achieve academic goals (Zimmerman, 2000).

2.4.3.2. Young Adults’ Knowledge and Self-Efficacy

Young adults are at a critical stage for developing self-efficacy intentions across domains. Globally, knowledge plays a key role in this age group, fostering confidence and intention in areas like career development, health behaviors, and academic achievement (Arnett, 2000). For instance, research by Luszczynska et al. (2004) found that university students with more knowledge about preventive health practices, such as exercise and diet, had stronger self-efficacy intentions to maintain these behaviors. Knowledge positively influences self-efficacy by reducing uncertainty and empowering young adults to make effective decisions that align with their goals (Chemers et al., 2001).

2.4.3.3. Knowledge and Self-Efficacy in Ethiopian Youth

Ethiopian studies highlight similar relationships between knowledge and self-efficacy intentions, though contextual factors such as limited access to information in rural areas and cultural norms play influential roles. In the health domain, for instance, a study by Bulto et al. (2019) found that Ethiopian university students with knowledge about reproductive health and family planning showed higher self-efficacy intentions to use contraception. Similarly, Mekonnen et al. (2020) reported that Ethiopian youth who had greater knowledge about HIV prevention demonstrated increased self-efficacy intentions to adopt safe practices. However, limited educational resources and traditional beliefs often hinder the development of self-efficacy intentions among Ethiopian young adults, especially in underserved regions (Taye & Gebremariam, 2021).

2.4.4. Knowledge and Outcome Expectancy

2.4.4.1. Global Perspective

Outcome expectancy refers to an individual's belief that certain actions will lead to specific outcomes, and empirical studies show that knowledge significantly influences these beliefs across various domains. According to Bandura's (1997) Social Cognitive Theory, knowledge enhances individuals' understanding of the relationship between actions and their consequences, shaping their outcome expectancies and promoting goal-directed behaviors. Studies in health behavior reveal that individuals with more health-related knowledge tend to have higher positive outcome expectancies for engaging in healthy behaviors (Maddux, 2000; Schwarzer, 2008). For instance, in a study on smoking cessation, individuals with greater knowledge about the risks of smoking had higher expectations that quitting would lead to improved health outcomes (McEwen et al., 2006).

2.4.4.2. Young Adults' Knowledge and Outcome Expectancy

In young adulthood, knowledge significantly impacts outcome expectancies, influencing decisions around health, education, and career. Young adults are in a developmental stage where they explore and make critical life decisions, and knowledge often strengthens positive outcome expectancies (Arnett, 2000). Research by Rosenstock et al. (1994) found that young adults with high awareness of the benefits of exercise and healthy eating had more favorable outcome expectancies, which increased their likelihood of engaging in these behaviors. Similarly, in academic settings, students with greater knowledge of study strategies and career paths held higher expectations for success in their studies and future careers (Chemers et al., 2001).

2.4.4.3. Knowledge and Outcome Expectancy in Ethiopian Youth

Ethiopian studies highlight similar associations between knowledge and outcome expectancy, particularly in health and education. In a study on reproductive health, Ethiopian university students who had higher knowledge about contraception and family planning were found to hold strong positive outcome expectancies about avoiding unplanned pregnancies and managing reproductive health (Dessie et al., 2020). Another study by Alemu and Molla (2017) showed that knowledge about HIV prevention among Ethiopian young adults increased positive outcome expectancies for adopting safe practices, enhancing their motivation to engage in protective behaviors. Cultural and economic challenges, however, can moderate these relationships, particularly in rural areas where access to reliable information may be limited (Beyene et al., 2018).

2.4.5. Risk Perception and Behavioural Intention

2.4.5.1. Global Perspective

Numerous studies show a significant relationship between risk perception and behavioral intention, particularly in health, safety, and environmental behaviors (Birley, & Iaia, 2015). The Theory of Planned Behavior and Protection Motivation Theory (PMT) emphasize that perceived risk often motivates individuals to adopt protective actions (Ajzen, 1991; Rogers, 1983). For example, Weinstein et al. (2007) demonstrated that individuals who perceived higher risks of smoking-related illnesses exhibited stronger intentions to quit smoking. Similarly, in environmental contexts, those aware of climate change risks often express stronger intentions to engage in eco-friendly behaviors (Steg & Vlek, 2009).

2.4.5.2.Young Adults' Risk Perception and Behavioral Intention

Young adults are especially influenced by risk perception when forming behavioral intentions, given their tendency toward exploration and susceptibility to both risk-taking and preventive intentions. Research on health behaviors reveals that young adults with higher perceived risks of consequences from unsafe sexual practices or substance abuse are more likely to intend to adopt safer behaviors (Sheeran et al., 2014). A study by Gerrard et al. (2008) indicated that perceived risk of STIs influenced college students' intentions to use condoms, showing that risk perception significantly impacts intentions among young adults in health-related areas.

2.4.5.3. Risk Perception and Behavioural Intention in Ethiopian Youth

In Ethiopia, studies similarly indicate a relationship between risk perception and behavioral intention, particularly in the context of public health and safety. For example, research by Tadesse and Taye (2018) found that Ethiopian university students who perceived high risks of HIV/AIDS were more likely to intend to engage in preventive behaviors, such as consistent condom use. Similarly, studies on road safety among Ethiopian youth show that those who perceive higher risks of traffic accidents are more inclined to adopt safe driving practices (Gebrehiwot & Sisay, 2020). However, cultural and social factors, including stigma and misinformation, sometimes reduce the perceived risks associated with certain behaviors, affecting behavioral intentions (Terefe et al., 2019).

2.4.6. Self-Efficacy and Behavioral Intention

2.4.6.1. Global Perspective

Self-efficacy is a critical predictor of behavioral intention across various domains, including health, education, and professional development. Bandura's (1997) Social Cognitive Theory posits that individuals with higher self-efficacy have stronger intentions to take action, as they believe in their ability to achieve desired outcomes. Empirical studies support this, showing that self-efficacy positively influences behavioral intentions in areas such as exercise, smoking cessation, and dietary change (Schwarzer, 2008). For instance, a study by Armitage and Conner (2001) found that individuals with high self-efficacy are more likely to form strong behavioral intentions to engage in health-promoting behaviors, emphasizing the critical role of self-efficacy in motivation and action.

2.4.6.2. Young Adults' Self-Efficacy and Behavioral Intention

In young adulthood, self-efficacy significantly affects intentions across domains including health, academics, and career. Young adults with higher self-efficacy are more likely to set and commit to specific goals, given their confidence in handling challenges (Zimmerman, 2000). For instance, Luszczynska and Schwarzer (2005) found that young adults with high self-efficacy intentions were more likely to practice health-promoting behaviors, such as regular exercise and safe sexual practices. Similarly, research in academic contexts shows that young adults with high academic self-efficacy set stronger intentions to excel in studies and pursue further education (Chemers et al., 2001).

2.4.6.3. Self-Efficacy and Behavioral Intention among Ethiopian Youth

Studies in Ethiopia reflect similar patterns, with self-efficacy playing a critical role in shaping behavioral intentions, particularly in health and education. In health contexts, research by Bulto et al. (2019) indicates that Ethiopian university students with higher self-efficacy are more likely to intend to use contraceptives, demonstrating a link between self-efficacy and preventive health behaviors. Another study by Alemayehu et al. (2021) highlights that Ethiopian students with high self-efficacy are more inclined to set educational goals and engage in career-related behaviors, showing that self-efficacy contributes to their motivation and intent to succeed academically and professionally. However, challenges such as limited resources and social norms can influence the relationship between self-efficacy and behavioral intentions, especially in rural areas (Mengesha & Mekonnen, 2020).

2.4.7. Outcome Expectancy and Behavioral Intention

2.4.7.1. Global Perspective

Outcome expectancy, which refers to an individual's belief that a particular behavior will lead to specific outcomes, has been shown to be a critical factor influencing behavioral intention. According to Social Cognitive Theory, outcome expectancies significantly impact an individual's motivation to act, especially in health and lifestyle behaviors (Bandura, 1997). For instance, a study by Maddux and Rogers (1983) found that people with high expectations of positive health outcomes are more likely to intend to engage in preventive health behaviors. In the context of environmental behaviors, studies show that individuals who believe their actions will contribute to positive environmental outcomes express stronger intentions to engage in eco-friendly practices (Steg & Vlek, 2009).

2.4.7.2. Young Adults' Outcome Expectancy and Behavioral Intention

For young adults, outcome expectancy is crucial in shaping intentions in areas such as health, academics, and career decisions. During this life stage, young adults are developing long-term behavioral patterns, and their beliefs about the outcomes of their actions strongly influence their intentions (Arnett, 2000). Research by Gibbons et al. (1998) showed that young adults with high outcome expectancy for academic and career success were more motivated to pursue educational and professional goals. Additionally, in health-related domains, young adults who believe in the positive outcomes of exercise or healthy eating are more likely to intend to adopt these behaviors (Sheeran et al., 2016).

2.4.7.3. Outcome Expectancy and Behavioral Intention in Ethiopian Youth

In Ethiopia, studies similarly indicate that outcome expectancy influences behavioral intention, particularly in health and educational contexts. In a study on reproductive health among Ethiopian youth, Gebremariam and Assefa (2019) found that students with high outcome expectancy regarding contraceptive use showed stronger intentions to adopt safe sexual practices. Additionally, research on educational intentions indicates that Ethiopian students with positive expectations about the outcomes of academic success tend to set higher educational goals and pursue further studies (Mekonnen & Fekadu, 2020). Social and cultural factors, including familial expectations and community beliefs, can also moderate the relationship between outcome expectancy and behavioral intention, particularly in rural areas where access to information is limited (Tadesse et al., 2018).

2.5. Theoretical and conceptual frame work

2.5.1. Theoretical frame work

The researcher adopts Protection Motivation Theory as a theoretical framework to understand how individuals cope with and make decisions during harmful or stressful life events. This theory provides insights into the motivations behind behavior changes aimed at protecting oneself from perceived threats. Essentially, it seeks to explain and predict how people respond to health-related threats. For instance, how might someone facing the threat of cancer respond to advice about quitting smoking? What cognitive evaluations are happening that ultimately influence this decision?

While this theory effectively highlights health behavior as a crucial outcome, the researcher believes it can be further refined. By incorporating additional elements like health status, the conceptual framework has been modified to enhance its completeness and robustness, making it more applicable to this research.

2.5.1.1. Cognitive Processes in Behavior

The decision to engage in health-related behaviors is influenced by two primary cognitive processes: threat appraisal and coping appraisal. Both processes examine the potential consequences of engaging in or abstaining from specific health behaviors, including how individuals anticipate the reactions of others.

a) Threat Appraisal

Threat appraisal focuses on how threatened an individual feels by a potential risk. For example, how alarming is the thought of possibly having breast cancer? This evaluation involves considering various factors that might lead someone to partake in unhealthy behaviors, such as smoking or drug use. Two key beliefs contribute to threat appraisals:

Perceived Vulnerability: This is the belief that one is susceptible to a health threat. For instance, individuals may rate their likelihood of developing lung cancer based on their smoking habits using a Likert scale.

Perceived Severity: This reflects how serious an individual believes the health threat to be. This can be measured through responses to statements like, "AIDS is a very dangerous disease," where individuals indicate their level of agreement or disagreement.

Additionally, fear arousal can gauge how much fear is triggered by perceptions of vulnerability and severity. For example, individuals might be asked how they feel at the thought of contracting a particular disease, with responses ranging from "not worried" to "very anxious" indicating their level of fear regarding the threat.

b) Coping Appraisal

Coping appraisal involves evaluating the factors that might motivate one to engage in preventive actions. For example, opting to take daily walks or use condoms as protective measures. Three belief categories are crucial here:

Response Efficacy: This belief pertains to the effectiveness of certain behaviors in reducing the health threat. For instance, an individual might think, “If I exercise more, I will lose weight and reduce my risk of heart disease.”

Self-Efficacy: This reflects the belief in one’s ability to carry out a health behavior. Individuals might respond to statements like, “It is easy to wake up early every day and exercise,” using agreement scales.

Perceived Response Cost: This belief pertains to the costs associated with engaging in a health behavior. For example, a woman might feel uncomfortable about getting a mammogram, which could deter her from following through with it.

Moreover, if someone believes that the benefits of not adopting a healthy behavior outweigh the advantages of making a change, they may continue with their negative habits. For example, they might keep using drugs for an escape or prefer fast food because it’s cheaper than healthier options.

The theory posits that for an individual to adopt a health behavior, they must recognize that a severe threat exists and believe that engaging in a specific behavior can effectively mitigate that threat. They should also feel confident in their ability to carry out the behavior and perceive the costs as manageable. An individual’s intention to engage in the recommended preventive behavior often serves as the primary indicator of protection motivation.

Based on this evaluation of the theoretical framework, the researcher has developed a new conceptual framework that refines previous models used in earlier research and validation workshops. This refinement involved removing variables like planning and behavioral practices while incorporating elements such as educational status, place of birth, and college streams to create a more comprehensive model.

2.5.2. Conceptual Frame Work

Sedentary lifestyles can lead to various health risks (Wood, Quinn, & Kashy, 2002) and may also impede economic and social development. While there is a rich array of theories explaining risk perception, the integration of constructs from different models to effectively motivate behavior remains largely unexplored. Combining key predictors of behavior could result in a more comprehensive understanding of health behavior (Jago et al., 2005). Nigg & Jordan (2005) emphasize that rather than simply comparing theories, a more productive approach might be to empirically integrate important components to formulate a holistic theory of behavior change.

This study proposes that an individual's knowledge, risk perception, self-efficacy, and outcome expectancy can influence their behavioral intentions. The selected independent variables are indicative of the motivational phase within health behavior change models. Some of these variables consist of distinct dimensions; for instance, risk perception includes two aspects: the perceived severity of potential consequences associated with NCDs and the perceived likelihood of being affected. Similarly, outcome expectancy comprises two dimensions: positive and negative expectancies.

The anticipated relationship between the independent and dependent variables is illustrated in Figure 1. It is hypothesized that individuals who perceive higher levels of risk are more likely to exhibit active behavioral intentions. Building on this theoretical framework, I have developed a new conceptual model to enhance the clarity and manageability of the research.

Figure 2.1. The basic figure was taken from Clubb & Hinkle (2015) framework for prevention motivation theory. Knowledge, Risk Perception, Self-Efficacy, Outcome Expectancy and Intention to Practice Healthy Behaviours Related to Non-Communicable Diseases in young adults in Ethiopia".

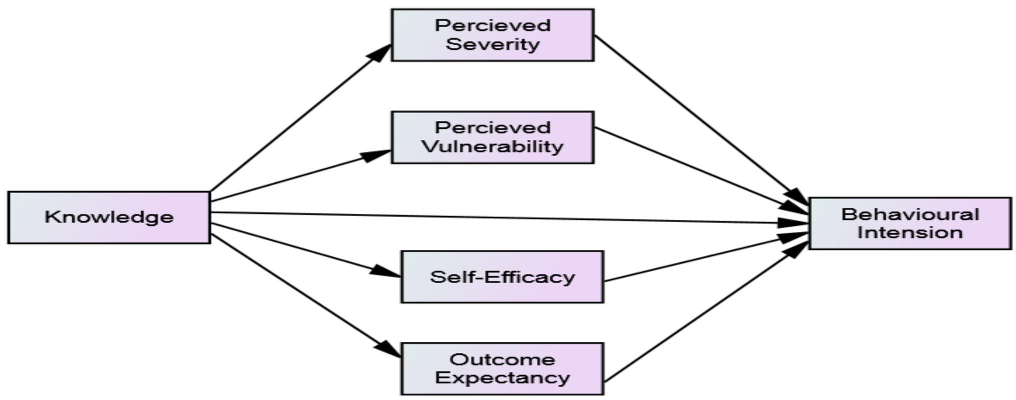


Figure 1: Conceptual Framework

CHAPTER THREE

Research Methods

In this chapter, the researcher outlines the primary methodological issues encountered during the study. These discussions are crucial for addressing the research questions effectively and steering the entire research process. By carefully considering these methodological aspects, the researcher aims to ensure a robust framework for data collection, analysis, and interpretation.

3.1. Research Paradigm, Design, Approach, and Method for This Study

3.1.1. Research Paradigm of the Current Study

The current study is grounded in the post-positivism paradigm, also known as critical realism. This perspective acknowledges the researcher's commitment to objectivity while recognizing the impact of social factors and processes that can shape the interpretation and behavior surrounding the phenomena under investigation.

In striving for objectivity, the researcher aimed to ensure that the data collected and interpreted were free from personal biases. However, there was also an awareness of the social influences that might affect young adults' behavioral intentions. To mitigate these influences, some variables were statistically controlled, with the assumption that any uncontrolled variables would be evenly distributed among study participants due to randomization.

Post-positivism seeks to develop research hypotheses grounded in existing theories and aims to arrive at conclusions that are thoroughly supported by statistical and objective measures (Flowers, 2009; Saunders et al., 2007). Consequently, the researcher formulated research objectives through a review of the relevant theories related to the variables being studied. These objectives were tested based on the data collected through questionnaires addressing Knowledge of NCDs (KON), Risk Perception (RP), Self-Efficacy (SE), Outcome Expectations (OE), and Behavioral Intentions (BI).

In line with the post-positivist approach, this research began by outlining the background to identify the research problems. This was followed by connecting relevant theories, formulating research objectives, collecting and analyzing quantitative data, interpreting and discussing the results, proposing solutions to the identified problems, and concluding with reflections on the findings.

3.1. 2. Research Design for the Current Study

The primary objective of this study is to investigate the relationships among Knowledge of NCDs (KON), Risk Perception (RP), Outcome Expectations (OE), Self-Efficacy (SE), and Behavioral Intentions (BI). To achieve this, a correlational research design was selected. This design allows for the prediction of scores and the explanation of relationships between variables. In social psychological research, correlational designs are often preferred when the goal is to examine how variables relate to one another rather than manipulating an independent variable, as would be done in experimental research (Creswell, 2013).

In this study, the focus is on exploring the relationships among KON, RP, OE, SE, and BI, rather than manipulating BI in an experimental context. Therefore, a correlational research design was deemed the most appropriate choice.

According to Creswell (2013), there are two types of correlational research designs: explanatory and predictive. Explanatory correlational research is used when researchers are interested in examining the co-variation of variables. In contrast, predictive correlational research is employed when researchers aim to anticipate outcomes based on certain predictor variables. This research aligns more closely with the predictive correlational design, as the aim is to forecast the outcomes of BI using KON, SE, OE, and RP as predictor variables.

3.1.3. Research approach for the current study

According to Sounders et al (2007) and Adams et al., (2007), there are deductive and inductive research approaches. Researchers that follow a deductive approach identify an existing theory, develop hypotheses/research equations and design a research strategy in hypothesis testing. On the contrary, researchers that follow the approach of inductive methods start their investigation by collecting data followed by theory development from the analysis of the collected data. Thus, the deductive approach was used to deal with the objectives of the current study as the current research objectives were developed based on existing theories.

3.1.4. Research method for the current study

The investigator takes a deductive strategy because the theory of relationship among KON, RP, SE, OE, and BI initiated the concept of the present study. The present researcher explores the relationship among KON, RP, SE, OE, and BI through the results to be determined in the present research. Since the deductive approach embraces with quantitative research method Haseman, (2006), the quantitative research method was used for the current research.

In this research, the data was collected and analysed using quantitative methods. This method is chosen because the researcher believes the methods help to evaluate the chosen variables (KON, RP, SE, OE, and BI) relationship. The methods also help to assess the predictive power of the predictor variable KON, RP, SE, and OE over the dependent variable BI, to test theories, to use statistical tools to answer research questions and to apply results to a large number of people. According to Creswell (2013), researchers tend to use quantitative methods when the research problem involves: measuring variables, evaluating their effect on outcomes, testing theories and wide explanations, and implementing the results to a large number of individuals.

However, a limitation of relying solely on a quantitative approach is that it may overlook the nuanced, subjective experiences of individuals, which qualitative methods could capture. By focusing only on statistical measurements, there is a risk of losing the contextual and personal insights that often enrich understanding, especially for complex, multifaceted phenomena. The mono-method approach may also limit the researcher's ability to explore unexpected variables or outcomes that emerge from the data, restricting the study’s depth and breadth. Consequently, while quantitative methods offer broad applicability and predictive capacity, they may lack the flexibility and depth needed to capture the full spectrum of human experience within the study's context.

3.2. Settings and Site

The research setting was higher education in Ethiopia currently includes education programs that are offered as an undergraduate degree for three, four, or more years and specialized degrees such as Master`s, Ph.D., Specialty, subspecialty, and equivalent programs. The researcher was interested in Universities because most of the young adults are found at colleges and universities. Since the researcher has familiarity and experience with the population in the government university the data was collected from government universities. Specifically speaking, data was collected at Debre Birhan University. Ethiopia is a multi-ethnic state endowed with diverse cultures, languages, faith, and religion (Dagnachew, Lucas, Hof, & Vuuren, 2018; and Tariku & Gara, 2016). Consequently, teachers and students of Ethiopian Universities come from different cultural, ethnic, religious, and language compositions. Because of this universities are commonly referred to by many Ethiopians as “Little Ethiopia” to describe the diverse nature of university society (Abebaw, 2013; Biru, 2019; Chanyalew & Solomon, 2018; Yared, 2000).

3.3. Population and Sample Size Determination

When conducting research, it's common to face the challenge of dealing with large populations that are impractical to study in their entirety. Instead, researchers typically focus on a sample drawn from this population. A well-chosen sample can provide most of the necessary information about a particular population parameter. However, it is crucial to ensure that the relationship between the sample and the population allows for accurate inferences about the larger group. This connection is what enables researchers to make valid conclusions based on their sample data (Creswell, 2013).

3.3.1. Population of the Study

The target population for this study were the young adults who were enrolled and admitted to university programs and were taking classes during the Spring 2020/21 semester.

3.3.2. Sampling Procedure

Recruiting of participants was done through the database of the available students in different programs maintained by the colleges and institutes in this selected university. The students’ status was varied in terms of the number of years studied, and undergraduate degree programs pursued.

During the study period, the number of government universities in Ethiopia was 45 (Tamrat, 2020). These universities are situated in different geographical areas with unique organizational culture which may influence variables of the present study directly or indirectly. On the other hand these universities accept students from all over the country. All the universities have similar compositions like students they enrolled in their programs. Selecting one from this might not be representative to all. As described in the study population section the characteristics of the students in the universities are similar on most of the cases. Thus, the researcher has chosen Debre Birhan University for familiarity and easiness of access. So Debre Birhan University was the sampled area of this study. The samples used for piloting and the main study were at different batches and colleges.

The criteria for selecting participants in this study included two main factors: (1) being enrolled in one of the specified programs and (2) being part of the 2020/21 academic year. From the database, a total of 2,000 students met these criteria. To ensure a representative sample, the study employed a multi-stage stratified random sampling method (Redline & Dillman, 1992).

In the first stage, 4 (i.e. health sciences, computing agriculture, social science, and business and economics) colleges or institutes were selected using simple random sampling. Then, in the second stage, 8 (i.e. nursing, midwifery, pharmacy, plant science, biology, computer science, sociology, and management) departments within those selected colleges were chosen through a lottery method. Finally, students from each selected department were sampled using systematic random sampling, based on a complete list of students in those departments.

3.3.3. Sample Size Determination

The piloting phase of this study was a crucial first step in implementing and refining the research techniques. Conducting a cognitive interview with 104 respondents served multiple purposes: it allowed for early testing and validation of the study instruments, ensuring that the questions were clear, unambiguous, and aligned with the study objectives. By involving participants from graduating classes, the researcher ensured that these respondents would not be included in the main sample, minimizing potential bias and preserving the integrity of the primary data. This approach is consistent with Loehlin's (2021) recommendations on pilot testing, which emphasize the importance of evaluating the reliability and clarity of instruments before proceeding to full-scale data collection.

The cognitive interview also provided insights into participants' thought processes as they answered the questions, highlighting any misunderstandings or ambiguities. Feedback from this process allowed the researcher to make adjustments to wording, question structure, or response options, ultimately enhancing the validity of the instrument. Additionally, the pilot phase helped identify any logistical issues, such as the estimated time needed to complete the survey, which informed planning for the main study. Overall, the piloting phase was essential not only for validation but also for fine-tuning the data collection process, ensuring that the instruments were ready for effective deployment in the primary research phase.

When planning a sample size for data collection, the primary goal is often to achieve reasonable statistical power for key analyses. Power calculations help determine the necessary sample size to ensure that a certain width of confidence interval or p-value corresponds to a scientifically meaningful effect size. However, sample size considerations go beyond just p-values; for example, Factor Analysis requires different considerations. In this study, both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were performed, with the latter requiring the use of Structural Equation Modeling (SEM).

The researcher aimed to understand the measurement model of an underlying construct. Similar to regression models, structural equation models, and latent class models, the focus is on comprehending the relationships among variables. Factor analysis specifically investigates which variables are associated with which latent constructs. While the approach differs slightly between exploratory and confirmatory models, the overall goal remains the same.

Determining an appropriate sample size for factor analysis is complex, as there is no universally correct answer. Researchers have various opinions on the necessary number of subjects and the criteria to use. For instance, some authors suggest that a sample size of 100 subjects is sufficient if a clear structure is present (Kline, 2014), while others indicate that 100 subjects are considered poor, 300 are good, and over 1000 is excellent (Comrey & Lee, 2013). Similarly, Tabachnik and Fidell (2007) argue that while 300 subjects are ideal, fewer may suffice if correlations among variables are high.

Other guidelines suggest a ratio of cases to variables, such as 10-15 subjects per variable (Pett, Lackey, & Sullivan, 2003) or 10 subjects per variable (Nunnally, 1978). Some propose using the larger of either 100 subjects or 5 per variable while others suggest 2 subjects per variable (Kline, 2014). A few researchers recommend a ratio of 20 subjects per factor (Arrindel & van der Ende, 1985).

Ultimately, these recommendations serve as rules of thumb rather than strict guidelines. Recent simulation studies indicate that the required sample size depends on multiple factors in the data and model working in tandem. A larger sample size, typically in the hundreds, is generally preferred. Some researchers suggest that fewer observations may suffice if the data behaves well—meaning there are no missing values and each variable strongly correlates with a single factor. However, relying on optimal data behavior is risky, much like depending on good weather during hurricane season.

The primary concern with small sample sizes is overfitting, where a model tailored to a specific small sample may yield results that cannot be replicated in another sample from the same population. In essence, parameter estimates become overly customized to the initial sample, rendering them unhelpful for broader application. This issue can arise in any model, including factor analysis.

Considering all these factors, the researcher planned for a total sample size of 1,000 participants, employing a split-half method. Half of this sample was allocated for piloting and EFA, while the other half was designated for CFA and the main study. Respondents engaged in regular degree programs were selected for participation. To minimize selection bias, simple random sampling procedure was implemented. Data collection took place over a two-week period (November 23 to December 6, 2022), with respondents stratified by age, gender, year of study, and place of birth (urban or rural) to ensure a representative sample. Before completing the survey, participants were provided with an informed consent information sheet and indicated their consent verbally.

3.4. Tools/ measures of the study

3.4.1. Behavioural Intentions

Behavioral Intention (BI) serves as the dependent variable in this study, measured using a validated BI scale developed after the pilot study. This assessment primarily utilizes dichotomous-graded items, such as “I intend to engage in vigorous physical activity at least twice a week.” Participants respond on a four-point Likert scale, ranging from "strongly disagree" to "strongly agree." This design helps avoid ceiling or floor effects that can distort results. Scores for BI are computed by summing the responses to all items on the scale.

3.4.2. Knowledge of NCDs

Knowledge of NCDs is another dependent variable in this study. Participants’ knowledge was measured using a scale specifically designed for this purpose. The total score is calculated by summing the responses across all items. This section assesses respondents' understanding of various aspects of NCDs, including symptoms, risk factors, fatality rates, and preventive measures. Items are rated on a two-point Likert scale: correct, or incorrect. Examples of questions include, “Do you know the causes of NCDs in general?” and “What protective measures can individuals take?

3.4.3. Outcome Expectancies

Outcome expectancies are evaluated through items that include "if/then" statements. Each item begins with a common stem describing the behavior under study, such as “If I start exercising regularly…” The subsequent "then" clause outlines a potential positive or negative outcome. For instance, a negative consequence might be, “…then I need to invest a lot of effort to organize it,” while a positive outcome could be, “If I start exercising regularly, I will be less vulnerable to diseases.” Responses are captured on a five-point Likert scale from (1) strongly disagree to (5) strongly agree. Scores for both positive and negative outcome expectancies are computed by summing or averaging responses across relevant items.

3.4.4. Perceived vulnerability:

Perceived vulnerability is measured using items that evaluate both absolute and relative vulnerability. For absolute vulnerability, items might ask, “How do you estimate the likelihood that you will ever suffer from (…)?” Relative vulnerability items incorporate a comparison group, such as, “If I compare myself with an average person of my sex and age, my risk of suffering from (…) is (...).” Responses are rated on Likert scales, where absolute vulnerability ranges from (1) very unlikely to (7) very likely, and relative vulnerability ranges from (1) very low to (7) very high.

3.4.5. Perceived Severity:

Perceived severity is assessed through items that inquire about the potential seriousness of various health-related issues. For example, participants might respond to statements like, “How severe would the following health-related problems be if they were not addressed?” Illnesses are rated on a Likert scale, with responses ranging from (1) not at all severe to (7) very severe. Individual severity ratings are evaluated using items such as, “How threatening is (…) for your health?” Scores for absolute vulnerability, relative vulnerability, and severity are calculated by summing the responses to all relevant items.

3.4.6. Self-efficacy

Self-efficacy is measured with a subscale specifically developed for this study. Each item begins with a statement about the target behavior or behavior change. For example, an item might state, “I am confident that I can be physically active regularly…,” followed by a barrier such as, “…even if it is hard for me.” When the item contains a specific behavioral criterion (e.g., “I am confident that I can go running at least twice a week for 30 minutes”), a general barrier may also be included, like, "…even if it turns out to be difficult." Participants respond on a four-point Likert scale ranging from (1) not at all true to (4) exactly true. Self-efficacy scores are computed by summing or averaging the responses across all items.

3.5. Data Collection Procedures

The purpose of the study and the confidentiality of responses were clearly explained to participants. They were informed that they could exempt themselves from the study at any time if they were not interested. Despite this, most randomly selected participants voluntarily chose to take part in the study. Participants were encouraged to ask questions or seek clarification on any unclear instructions or items. Additionally, they were invited to provide any oral or written feedback regarding the survey instrument.

3.6. Data Analysis

This section outlines the analytical procedures used to process, validate, and interpret the data collected for this study. A series of quantitative analyses were conducted to ensure the reliability and validity of the results and to test the hypothesized relationships among the study variables. The data analysis process began with initial data screening and descriptive statistics to identify and address potential issues such as missing data, outliers, and multicollinearity. These preliminary steps helped prepare the dataset for more complex statistical tests.

Subsequently, correlation and regression analyses were performed to explore the predictive power of the independent variables—Knowledge of NCDs (KON), Risk Perception (RP), Self-Efficacy (SE), and Outcome Expectancies (OE)—on the dependent variable, Behavioral Intention (BI). Factor analysis was conducted to validate the constructs within the instrument, followed by structural equation modeling (SEM) to assess the fit of the conceptual framework and the mediating effects of key variables. This multi-step approach provided both a broad understanding of data patterns and a rigorous evaluation of the study hypotheses, ensuring a comprehensive examination of the relationships among variables within the research model.

3.6.1 Descriptive Statistics

Before conducting statistical analyses, data screening was performed at both univariate and multivariate levels, as recommended by Fidell, Pearson, Tabachnick, and Howe (2000), as well as Kline (1998) and Tabachnick and Fidell (2013). This process involved computing descriptive statistics for all variables, which provided an overview of the data characteristics and revealed any potential issues such as missing values or outliers. Descriptive statistics for survey items were summarized in both text and tabular form, with frequency analyses conducted to determine the valid percentages for responses across all survey questions and sections. This foundational analysis allowed the researcher to detect irregularities and prepare the data for further statistical testing.

3.6.2 Correlation Analysis

Following data screening, correlation analyses were conducted to identify potential multicollinearity among predictor variables. Multivariate tests are particularly sensitive to high correlations, which can compromise model validity by inflating standard errors. By examining correlation matrices, the study assessed the relationships among the predictor variables—Knowledge of NCDs (KON), Risk Perception (RP), Self-Efficacy (SE), and Outcome Expectancies (OE)—to ensure that multicollinearity was not an issue. This analysis was crucial for confirming that the predictor variables could be used in the subsequent regression and SEM analyses without violating statistical assumptions.

3.6.3 Regression Analysis

A regression analysis was performed to explore the predictive relationships between the predictor variables (KON, RP, SE, and OE) and the dependent variable, Behavioral Intention (BI). The analysis allowed for the assessment of each predictor's contribution to the model and helped clarify the individual and collective influence of KON, RP, SE, and OE on BI. Outlying cases were excluded from this analysis to enhance model fit and accuracy, as recommended by Tabachnick and Fidell (2013). The results from the regression analysis provided insight into the strength and direction of the relationships among these variables, laying a foundation for more complex model testing.

3.6.4 Factor Analysis

To ensure the validity of the research instrument, expert panels were consulted for face and content validity. Initially, three specialists assessed face validity, followed by seven specialists who evaluated content validity. Their feedback, which included both written and oral comments, was incorporated into the survey design. After data collection, construct validity and reliability of the instrument were examined through Exploratory Factor Analysis (EFA) using SPSS Version 25 (Andy 2013). The EFA helped identify the underlying factor structure of the items and verified the grouping of items under each construct. Additionally, Cronbach’s alpha was used to assess the internal consistency of the scales, with SPSS

Version 25 providing reliability coefficients that confirmed the scales' stability and coherence.

3.6.5 Structural Equation Modeling (SEM)

To test the conceptual framework developed through literature review, Structural Equation Modeling (SEM) was conducted using SPSS AMOS Version 23. SEM was employed to examine the mediating roles of Risk Perception (RP), Self-Efficacy (SE), and Outcome Expectancies (OE) in the relationship between Knowledge of NCDs (KON) and Behavioral Intention (BI). Three primary approaches were considered for evaluating model fit: (1) a confirmatory approach to test whether the model aligned with the data, (2) alternative models or nested models to identify the best-fitting structure, and (3) model generation, which allowed for modifications to improve fit where needed. In AMOS, the model fit criteria included Chi-square (χ^2), Goodness-of-Fit Index (GFI), Adjusted GFI (AGFI), Root Mean Square Residual (RMR), Root Mean Square Error of Approximation (RMSEA), Tucker-Lewis Index, Normed Fit Index, Normed Chi-Square, Parsimonious Fit Index, and Akaike Information Criterion.

The confirmatory factor analysis indicated how well the data fit the hypothesized model, and specific fit indices provided insight into potential areas for adjustment or refinement in the conceptual framework.

CHAPTER FOUR
The Pilot Study Results

The purpose of the chapter is to report on the results of the statistical analysis and discuss the results of the scale validation process and piloting of the study. Under this section, pilot study concepts, pilot study purposes, pilot study procedures, and pilot study outcomes were discussed as well as the pilot study's implications for the final study.

4.1. Introduction

Before conducting the actual research project, it is vital to conduct a pilot study. The pilot study was conducted for a research project entitled “the psychological correlates of behavioural intentions of young adults towards non- communicable diseases in Ethiopia: the case of Debre Birhan university”. So this report has five subsections. The first section covers conceptualization of a pilot study. The second section covers the objective of this pilot study. The third section discusses the procedures of the pilot study. The (fourth) section presented the outcomes of the current pilot study and the last (fifth) section presented the preliminary test of the research objectives. The researcher will therefore first define a pilot study and state its value, clarify the procedure of piloting and explain the outcomes of the pilot study.

4.1.1. Results of the pilot study

As it has been explained before, the main objective of the pilot test was to check the validity and reliability of the instrument developed for the current study. As a result, some basic findings related to the aforementioned objectives that have direct implications for the current research are presented under the following three sub headings.

4.1.1.1.Feedbacks on the clarity of the instruments and feasibility of the full scale

Before the questionnaires were distributed to the participants who were selected for the pilot test, some steps were taken. For instance, words or phrases that are believed to have the potential to evoke emotions are removed. To this end, the survey has been revised many times so that it can fit into the context of the participants. The items which are constructed by the researcher are carefully drafted and the items which are adopted from others are checked so that they can be relevant to the participants. The developed questionnaire included the six scales and it was given for reviewer as a draft question. See appendix A. Draft questions.

Based on the obtained oral and written feedbacks from the experts, some modifications/extra explanations were made in the instruction and some items. Modifications were made without changing the original content (i.e., by giving extra clarifications in the brackets). From the oral and written feedbacks, it is possible to guess that the degree of ambiguity, missing out items and inappropriate responses were less. All the items were exposed to three experts in the field of psychology to check the importance of the items for the current research. After this, the questionnaire was given to seven experts to test the content validity of the items. Most of the experts agreed that repeated questions should be removed and some others merged to avoid the redundancy. Thus, comments on merging the items especially those which address each type of the NCDs were given.   As a result 114 items that were prepared as a pool of items has been reduced significantly, based on the two round expert's dialogue after the forward and backward translations of the items.

Additionally, during the expert's dialogue after the forward translation items that were designed to deal with specific diseases were merged to one at each mainquestion. These resulted in the reduction of the items by 21. Then cognitive interview with 104 graduating student which were not part of the study sample was conducted to evaluate the readability, comprehensibility and clearness of concepts. After this process some questions were evaluated as relevant but, redundant. Thus, 23 of the items were removed due to redundancy. Generally 44 items were removed and a translated 70 item questionnaire was developed as it can be seen in annex C table 4.7.

In this pilot study, 70 questionnaires were distributed across selected colleges and faculties at Debre Birhan University. The data collection process was conducted over three consecutive days in each college. All 70 questionnaires were successfully completed and returned. On average, participants took about 30 minutes to fill out and submit the questionnaire.

*4.1.1.2.*Data Screening

Before conducting the actual statistical tests, the researcher screened the collected data for any irregularity. According to Julie Pallant, (2011) screening is important to check: if data have been entered correctly, to identify outliers and missing values as well as to check assumptions before conducting tests (e.g. Normality).

In this pilot study, data from 70 completed questionnaires were analyzed using SPSS version 25 for quantitative analysis. A data cleaning process was conducted to ensure the accuracy of the numerical codes assigned to each variable. This process confirmed that each variable had the correct code values or ranges in accordance with the scales used in the questionnaire, which helped to minimize the risk of uncommitted responses. To summarize the minimum and maximum values for each variable across the 409 cases, a frequency table was created.

After reviewing the original questionnaire, the integrity of the data set was ensured by correcting any unusually high values associated with specific variables and cases. Additionally, a data screening process was conducted to eliminate responses with no variance or nearly zero variance. No responses exhibited abnormally low standard deviations, so all 409 case responses were included for further statistical analysis.

Outliers: Prior to conducting any statistical analyses, it was crucial to identify outliers—values that are significantly larger or smaller than the rest of the data. Using a dataset that includes inconsistent or unusual readings can distort statistical outcomes (Hair, Black, Babin & Anderson, 2018; Kline, 1998; Pallant, 2011). In this study, univariate outliers, defined as "extreme values on a single variable," were assessed through frequency distribution analysis, including range, minimum, and maximum values. No outliers were identified.

Normality Assessment: Evaluating the normality of continuous variable data is a vital initial step for methods that use inferential statistics (Shehu & Mahmood, 2014). Skewness and kurtosis serve as key indicators of whether the collected data meet the normality assumption (Pallant, 2011). Skewness measures the symmetry of the data, while kurtosis indicates whether the data distribution is peaked or flat compared to a normal distribution. A common guideline for acceptable values of skewness and kurtosis is between -2 and +2 (Garson, 2012).

The analysis of skewness and kurtosis for the collected data revealed that all variables fell within the acceptable range of -2 to +2, except for BIQ3 (2.061), BIQ9 (3.55) in the behavioral intention scale, and POSONCDs2 (3.131) in the perception of severity scale. Consequently, BIQ9 and POSONCDs2 were deleted from the analysis, while BIQ3 was retained for further statistical evaluation.

4.1.1.3.Validity of the scales

Validity is a crucial psychometric property of research instruments, as highlighted by Bajpai & Bajpai (2014), since it ensures the collection of intended data for specific constructs. Kimberlin & Winterstein (2008) define validity as the degree to which an instrument measures what it claims to measure. The key types of validity include face validity, content validity, criterion validity, and construct validity (Aravamudhan & Krishnaveni, 2015; Larsson et al., 2015; Masuwai et al., 2017).

According to scholars Elena and Zait (2004) and Zamanzadeh et al. (2015), face validity concerns the instrument's appearance, while content validity focuses on the relevance of its contents. In contrast, criterion validity relates to the instrument’s ability to predict outcomes, and construct validity pertains to its effectiveness in measuring the intended construct.

In this study, efforts were made to establish face validity, content validity, and construct validity for the instruments used. The validation process followed three traditional steps recommended by Delgado-Rico et al. (2012): defining the domain, constructing the items, and seeking expert judgment or evaluation. Validation of a newly developed or adapted instrument can be effectively achieved through expert feedback, which assesses its relevance to the subjects and the construct being studied (Larsson et al., 2015).

To assess the validity of this study’s instrument, expert judgment was sought regarding the adequacy of the format, clarity of instructions, and relevance of the items included. Ten scholars—three for face validity and seven for content validity—were purposefully invited based on their expertise in test construction and psychology to evaluate the instrument's relevance in measuring the targeted construct. The objectives of the study and the operational definitions of the constructs were also communicated to these experts. The validation process for all three types of validity (face, content, and construct) is addressed separately as follows:

4.1.1.4.Face validity

Face validity is defined by Arat et al., (2016) as “the extent to which a test is representative for covering the concept it purports to measure at first sight”. Gray Groth-Marnat, (2006) extended the concept of face validity as it represents the extent to which the instrument looks good for the participants who are going to take it. “Face validity is related to the appearance and apparent attractiveness of an instrument, which may affect the instrument acceptability by respondents” (Zamanzadeh et al 2015).

Thus, the present researcher has decided to check the face validity that could substantially affect the data obtained from the participants (Connell et al., 2018). To this end, a draft of this instrument was exposed to three experts (two assistant professors and one associate professor) in the field of psychology to check the face validity of the questionnaire.

The experts invited to validate the instruments for this study were asked to provide feedback on the suitability of the instrument for the target participants. They were also asked to address concerns related to the order of the items and the clarity of the scoring system. Nearly all experts agreed that the instrument was generally appropriate for the participants, noting that both the items and the instructions were clear. Consequently, the experts approved the face validity of all scales used in this study.

4.1.1.5.Content validity

Content validity focuses on the relevance of the items used to measure the variable of interest. It is defined as the extent to which the items in an instrument accurately represent the entire content domain to which the instrument applies (Taherdoost, 2016). This type of validity typically involves consulting a small group of experts to assess the appropriateness of the selected items for measuring a specific construct (Parsian & Dunning, 2007). These scholars highlighted that content validity was historically seen as the least favored approach for test validation because it was often perceived as a subjective judgment by researchers. However, in recent years, content validity has gained importance as researchers have made concerted efforts to strengthen the validity of their instruments.

Scholars have emphasized that content validity is crucial for developing research instruments (Delgado-Rico et al., 2012; and Masuwai et al., 2016). As noted by Hayes (2018) and cited in Masuwai et al. (2016), the significance of content validity lies in its ability to predict the tool's usefulness, thereby minimizing or eliminating measurement errors that may occur when multiple measures are required.

Drawing from the literature, the present researcher has chosen to assess the content validity of the instrument before evaluating its construct validity, as content validity is considered a prerequisite for other validity types. To achieve this, seven experts—including two assistant professors and five PhD candidates—were invited to participate in the validation process. They were asked to rate the relevance of each item for measuring the intended variables. According to Larsson et al. (2015), involving a minimum of five and a maximum of ten experts helps avoid random consensus in the ratings. The experts used a four-point scale, ranging from highly relevant (4) to not relevant (1), to determine the content validity of the instrument. Following the recommendations of Elena and Zait (2013), the four points were first dichotomized into relevant (4 and 3) and not relevant (2 and 1) before calculating both the item-level content validity index (I-CVI) and the scale-level content validity index (S-CVI).

While there are various procedures to examine the content validity of newly constructed instruments, this study utilized the content validity index (CVI), as it is the most favored method for assessing content validity (Polit, 2018; Tojib et al., 2008; Zamanzadeh et al., 2015). These scholars advocate for the CVI due to its simplicity in calculation, ease of understanding, and capability to provide insights into the relevance of the instrument at both the item and scale levels. The item-level content validity index (I-CVI) is calculated by dividing the number of experts who endorsed the relevance of a specific item by the total number of experts involved in the rating (Elena & Zait, 2013; Delgado-Rico et al., 2012; Morici et al., 2016; Zamanzadeh et al., 2015).

Different scholars suggested different cut-off points for I-CVI to determine which item is acceptable or not. For instance, Polit, (2018) explained the acceptable criteria of I-CVI as “when there are five or fewer experts, the I-CVI must be 1.00—that is, all experts must agree that the item is content valid. When there are more than five experts, there can be a modest amount of disagreement (e.g., when there are six experts, the I-CVI must be at least .83, reflecting one disagreement)”.

Larsson et al (2015) sets the excellent level of I-CVI to be 0.78. Some other scholars such as Aravamudhan and Krishnaveni (2015) set the minimum level of I-CVI to be 0.75 and Zamanzadeh et al (2015) preferred “if the I-CVI is higher than 79 %, the item will be appropriate. If it is between 70 and 79 %, it needs revision. If it is less than 70 %, it needs to be is eliminated”. This variation could be attributed to variation in the number of experts involved in the validation process. Some validation may involve only two experts while others involve more than ten. The important thing that the current researcher learned here is that the required I-CVI is high as the number of experts decreases and vice versa (Polit, 2018).

Accordingly, validation of an instrument with two or three experts may require 100% agreement among the experts (i.e. universal agreement) while 70% or 80% may be sufficient to a validation which involves five or more experts. Therefore, 0.70 seems to be a reasonably acceptable cut-off point, which has been endorsed, and being used until now as a standard by many researchers (e.g. Larsson et al 2015). As a result, I-CVI of all the scales in this study were calculated.

Only 70 out of 114 items of the scales in this study fall under the range from 0.71 to 1.00. Thus, 44 of the items were subjected to be eliminated based on this result. The elimination of these items was not only by the result but also due to redundancy of items which has been pointed out through experts' dialogue at each stage.

After reviewing various methods and criteria proposed by researchers, Polit (2018) concluded that the item-level content validity index (I-CVI) should be adjusted using Kappa statistics (K*) to account for potential agreement by chance (Pc). This consideration is particularly important in studies evaluating agreement indices among assessors, especially when using a four-point scoring system categorized into relevant and not relevant classes (Zamanzadeh et al., 2015).

Zamanzadeh et al. (2015) established specific thresholds for interpreting Kappa statistics: an item is deemed excellent if Kappa is greater than 0.74, fair if it falls between 0.40 and 0.59, and good if it ranges from 0.60 to 0.74. According to Polit (2018), Kappa statistics are calculated as follows:

$$\mathbf{K} = \frac{\mathbf{ProportionAgreement} - \boldsymbol{Proportion\ Chance\ Agreement}}{\mathbf{1} - \boldsymbol{ProportionChance\ Agreement}}$$

Based on this information the Kappa statistics of the items were calculated. Inspection of k* statistics all of the time for the scales meets the standards or criteria set for I-CVI (i.e. 0.40 and above (Zamanzadeh et al 2015). Based on these criteria, 15 of the items can be considered as fair, 10 of the items can be considered as good and the rest 45 of the items considered as excellent. The detailed data could be checked on table 4.8 annexed at the end.

Securing item level content validity is not a sufficient condition to have a valid research instrument. Scale level content validity CVI (S-CVI) is also important (Rodrigues et al., 2017). To this end the scale level content validity of all the scales were calculated and reported as follows.

Scale-level content validity (S-CVI) can be assessed using two methods: universal agreement and averaging. The universal agreement method calculates the proportion of items that all experts rate as relevant, while the averaging method takes the mean of the item-level content validity indices (I-CVI) for all items in the scale (Polit, 2018).

For this study, the averaging approach was employed to determine the content validity of the instrument, as the universal agreement method was considered too conservative. According to Polit, (2018), achieving universal agreement becomes increasingly challenging as the number of experts involved in item validation grows. The averaging approach not only provides a more flexible assessment of content validity but also reflects the performance of each item by considering their average ratings.

In this study, it was difficult to get all the seven experts equally agreed on each item. Using an averaging approach which seems more liberal, S-CVIs were found to be 0.92 for knowledge of NCDs, 0.90 for perception about seriousness of NCDs, 0.91 for perception of vulnerability to NCDs, 0.93 for self-efficacy, 0.92 for outcome expectancy 0.95 for risk perception, and 0.93 for behavioural intentions scales. Like that of I-CVI, the standard or criterion of S-CVI to determine the relevance of the scale to measure the constructs under study vary from author to author. For many scholars, however, a scale which yields 0.90 and above I-CVI/Ave are adequate instruments to measure the construct of interest (Rodrigues et.al. 2017; and Zamanzadeh et al 2015). Thus, all the scales developed to be used to measure the variables in this study are found adequate since they bear the minimum standard or criteria of S-CVI (i.e., 0.90).

4.1.1.6.Construct validity

Construct validity refers to the extent to which scores on an instrument accurately measure a theoretical construct that is not directly observable. This construct is considered latent, meaning it can only be assessed indirectly through its indicators (Harrington, 2009). Face validity and content validity alone are not enough to measure constructs as we intend to measure. They should go together with construct validity because construct validity is the central element in validation work (Chan et al., 2014). The objective of the next section is to discuss the construct validation process.

To evaluate the construct validity of the instruments in this study, factor analysis was conducted using data from 104 participants in the pilot study. Despite ongoing debates regarding the subjectivity involved in selecting extraction methods, determining the number of factors, and deciding which items to retain, many scholars agree that factor analysis is a crucial statistical technique for providing evidence of construct validity (Froman, 2001; Matsunaga & Masaki, 2010). These researchers emphasize that factor analysis should be performed early in the development of a scale or test.

The primary aim of factor analysis is to uncover the underlying structure among the variables in a given instrument (Froman, 2001; and Hair et al., 2018). As noted by Williams, Hartman, and Cavazotte (2010), factor analysis is an invaluable tool for developing, refining, and evaluating tests and measures in both educational and clinical contexts. This process helps reduce a large number of variables into a more manageable set, revealing fundamental dimensions that connect measured factors to latent constructs, which in turn aids in theory formation and refinement. Factor analysis also provides evidence of construct validity for self-report scales.

Research has shown that the two most commonly used types of factor analysis are exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Scholars recommend conducting these analyses sequentially, with EFA performed first, followed by CFA (Froman, 2001; Matsunaga & Masaki, 2010; Yong & Pearce, 2013). EFA serves as an initial step to explore the underlying structure during scale development, while CFA verifies whether the identified structure holds in a new sample. Consequently, EFA is considered a data-driven method, whereas CFA is theory-driven, both contributing to the development and testing of theories (Matsunaga & Masaki, 2010; Pallant, 2011; Plucker, 2003).

Although both EFA and CFA are intended for this study to establish the instruments' construct validity, only EFA was conducted during the pilot study. CFA, which requires a different sample, will be carried out in the main study with data collected from a separate sample.

In this pilot study, EFA was performed to assess the construct validity of the instruments based on the relationships among indicators and the latent factors of the scales. EFA is a statistical technique that enhances the reliability of the scale by identifying items that may be unsuitable for retention and examining the relationships between items and variables when data dimensionality is limited (Yu & Richardson, 2015).

Researchers utilizing EFA need to make key decisions on four main issues: the method of factor extraction, the number of factors to retain, strategies for rotating factors, and criteria for keeping or removing items (Cater & Machtmes, 2008; Costello & Osborne, 2005; J. Kellow & Brett, 2005; Izquierdo et al., 2014). There is no consensus among researchers regarding the optimal choices, as these decisions often depend on the specific context and objectives of the study. While discussing the various arguments for different methods of factor extraction, factor retention, and rotation is beyond the scope of this study, an effort will be made to explain the rationale behind the chosen methods.

Among the techniques available in SPSS for variable extraction, Principal Component Analysis (PCA) and Common Factor Analysis (also known as Principal Axis Factoring or PAF) are commonly used (J. Pallant, 2011; Pett et al., 2003; B. Tabachnick & Fidell, 2013). For this study, Principal Component Analysis (PCA) was selected, as it is widely recognized as a standard method in factor analysis. Consequently, the 65 items related to knowledge, self-efficacy, outcome expectancy, and risk perception—correlates of behavioral intentions—were analyzed using PCA in SPSS Version 25.

Before performing PCA, the suitability of the data for factor analysis was assessed. Key assumptions include the Bartlett Test of Sphericity, which checks whether the scale subscales are interdependent, and the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy, which evaluates sample sufficiency (Demircioglu et al., 2014). For factor analysis to be considered suitable, Bartlett's sphericity test must be significant ($p < 0.05$), and the KMO value should be at least 0.6 (J.Pallant, 2011). The results of these tests for the variables involved will be presented below.

Table 1: KMO and Bartlett's Test for Items of knowledge about NCDs

Test	Statistic	Values
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.806
Bartlett's Test of Sphericity	Approx. Chi-Square	1383.380
	df	171
	Sig.	.000

As indicated in Table 1, the Kaiser-Meyer-Olkin (KMO) value for the knowledge about NCDs scale was measured at 0.806. This evaluation included examining the scale's reliability by considering the effects of item deletion. Additionally, Bartlett's test yielded significant results ($\chi^2(171) = 1383.380$, $p < .000$), confirming that the KMO value exceeded the recommended threshold of 0.7. The significant result from Bartlett's test ($p < 0.05$) also supports the factorability of the correlation matrix (B. G.Tabachnick & Fidell, 2013). Therefore, the knowledge about NCDs scale meets both assumptions necessary for conducting factor analysis.

Table 2: KMO and Bartlett's Test for Items of (perception about seriousness of NCDs) POSONCDs

Test	Statistics	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.871
Bartlett's Test of Sphericity	Approx. Chi-Square	1608.584
	df	36
	Sig.	.000

As shown in Table 2, the Kaiser-Meyer-Olkin (KMO) value for the perception about seriousness of NCDs (POSONCDs) scale was recorded at 0.871. Furthermore, Bartlett's test produced significant results ($\chi^2(36) = 1608.584$, $p < .000$). This indicates that the KMO value surpassed the recommended threshold of 0.6, and the significant outcome from Bartlett's Test of Sphericity ($p < 0.05$) confirms the factorability of the correlation matrix. Consequently, both assumptions necessary for conducting factor analysis are fulfilled for the POSONCDs scale.

Table 3: KMO and Bartlett's test for items of (perceived vulnerability to NCDs) POVTNCDs

Test	Statistics	value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.856
Bartlett's Test of Sphericity	Approx. Chi-Square	3919.825
	df	210
	Sig.	.000

As shown in Table 3, the Kaiser-Meyer-Olkin (KMO) value for the perceived vulnerability to NCDs (POVTNCDs) scale was found to be 0.856. Additionally, Bartlett's test yielded significant results ($\chi^2(210) = 3919.825$, $p < .000$). This indicates that the KMO value exceeded the recommended threshold of 0.6, and the significant outcome from Bartlett's Test of Sphericity ($p < 0.05$) supports the factorability of the correlation matrix. Therefore, both assumptions necessary for conducting factor analysis are met for the POVTNCDs scale.

Table 4: KMO and Bartlett's Test for Items of (Self- Efficacy) SE

Test	Statistics	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.902
Bartlett's Test of Sphericity	Approx. Chi-Square	1310.585
	df	36
	Sig.	.000

As illustrated in Table 4, the Kaiser-Meyer-Olkin (KMO) value for the self-efficacy (SE) scale was found to be 0.902. Additionally, Bartlett's test showed significant results ($\chi^2(36) = 1310.585$, $p < .000$). This indicates that the KMO value exceeded the recommended threshold of 0.6, and the significant outcome from Bartlett's Test of Sphericity ($p < 0.05$)

further supports the factorability of the correlation matrix. Consequently, both assumptions necessary for conducting factor analysis are met for the SE scale.

Table 5: KMO and Bartlett's test for Items of (Outcome Expectancy) OE

Test	Statistics	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.898
Bartlett's Test of Sphericity	Approx. Chi-Square	1390.178
	df	36
	Sig.	.000

As shown in Table 5, the Kaiser-Meyer-Olkin (KMO) value for the outcome expectancy (OE) scale was 0.898. Furthermore, Bartlett's test yielded significant results ($\chi^2(36) = 1390.178$, $p < .000$). This indicates that the KMO value surpassed the recommended threshold of 0.7, and the significant outcome of Bartlett's Test of Sphericity ($p < 0.05$) confirms the factorability of the correlation matrix. Therefore, both assumptions necessary for conducting factor analysis are satisfied for the OE scale.

Table 6: KMO and Bartlett's test for Items of (Behavioural Intensions) BI

Test	Statistics	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.890
Bartlett's Test of Sphericity	Approx. Chi-Square	1349.705
	df	66
	Sig.	.000

As illustrated in Table 6, the Kaiser-Meyer-Olkin (KMO) value for the perception about seriousness of NCDs (POSONCDs) scale was 0.890. Additionally, Bartlett's test was significant ($\chi^2(66) = 1349.705$, $p < .000$). This indicates that the KMO value exceeded the recommended threshold of 0.6, and the significant result from Bartlett's Test of Sphericity ($p < 0.05$) confirms the factorability of the correlation matrix. Consequently, both assumptions necessary for conducting factor analysis are satisfied for the behavioral intentions (BI) scale.

The possible methods that can be employ for dimensionality analysis includes:- PCA: which used when variance retention and simplicity are priorities (e.g., exploratory data analysis, feature engineering). Independent Component Analysis (ICA), Unlike PCA, ICA separates signals based on statistical independence rather than variance. It is uses signal processing, like separating mixed audio sources (e.g., the "cocktail party problem").

Additionally, t-SNE (t-Distributed Stochastic Neighbor Embedding) which is non-linear dimensionality reduction focused on preserving local structure rather than global variance. It is used for cases where data visualization of high-dimensional data, especially in clusters (e.g., gene expression data). UMAP (Uniform Manifold Approximation and Projection) is similar to t-SNE but faster and capable of capturing both local and global data structures. It is used case for visualization and exploratory data analysis for very large datasets.

Principal Component Analysis (PCA) is preferred in many for this study because it offers a straightforward, efficient, and interpretable way to reduce the dimensionality of datasets while retaining as much variance as possible.

Several methods can be employed to determine the number of factors to retain during principal component analysis (PCA). These methods include the theory-driven approach, Kaiser Criterion, scree plot, parallel analysis, and minimum average partial criteria. The theory-driven approach is based on the researcher’s conceptual framework; in this study, the constructs are assumed to be one-dimensional.

To explore the factor structure underlying the 15 items formulated to measure knowledge about non-communicable diseases (NCDs)—after excluding 5 items and converting the scale in to right or wrong dichotomous options or levels due to reliability concerns—PCA with Varimax rotation was conducted. According to Pedhazur (1997), PCA serves as a data reduction technique designed to extract a smaller number of indicators that account for most of the variance within a larger set of indicators. Varimax is an orthogonal rotation technique commonly employed by researchers to enhance the interpretability of the extracted factors (Pedhazur, 1997). Therefore, PCA was utilized for factor extraction, with the Varimax procedure applied for rotation.

Table 7: Factor Loadings and percentage of Variance for Principal components analysis with Varimax Rotation on Items to Measure knowledge of NCDs

Items	Component 1	Component 2	Component 3	Component 4
KONCDs15	.755			
KONCDs19	.675			
KONCDs6	.616			
KONCDs11	.599			
KONCDs18		.700		
KONCDs16		.655		
KONCDs17		.593		
KONCDs13		.581	.423	
KONCDs14		.551		
KONCDs12			.769	
KONCDs8			.562	
KONCDs9			.515	
KONCDs4				.667
KONCDs5				.624
KONCDs3				.618

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 8 iterations.

As can be seen from Table 7, 4 factors were extracted with varimax rotation using eigenvalue >1 after removing items, 1, 2, 7 and 10 for they were cross loading and not making sense.

On top of that the analysis of the scree plot has also supported the extraction of four factors.

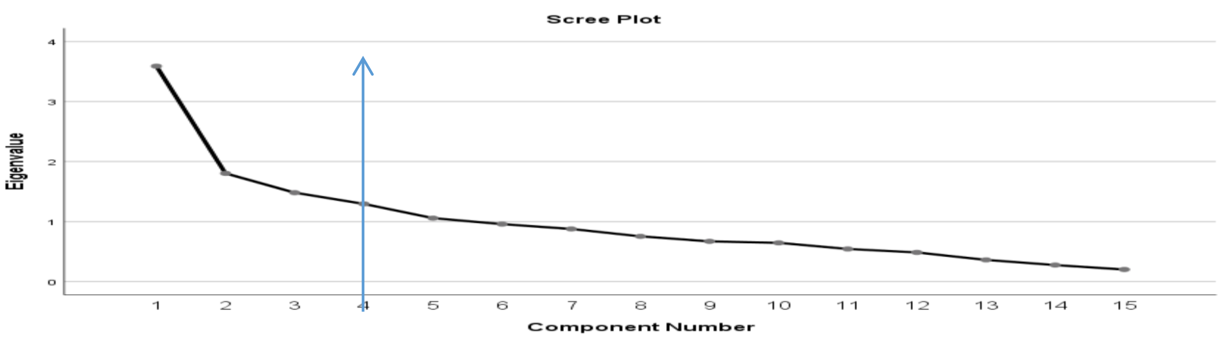


Figure 2: Scree Plot for Underlying Factors in Knowledge of NCDs items

The examinations of the scree plot with the help of two straight-lines have also indicated that there are clearly demarcated four factors before the intersection of the two lines (see Figure: 2). This suggests there are four factors that are accounted for the variance among variables.

Furthermore, parallel analysis was carried out using syntax and the result indicated that all the four factors identified using the Kaiser criterion and scree plot of the SPSS should be retained. Thus, four factors extracted with the help of eigenvalue >1 were considered for further analysis.

It is also mandatory to check the reliability of the items that constitute each of the four factors extracted. Thus the first factor which is loaded by four items and inquires about the protective measures of NCDs originally have a reliability of 0.683. The other 5 items load to the second factor which deals with signs of NCDs yielded a reliability of .667. Even if, the reliability of these factor do not reach the recommended .70 there was any other choice of improving its reliability by deleting items. The third component was loaded by 3 items deals with risk factors of NCDs have the reliability of 0.489. Finally, the fourth component was loaded by 3 factors talking about signs of diabetes specifically and has the reliability of 0.464. The component level reliability indicates if one or more items deleted for both factor three and four. However since the number of items are few. It was decided to keep the three items because they are all logically sound.

Principal component analysis with Varimax rotation was also carried out to examine the factor structure underlying the 12 items formulated to measure perception of seriousness of NCDs. One item POSONCDs2 have been deleted for its high kurtosis value.

Table 8: Factor Loadings and percentage of Variance for PCA with Varimax Rotation on Items to Measure Perception of Seriousness of NCDs.

Items	Component 1	Component 2
POSONCDs4	.791	
POSONCDs8	.753	
POSONCDs7	.749	
POSONCDs3	.743	
POSONCDs5	.737	
POSONCDs6	.711	
POSONCDs1	.653	
POSONCDs10	.510	.502
POSONCDs11		.838
POSONCDs12		.826
POSONCDs13		.802
POSONCDs9	.418	.629

Extraction Method: Principal Component Analysis (PCA)

Rotation Method: Varimax with Kaiser Normalization

a. Rotation converged in 3 iterations.

As can be seen from Table 8, three factors were extracted with varimax rotation using eigenvalue >1.

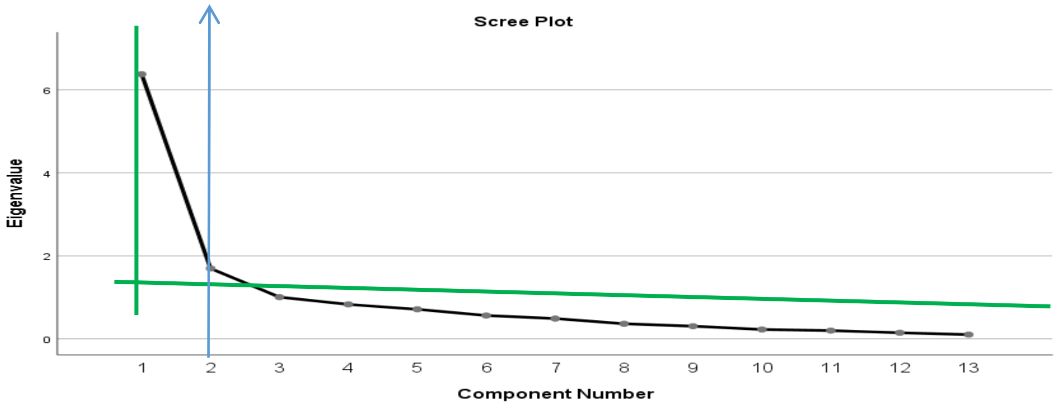


Figure 3: Scree Plot for underlying factors in perception of seriousness of NCDs items

Once again, the examinations of the scree plot with the help of two straight-lines have also indicated that there are clearly demarcated three factors before the intersection of the two lines (see Figure: 3). This suggests there are two factors that are accounted for the variance among variables. Thus, three factors extracted with the help of eigenvalue >1 were considered for further analysis.

Similarly the parallel analysis results are lower than the equine values in the scree plot and the Kaiser criterion. Thus, this indicates that all the two factors has to be retained for further analysis.

Individual reliability analysis was done for each of the components extracted. Thus the result showed that component one loaded by eight items exploring perceived seriousness have a reliability of .873. The other component loaded by four items exploring the anticipated feelings about contracting NCDs showed a reliability of .808. Both of the extracted components from the pool of items for perceived severity exceeded the recommended alpha value of .70 suggesting all of these components has to be considered for further analysis.

Principal component analysis with Varimax rotation was also carried out to examine the factor structure underlying the items formulated to measure the other four variables too. These includes: self-efficacy, outcome expectancy, perceived vulnerability and behavioural intentions.

Table 9: Factor Loadings and %age of Variance for PCA with Varimax Rotation on Items to Measure Self-efficacy.

Items	Component- 1
SEQ2	.786
SEQ3	.741
SEQ5	.731
SEQ6	.714
SEQ1	.709
SEQ7	.671
SEQ8	.646
SEQ4	.637
SEQ9	.619

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

As can be seen from Table 9, only one factor was extracted with varimax rotation using eigenvalue >1.

The examination of the scree plot indicated that there are clearly demarcated six factors above the eigenvalue of 1 (see Figure: 4). This suggests there are six factors that are accounted for the variance among variables. Thus, six factors extracted with the help of eigenvalue >1 were considered for further analysis.

The reliability of the items for self-efficacy is .865 as reported in the reliability of the scales section.

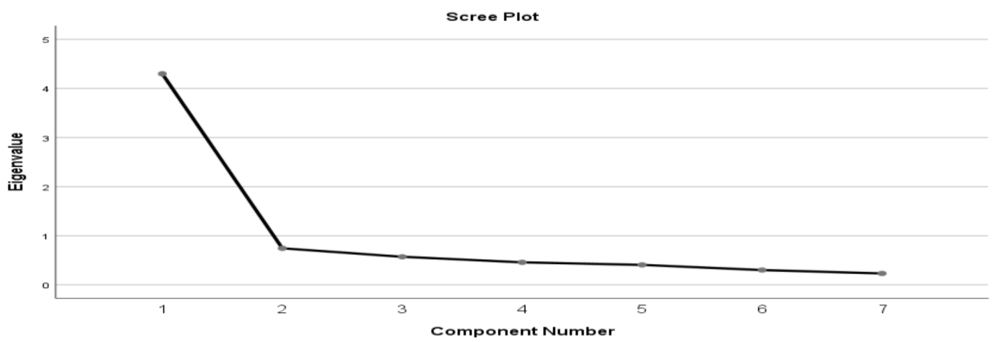


Figure 4: Scree Plot for underlying factors in self -efficacy items

As can be seen from Table 4.10, three factors were extracted with varimax rotation using eigenvalue >1 for outcome expectancy.

Table 10: Rotated Component Matrix Outcome Expectancy

Items	Component 1	Component 2	Component3
OEQ8	.767		
OEQ6	.753		
OEQ5	.725		
OEQ7	.692		
OEQ3	.614		
OEQ9	.557		
OEQ4	.507		
OEQ11		.866	
OEQ12		.820	
OEQ10		.774	
OEQ1			.827
OEQ2	.		.489

Extraction Method: Principal Component Analysis (PCA)

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 4 iterations.

As can be seen from Table 10, three factors were extracted with varimax rotation using eigenvalue >1.

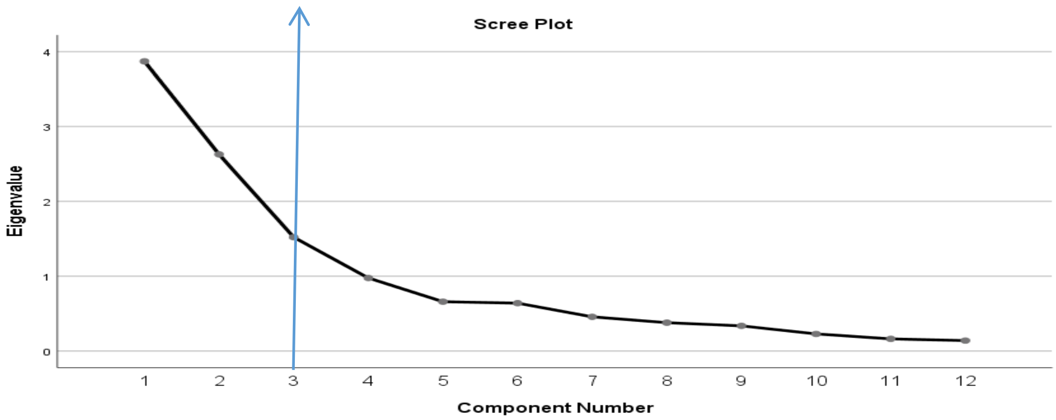


Figure 5: Scree Plot for underlying factors in outcome expectancy items

The examination of the scree plot indicated that there are clearly demarcated five factors above the eigenvalue of 1 (see Figure: 5). This suggests there are five factors that are accounted for the variance among variables. Thus, five factors extracted with the help of eigenvalue >1 were considered for further analysis.

Reliability was calculated for each of the three components of the outcome expectancy. The first components which have been loaded by 7 items exploring positive expectancy have reliability of .823. The second which was loaded by three items exploring negative expectancy have a reliability of .761 and the third component loaded by two items dealing with belief on the benefits of taking protective measures have the reliability of .369. All of the reliabilities of the components exceeded the recommended alpha value of .70.

Table 11: Rotated Component Matrix for Perceived Vulnerability to NCDs

items	Component 1	Component 2
POVTNCDs7	.833	
POVTNCDs8	.791	
POVTNCDs6	.767	
POVTNCDs4	.662	.
POVTNCDs3		.829
POVTNCDs1		.763
POVTNCDs2		.689
POVTNCDs5		.513

Extraction Method: Principal Component Analysis (PCA)

Rotation Method: Varimax with Kaiser Normalization

a. Rotation converged in 3 iterations.

As can be seen from Table 11, two factors were extracted with varimax rotation using eigenvalue >1.

Reliability analysis was carried for these two components extracted. The first component loaded by six item exploring with behavioural vulnerability has the reliability of .810 and the second component loaded by four exploring personal probability of contracting NCDs have the reliability of .707. Accordingly the first component has exceeded the recommended alpha value while the second do not.

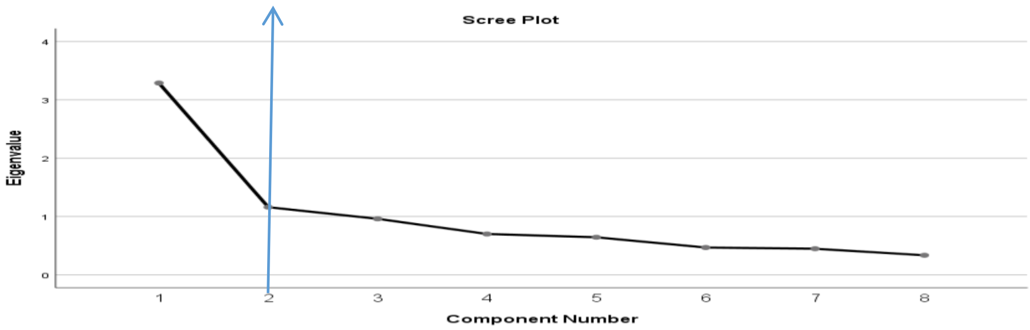


Figure 6: Scree Plot for underlying factors in perceived vulnerability items

The examination of the scree plot indicated that there are clearly demarcated four factors above the eigenvalue of 1 (see Figure: 6). This suggests there are four factors that are accounted for the variance among variables. Thus, four factors extracted with the help of eigenvalue >1 were considered for further analysis.

Table 12: Component Matrix for Behavioural Intentions

	Component
	1
BIQ2	.800
BIQ7	.798
BIQ3	.781
BIQ1	.712
BIQ6	.669
BIQ4	.648
BIQ8	.643
BIQ5	.640
BIQ9	.566

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

As can be seen from Table 4, only one factor was extracted with varimax rotation using eigenvalue >1.

The reliability of the component extracted loaded by nine items was .866 which exceeded the recommended alpha value .70.

The examination of the scree plot also indicated that there is only one clearly demarcated factor above the eigenvalue of 1 (see Figure: 7). This suggests that all the items are accounted for the variance for this variable. Thus, a factor extracted with the help of eigenvalue >1 were considered for further analysis.

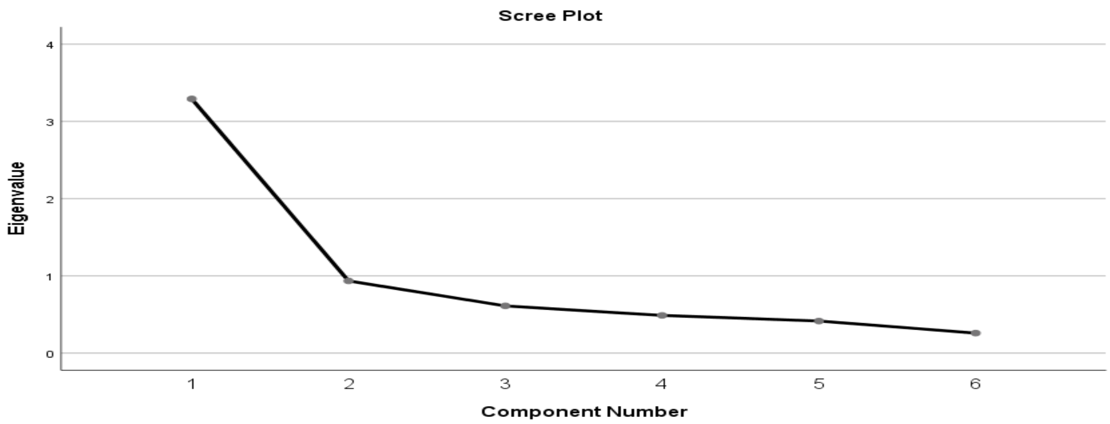


Figure 7**:** Scree Plot for underlying factors in behavioural intentions items

In factor analysis, factor loadings serve as a crucial metric for evaluating the validity of the items used to measure a particular construct. They represent the Pearson correlation between each item and the corresponding factor (B. G. Tebachinik & Field, 2013). High factor loadings indicate a strong relationship between an item and the factor, which enhances the reliability of the measurement. According to Hair et al. (2014), the strength of these loadings signifies the extent to which a variable corresponds with the factor, with higher values reflecting a stronger relationship.

For this study, a threshold of factor loadings greater than 0.40 was established. As a general guideline, loadings above 0.71 are deemed excellent, 0.63 very good, 0.55 good, 0.45 fair, and 0.32 poor. Ultimately, the decision on the cut-off for interpreting loading sizes depends on the researchers' judgment (Comrey & Lee, 2013, cited in Hair et al., 2014).

Additionally, it is important to consider the minimum total variance explained when deciding on the cut-off point for factor loadings. Hair et al. (2014) suggest that achieving a cumulative percentage of total variance extracted by successive factors ensures the practical significance of the derived factors. They recommend that a minimum of 60% of total variance should be explained, although in some cases, slightly lower values may also be acceptable.

Consequently, in this study, an item was included in the final scale for data collection if its factor loading exceeded 0.40 and the total percentage of explained variance for the scale was above 50%. After removing items with loadings below this threshold, the total variance explained was found to be as follows:

- Knowledge scale: 50.247%
- Perceived severity scale: 59.048%
- Perceived vulnerability scale: 60.908%
- Self-efficacy scale: 48.555%
- Behavioral intention scale: 51.702%
- Outcome expectancy scale: 57.4%

In total, 64 items were retained for measuring all variables in the final data collection.

4.1.2. Reliability of the scales

The reliability of a measuring instrument is crucial as it reflects the instrument's ability to consistently measure the intended phenomenon, free from random error. Essentially, reliability indicates how consistently a measuring tool assesses a specific construct (J. Pallant, 2011). As noted by Mathers, Fox, and Hunn (2013), researchers often use multi-item questionnaires designed to measure a single construct. To ensure the validity of the measurements, it is essential to evaluate the internal consistency of these items, which refers to the degree to which the questionnaire items correlate with one another.

Internal consistency suggests that all items within the scale assess the same underlying construct, meaning that items measuring the same concept should logically group together (B. G. Tabachnick & Fidell, 2013). Evaluating internal consistency allows researchers to identify and address elements that may not align with the intended measurement, leading to modifications or removals of inconsistent items to enhance the overall reliability of the test.

While various methods exist to assess internal consistency, Cronbach's alpha (α) is the most widely used measure. It provides an estimate of the average correlation among all items in a scale (B. G. Tabachnick & Fidell, 2013). Typically, a Cronbach's alpha value ranging from .70 to .80 is considered acceptable for ensuring internal consistency (Tomarken & Waller, 2005).

In this study, reliability analysis was performed to assess the internal consistency of the scales developed by the researcher. As discussed in the previous section regarding construct validity, six scales were evaluated: Knowledge about NCDs (KONCDs), Perception about the Seriousness of NCDs (POSONCDs), Perceived Vulnerability to NCDs (POVTNCDs), Outcome Expectancy (OE), Self-Efficacy (SE), and Behavioral Intention (BI). Reliability tests were conducted for all these scales to ensure their consistency and reliability.

Table 13: The Cronbach's alpha of the Scales with Their Respective Number of Items

S. No	Scale	No. of Items	Mean	Cronbach's αlpha values of the scales
1	KNONCDs	15	1.445	0.764
2	POSONCDs	12	3.78	0.869
3	POVTNCDs	8	3.541	0.821
4	OE	12	3.694	0.766
5	SE	9	3.751	0.865
6	BI	8	3.681	0.862

As shown in Table 13, the Cronbach's alpha values for all scales exceeded 0.70, demonstrating a strong level of internal consistency. These results confirm that the reliability of all scales aligns with the widely accepted benchmark for reliability, where an alpha coefficient of 0.70 is considered acceptable (Tomarken & Waller, 2005; J. Pallant, 2011). Therefore, we can confidently conclude that all scales utilized in this study possess reliable measurement properties.

4.1.3. Confirmatory Factor Analysis

As previously mentioned, both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were employed to establish the construct validity of the instruments used in this study. The EFA, which is typically conducted early in the scale development process, was presented at the preceding section of this chapter. Following this validation process, CFA was performed using data collected from the same sample during the pilot study.

CFA is a statistical technique that examines the hypothesized relationships between observed variables and their underlying latent variables or factors (Jackson et al., 2009; Finney, 2007). In this research, the items designed to measure each variable act as observed variables, while constructs such as knowledge about NCDs (KONCDs), perception about the seriousness of NCDs (POSONCDs), perceived vulnerability to NCDs (POVTNCDs), self-efficacy (SE), outcome expectancy (OE), and behavioral intention (BI) are treated as latent variables or factors. According to Kim (2008), CFA is essential for quantitatively testing and confirming the previously proposed relationships among these variables.

CFA serves as an appropriate method for validating the measurement models identified through EFA and facilitates further refinement of these models. As noted by Pai et al. (2007), EFA is often followed by CFA to assess the convergent validity of the measurement models. This indicates that the conceptual model, which was modified based on EFA results, requires additional refinement to accurately depict how the observed variables are related to the latent constructs. Therefore, a series of CFAs was conducted on the items intended to measure the constructs included in the conceptual model. Measurement models comprising the constructs extracted from the EFA were developed for each scale using Amos version 23.

The goal of the CFAs was to evaluate how well each measurement model fit the data collected during the pilot study. Following the guidelines established by Schumacker and Lomax (1996), the development and evaluation of the CFAs involved five essential steps: model specification, model identification, model estimation, model evaluation, and model re-specification or modification. The CFA for the current measurement model was conducted in accordance with these steps, and the results for each measurement model are presented in the following sections.

4.1.3.1.Measurement model of knowledge of NCDs (KNCDs)

The first and crucial step in conducting Confirmatory Factor Analysis (CFA) of measurement models is model specification, as highlighted by Crockett et al. (2017) and Saunders & Lewis (2018). During this stage, researchers articulate the model by defining the expected relationships between latent variables (constructs) and observed variables, as well as how these variables interact with each other (Crockett et al., 2017; Saunders & Lewis, 2018; Weston & Gore, 2006).

According to Shumacker and Lomax (2016), both the structural and measurement models should be developed based on a thorough review of existing literature and theoretical frameworks. In this context, the observed and latent variables for the KONCDs measurement model were identified through literature review and exploratory factor analysis (EFA). Initially, 19 items were created to assess knowledge of non-communicable diseases (NCDs) based on prior studies. Out of these, 15 items underwent EFA, and all were retained to measure four distinct factors related to KONCDs. Consequently, the researcher identified these four factors, each represented by the 15 items, for inclusion in the measurement model.

As noted by Crockett (2012), “A path diagram can be constructed to visually represent the hypothesized relationships among variables in the theoretical model.” Following this guidance, a path diagram for the initial KONCDs model was developed to illustrate these relationships clearly.

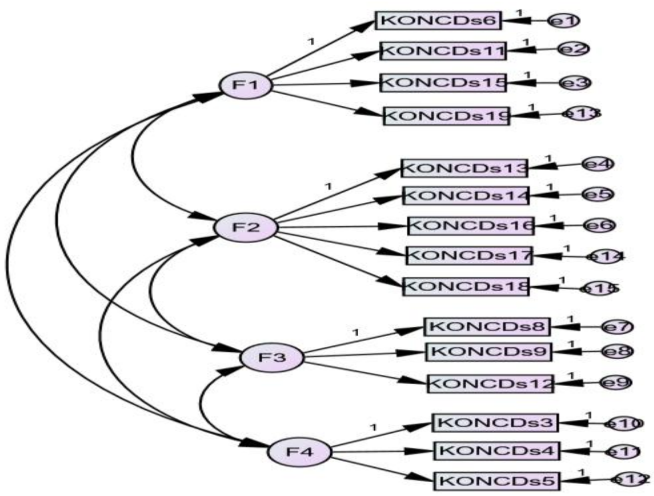


Figure 8: Path Diagram of initial KONCDs measurement model

After model specification, the next crucial step in Confirmatory Factor Analysis (CFA) is model identification. This process involves determining whether there is sufficient information in the sample variance-covariance matrix to identify a solution (Karakaya-Ozyer et al., 2018). A model is deemed identified when there is a unique numerical solution for each parameter or when each free parameter has a single best value (Levine et al., 2008; Ullman, 2006a).

To assess model identification, it's important to compare the number of data points (the variances and covariances present in the sample covariance matrix) against the number of parameters that need estimation (Ullman, 2006a). In the KONCDs model, there are 15 observed variables designed to measure the construct, along with an additional 15 error terms corresponding to these variables. This results in a total of 30 parameters to estimate, which includes 15 factor loadings and 15 error variances.

According to Shumacker & Lomax (2016), the order condition states that the number of free parameters that need to be estimated must be less than or equal to the number of distinct values in the sample's covariance matrix. To calculate the number of distinct values in the sample variance–covariance matrix, you can use the formula suggested by Shumacker & Lomax (2016) and Byrne (2013):

$$\boxed{\frac{p(p+1)}{2}}$$

In Confirmatory Factor Analysis (CFA), model identification follows model specification as the next critical step. This process assesses whether there is enough information in the sample variance-covariance matrix to pinpoint a solution (Karakaya-Ozyer et al., 2018). A model is considered identified when each parameter has a unique numerical solution or a single best value (Levine et al., 2008; Ullman, 2006a).

To identify the model, researchers must compare the number of data points (the variances and covariances in the sample covariance matrix) with the number of parameters to be estimated (Ullman, 2006a). In the KONCDs model, there are 15 observed variables and an additional 15 error terms, resulting in a total of 30 parameters to estimate—comprising 15 factor loadings and 15 error variances.

As explained by Shumacker and Lomax (2016), the order condition requires that the number of free parameters to be estimated should be less than or equal to the number of distinct values in the covariance matrix. The number of distinct values can be calculated using the formula: p(p+1)2\frac{p(p + 1)}{2}2p(p+1) where "p" represents the number of measured variables. Substituting "p" with 15 gives: 15(15+1)2=120\frac{15(15 + 1)}{2} = 120215(15+1)=120

To determine if the model is identified, we subtract the number of parameters to be estimated (36) from the number of distinct values (120): 120−36=84120 - 36 = 84120−36=84. A positive result (84) indicates that the model is over-identified, meaning the order condition is satisfied (Ullman, 2006a; Shumacker & Lomax, 2016).

The third step in CFA is model estimation, which involves estimating the unknown parameters and assessing the associated errors (Weston & Gore, 2006). This process estimates how closely the theoretical parameter values approximate the actual covariance matrix (Crockett et al., 2017). Various estimation methods are available, including ordinary least squares (OLS), generalized least squares (GLS), and maximum likelihood (ML) methods (Khine, 2013; Teo et al., 2013). While multiple methods can be employed, the maximum likelihood method is the most commonly used in practice (Saunders & Lewis, 2018; Ullman, 2006). For this research, the ML method was utilized, leading to the proposal, construction, and estimation of a three-factor measurement model containing 36 free parameters using SPSS Amos version 23.

The fourth step in the CFA measurement process is model evaluation, which assesses how well the proposed model fits the observed data (Lewis, 2017). This evaluation compares the sample variance-covariance matrix (S) to the variance-covariance matrix predicted by the specified factor model, effectively examining whether the hypothesized relationships between the measured and latent variables align with the empirical data (Weston & Gore, 2006).

Several model fit indices, including chi-square, CFI, RMSEA, and SRMR, are used to quantify the fit between the proposed model and the observed data. A good model fit suggests that the hypothesized factor model reasonably explains the covariances among the measured variables, thereby supporting the validity of the measurement model. After estimating the 36 parameters, the model was evaluated using various fit indices. Different scholars recommend various thresholds for acceptable fit indices. For example, Wood (2008) suggested that RMSEA should be close to 0.06 or less, SRMR should be close to 0.08 or less, and both CFI and TLI should be 0.95 or greater. On the other hand, Tomarken and Waller (2005) indicated that an RMSEA $\leq$ .05 represents a close fit, values between .05 and .08 suggest reasonable fit, and RMSEA $\geq$ .10 indicates poor fit. Generally, CFI and TLI values greater than .90 and SRMR values less than .10 are considered favorable.

Using these guidelines, the proposed measurement model was evaluated with these fit indices, which are widely used in psychological research published in APA journals (Jackson, Gillaspy, & Purc-Stephenson, 2009). The results indicated poor model fit with the data: $\chi^2(84, N=420) = 209.889$, $p = .000$, TLI = .82, CFI = .856, RMSEA = .060. This prompted post-hoc modifications to improve the model fit.

The final step in the CFA process is model modification. It's not uncommon for proposed models to show poor fit with the sample data, and in such cases, modifications can help enhance the fit (Lewis & Lewis, 2017). According to Hoofs et al. (2018) and Lewis and Lewis (2017), model modification often involves removing non-significant parameters, adding new parameters, or allowing error terms to co-vary.

Using modification indices generated from the analysis output, the proposed model was revised by permitting some parameters to co-vary. After re-estimating the parameters in this revised model, the fit indices showed improvement, indicating that the revised model fits the data well: $\chi^2(79, N=420) = 142.211$, $p = .000$, TLI = .904, CFI = .928, RMSEA = .044.

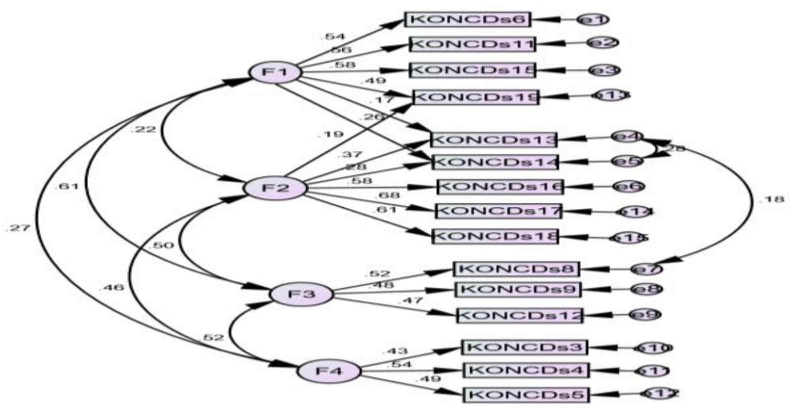


Figure 9: Path Diagram of modified knowledge of measurement model

4.1.3.2.Measurement Model of perception of severity of NCDs (POSONCDs)

The observed and latent variables (constructs) included in the POSONCDs measurement model were defined based on a thorough review of the literature and the results from exploratory factor analysis (EFA). Initially, 13 items were developed to assess perceptions of the severity of non-communicable diseases (NCDs) based on previous studies. After conducting the EFA, one item was removed, leaving 12 items that effectively measured two factors related to POSONCDs. Consequently, the researcher identified three factors of POSONCDs, each represented by these 12 items, for inclusion in the measurement model.

The path diagram for the initial POSONCDs model was then constructed to visually represent these relationships.

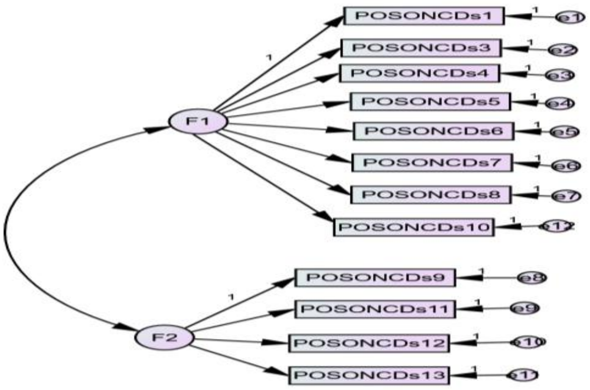


Figure 10: Path Diagram of initial POSONCDs measurement model

Following model specification, the POSONCDs model comprises 12 observed variables that measure the construct. Additionally, there are 12 error terms corresponding to these measured variables, resulting in a total of 24 parameters to estimate (12 factor loadings and 12 error variances).

When the number of parameters to be estimated (25) is subtracted from the number of distinct values (78), the calculation yields a degree of freedom of 53 (78 - 25 = 53). A positive degree of freedom, in this case, indicates that the model is over-identified, which means the order condition is satisfied.

For model estimation, the maximum likelihood (ML) method was applied in this research. Consequently, a two-factor measurement model that includes the 25 free parameters was proposed, constructed, and estimated using SPSS Amos version 23.

The fourth step in the CFA process involves model evaluation, which tests the fit of the proposed model. This evaluation compares the sample variance-covariance matrix (S) to the predicted (or specified) model (Lewis, 2017). Weston and Gore (2006) describe model evaluation as assessing whether the relationships between the measured and latent variables in the proposed model accurately reflect those observed in the data.

Using various fit indices, the proposed measurement model was evaluated. The results indicated a poor fit with the data: $\chi^2(53, N=420) = 509.769$, $p = .000$, TLI = .751, CFI = .800, RMSEA = .143. These findings suggested the need for post-hoc modifications to improve the model fit.

With the assistance of modification indices generated from the output, the proposed model was revised by allowing some parameters to co-vary. The revised model, as shown in

Figure 11, was re-estimated. The updated fit indices revealed a significant improvement, indicating that the revised model fits the data well: $\chi^2(34, N=420) = 140.929$, $p = .000$, TLI = .909, CFI = .953, RMSEA = .087.

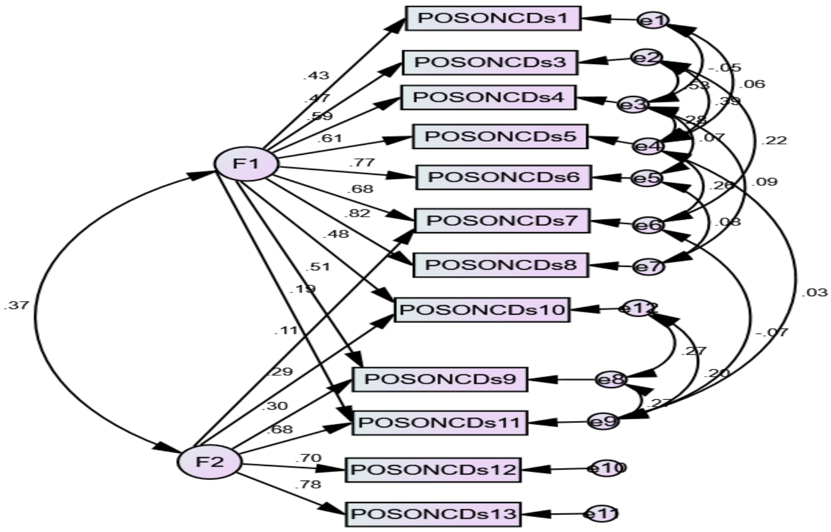


Figure 11: Path Diagram of modified perception of severity measurement model

4.1.3.3.Measurement Model of Perceived vulnerability

To measure the two factors of perception of vulnerability to non-communicable diseases (NCDs), 17 items were initially developed based on prior literature. During expert validation, 9 items were deemed unsuitable and removed, leaving 8 items for exploratory factor analysis (EFA). After conducting the EFA, all 8 items were retained for further analysis. Consequently, the researcher specified two factors: **Behavioral Vulnerability (BV)**, represented by 4 items, and **Future Vulnerability (FV)**, also represented by 4 items, to be included in the measurement model. The path diagram for the initial POVTNCD model was then constructed to visually depict these relationships.

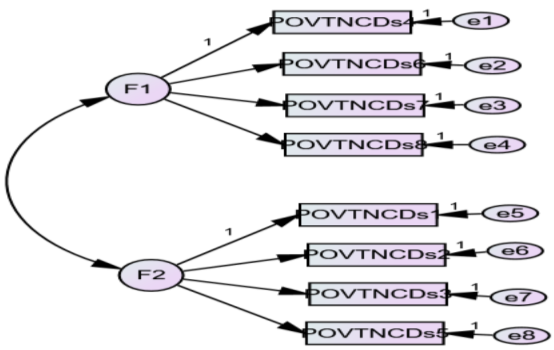


Figure 12: Path Diagram of initial POVTNCDs measurement model

For model identification, the POVTNCDs model comprises 8 observed variables used to measure the construct. Additionally, there are 8 error terms corresponding to these measured variables, resulting in a total of 17 parameters (8 factor loadings, 8 error variances, and 1 correlation between the two latent variables).

To determine the number of distinct values, we apply the formula: p(p+1)2\frac{p(p + 1)}{2}2p(p+1), where ppp is the number of observed variables. Substituting in our values gives us 8(8+1)2=36\frac{8(8 + 1)}{2} = 3628(8+1)=36.

Next, we can assess model identification by subtracting the number of parameters to be estimated (17) from the number of distinct values (36). This calculation yields a degree of freedom of 19 (i.e., 36−17=1936 - 17 = 1936−17=19). A positive degree of freedom indicates that the model is over-identified.

To estimate the model, the maximum likelihood (ML) method was applied. Using this approach, a two-factor measurement model that includes 18 free parameters was proposed, constructed, and estimated with the help of SPSS Amos version 23. The model was evaluated using fit indices such as CFI, TLI, and RMSEA. The results indicated a good fit for the model, although TLI fell slightly short of the desired threshold: $\chi^2(19, N=420) = 105.538$, $p = .000$, TLI = .889, CFI = .924, RMSEA = .104. These findings suggested the need for post-hoc modifications to enhance model fit.

With the assistance of modification indices generated from the output, the proposed model was revised by removing variables with lower regression weights and allowing certain parameters to co-vary. The revised model, depicted in Figure 17, was re-estimated. The updated fit indices revealed significant improvements, indicating that the revised model fits the data well: $\chi^2(11, N=420) = 31.288$, $p = .000$, TLI = .955, CFI = .982, RMSEA = .066.

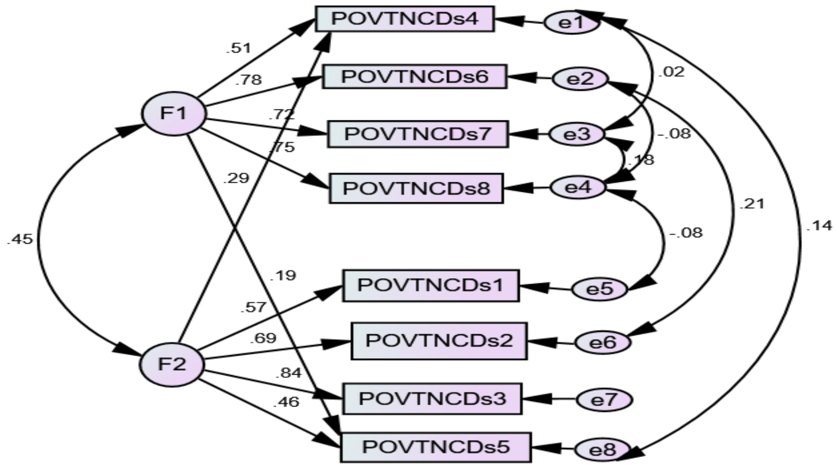


Figure 13: Path Diagram of modified perception of vulnerability measurement model

4.1.3.4.Measurement Model of Self-Efficacy

To assess the two factors of Self-Efficacy (SE), 27 items were initially developed based on prior literature. During the expert validation process, 19 items were removed, leaving 9 items for exploratory factor analysis (EFA). After conducting the EFA, all 9 items were retained for further analysis. As a result, the researcher identified one factor representing Self-Efficacy, which is loaded by 7 items for inclusion in the measurement model. The path diagram for the initial SE model was then constructed to visually represent these relationships.

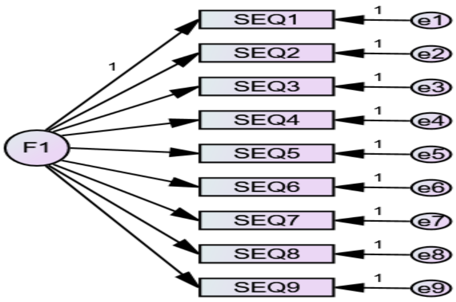


Figure 14: Path Diagram of initial SE measurement model

For model identification in the Self-Efficacy (SE) model, we consider 9 observed variables that measure the construct. Additionally, there are 9 error terms corresponding to these measured variables, resulting in a total of 18 parameters (9 factor loadings and 9 error variances).

To determine the number of distinct values, we use the formula p(p+1)2\frac{p(p + 1)}{2}2p(p+1), where ppp represents the number of observed variables. Applying this gives us 9(9+1)2=45\frac{9(9 + 1)}{2} = 4529(9+1)=45.

Next, we assess model identification by subtracting the number of parameters to be estimated (18) from the number of distinct values (45). This calculation yields a degree of freedom of 27 (i.e., 45−18=2745 - 18 = 2745−18=27). A positive degree of freedom indicates that the model is over-identified.

To estimate the model, the maximum likelihood (ML) method was applied. Using this approach, a one-factor measurement model with 27 free parameters was proposed, constructed, and estimated using SPSS Amos version 23. The model was evaluated with fit indices, including CFI, TLI, and RMSEA. The results showed that the model had a good fit, although RMSEA did not meet the desired criteria: $\chi^2(27, N=420) = 229.992$, $p = .000$, TLI = .758, CFI = .818, RMSEA = .134. These findings indicated the need for post-hoc modifications to improve model fit.

With the assistance of modification indices from the output, the proposed model was revised by removing variables with lower regression weights and allowing certain parameters to co-vary. The revised model, illustrated in Figure 15, was re-estimated. The updated fit indices indicated that the revised model fits the data well: $\chi^2(22, N=420) = 79.596$, $p = .000$, TLI = .916, CFI = .948, RMSEA = .079.

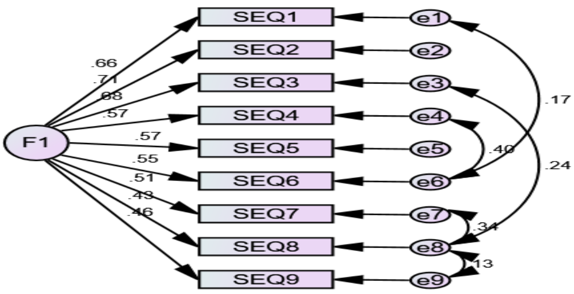


Figure 15: Path Diagram of modified Self-Efficacy measurement model

4.1.3.5.Measurement Model of Outcome Expectancy

To evaluate the two factors of Outcome Expectancy (OE), a total of 27 items were initially developed based on prior literature. During the expert validation phase, 15 items were removed, leaving 12 items for exploratory factor analysis (EFA). Following the EFA, all 12 items were retained for further analysis.

Based on the results, the researcher identified three distinct factors for the measurement model:

- Positive Expectancy (PE), which comprises 7 items,
- Negative Expectancy (NE), which consists of 3 items,

- Fear of Non-Communicable Diseases (FNCDs), which includes 2 items.

The path diagram illustrating the initial Outcome Expectancy model was subsequently constructed to visually represent these relationships.

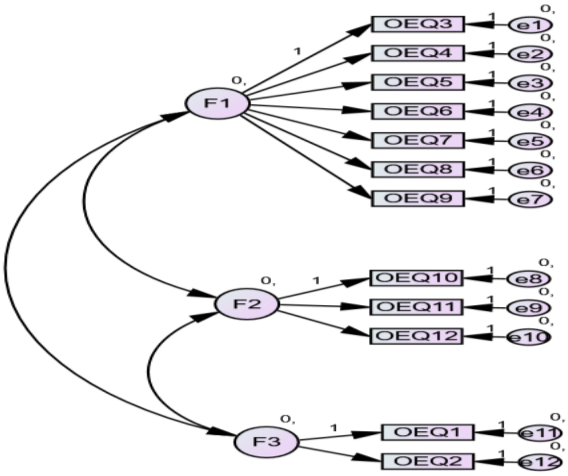


Figure 16: Path Diagram of initial OE measurement model

For model identification in the Outcome Expectancy (OE) model, the process begins by counting the variables involved. In this model, there are 12 observed variables that measure the constructs, alongside 12 error terms corresponding to each observed variable. This totals 24 parameters (12 factor loadings and 12 error variances), along with 3 correlations among the extracted components.

To determine the number of distinct values, we use the formula p(p+1)2\frac{p(p+1)}{2}2p(p+1), where ppp represents the number of observed variables. Substituting p=12p = 12p=12 yields 12(12+1)2=78\frac{12(12+1)}{2} = 78212(12+1)=78 distinct values.

Next, we calculate the degree of freedom by subtracting the number of parameters to be estimated (27) from the number of distinct values (78). This results in 78−27=5178 - 27 = 5178−27=51. A positive degree of freedom (51) indicates that the model is over-identified, confirming that there is sufficient information to estimate the parameters.

For model estimation, the Maximum Likelihood (ML) method was employed. This approach proposed a one-factor measurement model with 51 free parameters, constructed and analyzed using SPSS Amos version 23. The fit indices, including CFI, TLI, and RMSEA, initially indicated poor model fit: χ2(51,N=420)=309.642,p=.000\chi^2 (51, N=420) = 309.642, p = .000χ2(51,N=420)=309.642,p=.000, TLI=.734TLI = .734TLI=.734,

CFI=.795CFI = .795CFI=.795, RMSEA=.110RMSEA = .110RMSEA=.110. These results suggested that post-hoc modifications were necessary for improving model fit.

Utilizing the modification indices from the output, the model was revised by removing variables with lower regression weights and allowing some parameters to co-vary. Allowing some factors to co-vary in structural equation modeling (SEM) or confirmatory factor analysis (CFA) is typically done to address issues in model fit, and it is supported by theoretical or empirical justifications. Here's why this adjustment was necessary. Modification indices suggest potential adjustments to the model that could reduce discrepancies between the observed data and the model's predictions. If certain factors show unexplained correlations, allowing them to co-vary can improve fit indices (like χ^2, RMSEA, CFI, and TLI), indicating a better representation of the data. The revised model, illustrated in Figure 17, was then estimated again. The updated fit indices indicated a significant improvement in model fit, resulting in χ2(41,N=420)=93.615,p=.000\chi^2 (41, N=420) = 93.615, p = .000χ2(41,N=420)=93.615,p=.000, TLI=.920TLI = .920TLI=.920, CFI=.955CFI = .955CFI=.955, and RMSEA=.060RMSEA = .060RMSEA=.060.

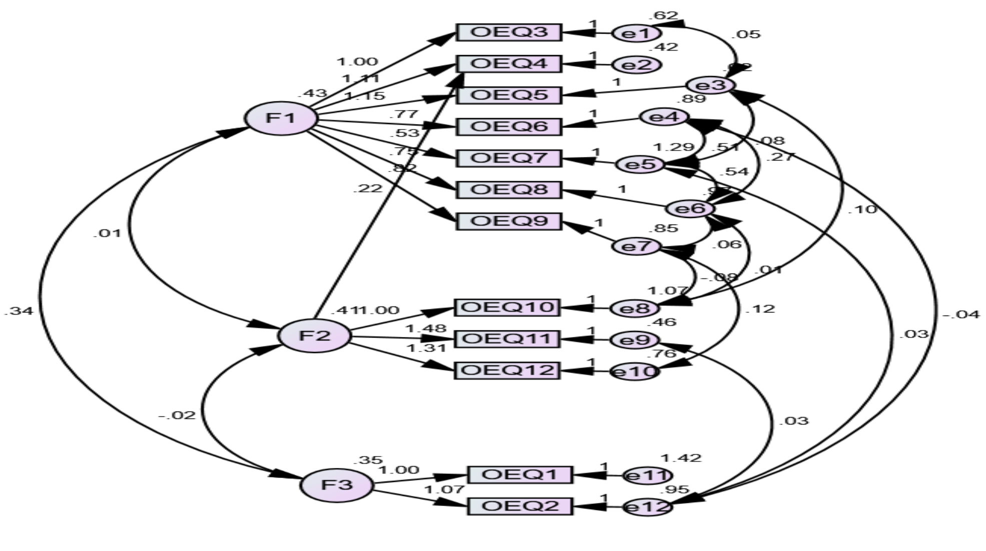


Figure 17: Path Diagram of modified Outcome Expectancy measurement model

4.1.3.6.Measurement Model of Behavioural Intentions

To assess perceptions of Behavioral Intentions (BI), 10 items were initially developed based on previous literature. After expert validation, one item was removed, leaving 9 items for further analysis through Exploratory Factor Analysis (EFA). Following the EFA, another item was excluded, resulting in 8 items being retained for the next steps. These 8 items were used to define a single factor, which was incorporated into the measurement model. The initial BI model's path diagram was then created to represent this structure.

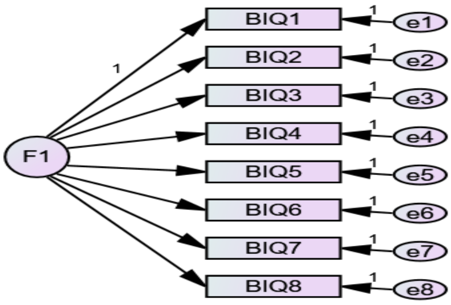


Figure 18: Path Diagram of initial BI measurement model

For model identification, the Behavioral Intentions (BI) model includes 8 observed variables, each associated with its own error term. This results in a total of 16 parameters (8 factor loadings and 8 error variances).

To determine if the model is identified, we first calculate the number of distinct values using the formula 8(8+1)2=36\frac{8(8+1)}{2} = 3628(8+1)=36. By subtracting the 16 parameters to be estimated from these 36 distinct values, we arrive at a positive degree of freedom of 20 (36−16=2036 - 16 = 2036−16=20), indicating that the model is over-identified. For model estimation, the Maximum Likelihood (ML) method was applied, constructing and estimating a one-factor measurement model with the 20 free parameters using SPSS Amos version 23. The initial fit indices suggested that the model had a poor fit to the data: $\chi^2(20, N=420) = 138.647$, $p=.000$, TLI=.838, CFI=.884, RMSEA=.119. This result indicated the need for post-hoc modification to improve model fit.

Using the modification indices provided in the output, adjustments were made by deleting items with lower regression weights and allowing certain parameters to co-vary. After revising the model, it was re-estimated, and the new fit indices showed a much-improved fit: $\chi^2(17, N=420) = 49.083$, $p=.000$, TLI=.948, CFI=.969, RMSEA=.067.

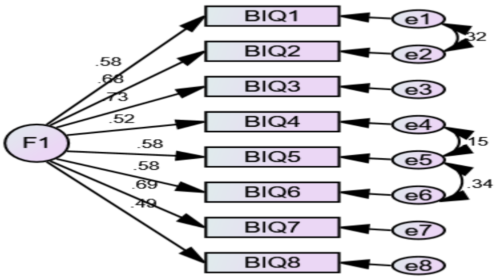


Figure 19: Path Diagram of modified Outcome Expectancy measurement model

4.1.4. Conclusions from the pilot

As a result of the piloting process the knowledge about NCDs scale was converted in to a write or wrong option/ level items.

- Experts validated the face validity of the instrument, confirming that it is generally appropriate for participants, with both the items and instructions being clear.
- Of the 114 items rated for the scales, only 65 met the item-level content validity standard, achieving an Item-Level Content Validity Index (I-CVI) greater than 0.7. Consequently, these 65 items were selected for further statistical analysis.
- Exploratory Factor Analysis (EFA) was conducted to assess the construct validity of the instruments. This analysis focused on the magnitude and direction of the relationships among indicators and the latent factors of the scales.
- The analysis of the internal consistency of the developed measures indicated that all scales demonstrated adequate reliability. The scale with the highest reliability was the perception about the seriousness of NCDs (POSONCDs), with a Cronbach's alpha value of 0.869, while the scale for knowledge exhibited the lowest reliability at 0.764. All scales met the commonly recommended reliability threshold of an alpha coefficient of 0.70.
- CFA was employed to validate the measurement models derived from the exploratory factor analysis (EFA). The analysis tested how well observed variables represent their respective latent constructs, including knowledge about NCDs (KONCDs), perception of seriousness (POSONCDs), perceived vulnerability (POVTNCDs), self-efficacy (SE), outcome expectancy (OE), and behavioral intention (BI). Conducted using SPSS Amos (version 23), the CFA process followed established steps: model specification, identification, estimation, evaluation, and modification (Schumacker & Lomax, 1996).

4.1.4.1.Knowledge of NCDs (KONCDs)

- 19 items were initially created to measure KONCDs; EFA reduced this to 15 items representing four factors.
- With 15 observed variables and their error terms, 30 parameters were estimated. The model's degrees of freedom (df = 84) indicated over-identification, satisfying the order condition.
- The initial fit indices suggested a poor fit (e.g., TLI = .82, CFI = .856).

- Post-hoc adjustments, such as allowing certain parameters to co-vary, improved fit indices significantly (e.g., TLI = .904, CFI = .928, RMSEA = .044).

4.1.4.2.Perception of Seriousness (POSONCDs)

- Based on EFA, 12 items were retained, grouped into two factors.
- The model was over-identified (df = 53).
- The initial model showed poor fit (TLI = .751, CFI = .800, RMSEA = .143).
- Revisions improved fit indices (e.g., TLI = .909, CFI = .953, RMSEA = .087).

4.1.4.3.Perceived Vulnerability (POVTNCDs)

- Eight items grouped into two factors (Behavioral Vulnerability and Future Vulnerability) were retained after EFA.
- The model had 19 degrees of freedom, indicating over-identification.
- Initial fit indices suggested moderate fit (TLI = .889, CFI = .924, RMSEA = .104).
- After adjustments, the revised model demonstrated better fit (TLI = .955, CFI = .982, RMSEA = .066).

4.1.4.4.Self-Efficacy (SE)

- Seven items representing one factor were retained from an initial 27.
- The model had 27 degrees of freedom, indicating over-identification.
- Initial fit indices were suboptimal (TLI = .758, CFI = .818, RMSEA = .134).
- Refinements improved model fit (TLI = .916, CFI = .948, RMSEA = .079).

4.1.4.5.Outcome Expectancy (OE)

- Twelve items, organized into three factors—Positive Expectancy (PE), Negative Expectancy (NE), and Fear of NCDs (FNCDs)—were finalized.
- Fit indices and modifications are detailed in subsequent sections.

4.1.5. Implications to the Final Study

This pilot study has provided good lessons to the present researcher on how the development and validation of instruments require rigorous effort from researchers. The present researcher has learnt that research has no smooth linear path to move forward alone. He was thinking that researchers move forward smoothly from problem identification through data collection and analysis to report writing. But, this was not the case in reality.

An important lesson that can be raised here is that passing through several processes of instrument development is helpful to have a relatively better instrument. The present researcher has passed through several processes to develop and validate the instrument to be used in this study. For instance, he has started his study by reviewing related literature. Based on the data from the literature, the present researcher has generated a pool of items with the intention to measure the variables of interest. The literature helped him to search for relevant measures with detailed description of its psychometric characteristics. After this, the instrument was validated with the help of expert judgement and factor analysis. Finally, the present researcher was successful to have an instrument to be used in the final study, ensuring its acceptability with the help of validity and reliability. The implication of this pilot results can be seen in four major areas.

1. Methodological Implications

- **Instrument Design and Refinement**:
  - The process of validation and refinement indicates that a rigorous, stepwise approach to instrument development is essential for achieving clarity and precision.
  - Post-hoc model modifications to improve fit indices suggest that initial theoretical models may not fully capture the complexities of real-world data. Researchers must be flexible in refining instruments based on empirical findings.
- **Reliability of Measures**:
  - The high internal consistency across scales confirms that the selected items measure their respective constructs effectively.
  - The variability in Cronbach's alpha values (0.764–0.869) highlights the need for further refinement in scales with lower reliability, such as the knowledge scale, to ensure robust measurement.
- **Factor Analysis Applications**:
  - The successful use of EFA and CFA emphasizes the importance of combining exploratory and confirmatory approaches in validating complex psychological and health-related constructs.

2. Theoretical Implications

- **Construct Validation**:
  - The findings validate the theoretical framework underlying the scales. Constructs like self-efficacy, outcome expectancy, and perceived vulnerability are measurable and relevant in understanding NCD-related behaviors.
  - Multi-dimensional constructs (e.g., Outcome Expectancy) reflect the nuanced ways in which individuals perceive and respond to NCD risks.
- **Interrelation of Constructs**:

- The results suggest that constructs such as perception of seriousness and perceived vulnerability may serve as mediators or moderators in influencing behavioral intentions. Future research can explore their interconnections.

3. Practical Implications

- **Improving NCD Awareness Campaigns**:
  - Reliable and valid scales enable stakeholders to assess baseline knowledge, perceptions, and behaviors, which are critical for designing targeted interventions.
  - The scales for seriousness perception and vulnerability, in particular, can be used to identify groups with low awareness or high perceived risk, guiding resource allocation.
- **Behavior Change Interventions**:
  - The knowledge, self-efficacy, and outcome expectancy scales provide a basis for crafting interventions to improve awareness, foster confidence in managing NCD risks, and address misconceptions.
- **Program Evaluation**:
  - These instruments can serve as tools for monitoring and evaluating the effectiveness of NCD-related programs. Pre- and post-intervention assessments can track changes in knowledge, perceptions, and behavioral intentions.
- **Policy Development**:
  - Insights from these validated tools can inform policy frameworks by highlighting key areas where public health strategies can have the most impact, such as knowledge dissemination, enhancing self-efficacy, and addressing outcome expectations.

4. Implications for the Main Research

- **Scale Generalizability**:
  - While these scales show promise, additional validation is needed across diverse populations to confirm their generalizability and cross-cultural relevance.
- **Addressing Poor Model Fit**:
  - Scales with initially poor fit indices suggest areas for further theoretical refinement or the inclusion of additional items to better capture latent constructs.
- **Dynamic Behavioral Models**:
  - Future studies could explore how these constructs evolve over time or interact dynamically in response to external factors like health campaigns, socioeconomic changes, or disease prevalence.

In summary, these results emphasize the critical importance of using scientifically validated tools to measure constructs related to NCDs. They provide a foundation for designing, implementing, and evaluating effective interventions, thereby contributing to improved health outcomes and informed policy decisions.

CHAPTER FIVE

Study Results and Interpretations

5. Introduction

This chapter presents the findings from the main study, which aimed to explore the psychological factors influencing behavioral intentions regarding preventive measures for non-communicable diseases (NCDs). Through careful data collection and analysis, we have uncovered insights that illuminate key phenomena in this area. These findings not only contribute to the theoretical understanding of the topic but also have practical implications for professionals in related fields.

By examining these results, readers will gain a deeper understanding of the complexities associated with our research topic and how these insights can be applied in real-world settings. Additionally, the researcher tested both the measurement and path models to ensure the robustness of the findings. Therefore, this chapter will begin with a discussion of the confirmatory factor analysis, which was used to evaluate the measurement model, followed by an exploration of structural equation modeling (SEM) to assess the path model.

5.1.Results of Descriptive Analysis

5.1.1.1.Descriptive Statistics for Demographic Variables

After conducting data screening to eliminate errors and outliers, descriptive statistical analysis was carried out for the study variables. The initial focus was on analyzing the demographic variables. Frequencies and percentages were utilized to summarize each demographic category, providing a clear overview of the sample composition. These results, including the frequencies and their corresponding percentages, are presented in Table 14.

Table 14: Descriptive Analysis of Demographic Variables

Sex		Frequency	%
Valid	Male	254	60.5
	Female	166	39.5
Age	19.00	3	0.7
	20.00	48	11.4
	21.00	110	26.2
	22.00	126	30.0
	23.00	72	17.1
	24.00	31	7.4
	25.00	17	4.0
	26.00	7	1.7
	27.00	2	.5
	28.00	4	1.0
Study year	2.0	213	50.7
	3.0	61	14.5
	4.0	105	25.0
	5.0	41	9.8
Birth place	Rural	198	47.1
	Town	222	52.9
Study stream	Health	167	39.8
	"None Health"	253	60.2

As shown in Table 14., the gender distribution of the analysis group revealed that 254 participants (60.5%) were male, while 166 participants (39.5%) were female. In terms of age, the respondents ranged from 21 to 28 years, with over 85% being 23 years old or younger. Regarding their academic year, the majority of participants were in their second and fourth years, representing 50.7% and 25% of the sample, respectively. Another demographic variable assessed was the respondents' birthplace, with more than half coming from urban areas, where access to information about non-communicable diseases (NCDs) is presumed to be more readily available.

Lastly, when examining the students' streams of study, over 60% of the participants were enrolled in non-health-related fields. This indicates that, proportionally, fewer students chose to pursue health-related streams.

5.1.1.2.Descriptive Statistics for dependent and independent variables

The distribution of the measured variables included in the study was evaluated using descriptive statistics. Table 5.2 provides a summary of key statistics such as minimum, maximum, mean, standard deviation, skewness, and kurtosis values, which illustrate the distribution of scores for the dependent variables.

In this study, Behavioral Intentions (BI) was the dependent (endogenous) variable. The independent (exogenous) variables were Knowledge of NCDs (KONCDs), Perception of Severity of NCDs (POSONCDs), Perception of Vulnerability to NCDs (POVTNCDs), Self-Efficacy (SE), and Outcome Expectancy (OE).

As shown in Table 5.2, the mean scores for each measure fall within their respective minimum and maximum values, reflecting an appropriate spread of the data for further analysis. The skewness and kurtosis values indicate the normality of the distribution, with most variables showing acceptable values for further modeling.

Table 15: Descriptive Analysis of Study Variables N=420

	Range	Minimum	Maximum	Mean	Std. Deviation	Skewedness	Kurtosis
TKONCDs	14.00	1.00	15.00	9.3667	2.63786	-.019	-.026
TPOVTNCDs	31.00	9.00	40.00	29.2762	6.53209	-.561	-.128
TPOSONCDs	47.00	13.00	60.00	43.0881	9.88040	-.371	-.251
TSE	30.00	10.00	40.00	29.6714	6.28797	-.756	.152
TBI	32.00	8.00	40.00	29.8476	6.94029	-.830	.110
TOE	36.00	21.00	57.00	43.1095	8.15819	-.780	-.025

The results presented in **Table 15** show that the distribution of the study variables falls within the normal limits of skewness and kurtosis, which is a positive indicator for conducting further analyses that rely on the assumption of normality. Additionally, the variances of these variables demonstrate good variability in the participants' responses, suggesting diverse perspectives within the sample.

For example, the mean score for Knowledge of NCDs (KONCDs) is 9.3667, slightly higher than the midpoint of the total possible score, which is 7.5. This implies that more than half of the participants scored above the halfway point, indicating a relatively high level of knowledge about non-communicable diseases (NCDs) among the respondents. In other words most of the participants have a moderate level of knowledge about NCDs. This data supports further exploration and analysis of how knowledge may influence other related factors in the study.

5.2.The relationship among knowledge of NCDs (KONCDs), Self-efficacy (SE), Outcome Expectancy (OE), Risk Perception (RP) and Behavioural Intention (BI)

Correlation analysis is a useful technique for assessing the strength and direction of the relationships between two or more variables (Mertler & Reinhart, 2016). In this study, the data collected was analyzed using this method to explore the connections between the variables.

To determine the strength of the relationship between the independent variables (KONCDs, POSONCDs, POVTNCDs, OE, and SE) and the dependent variable (BI), as well as the relationships among the independent variables themselves, zero-order correlations were applied. The inter-correlation matrix was utilized to measure the magnitude and significance of these relationships, offering insights into how these variables interact within the scope of the study.

Table 16: Zero-Order Correlation Matrix among the Variables under Study, N=420

	TKONCDs	TPOVTNCDs	TPOSONCDs	TSE	TBI
TPOVTNCDs	.536**				
TPOSONCDs	.448**	.404**			
TSE	.629**	.621**	.551**		
TBI	.771**	.568**	.538**	.766**	
TOE	.526**	.546**	.613**	.625**	.624**

Correlation is significant at the $p<0.01$ level (2-tailed).

Note:

TKONCDs= Total Score of knowledge of NCDs

TSE= Total Score of Self-efficacy

TOE= Total Score of Outcome Expectancy

TPOVTNCDs = perception of vulnerability to NCDs

TPOSONCDs = perception of severity of NCDs

TBI= Total Score of Behavioural Intention

The results presented in Table 16 highlight that all independent variables (KONCDs, POSONCDs, SE, OE, and POVTNCDs) are positively and significantly associated with the dependent variable, BI. This means that as the values of these independent variables increase, so does the value of the dependent variable. Specifically, the knowledge of NCDs (KONCDs) shows a strong positive correlation with BI, with a coefficient of 0.771, indicating a robust relationship. The p-value for this correlation is less than 0.01, confirming the statistical significance of the relationship.

Similarly, POSONCDs has a moderate positive correlation with BI, with a coefficient of 0.538, and this too is statistically significant with a p-value below 0.01. The self-efficacy (SE) variable also demonstrates a strong positive correlation with BI, with a coefficient of 0.766, and a significant p-value below 0.01. Outcome expectancy (OE) correlates moderately with BI, showing a coefficient of 0.624, again with a statistically significant p-value of less than 0.01. Lastly, POVTNCDs has a moderate positive correlation of 0.568 with BI, and this relationship is also statistically significant ($p < 0.01$).

Additionally, the analysis shows that the independent variables (KONCDs, POSONCDs, SE, OE, and POVTNCDs) are significantly interrelated, suggesting direct relationships among them. This indicates that individuals who have greater knowledge of NCDs are also more likely to perceive themselves as vulnerable to these diseases. Overall, these results demonstrate strong and meaningful connections between knowledge of NCDs, perceptions of vulnerability, self-efficacy, outcome expectancy, and behavioral intentions, suggesting a coherent pattern in how individuals view and respond to NCD risks.

5.3.The Effects of Knowledge about NCDs, Risk Perception (RP), Self- Efficacy (SE) and Outcome Expectancy (OE) on Behavioural Intention (BI)

The objective of this research goes beyond simply identifying the relationship between each exogenous variable and the endogenous variable. It also aims to explore the combined predictive power of two or more exogenous variables on the endogenous variable. To achieve this, multiple regression analysis was selected as the appropriate method. According to Sarma and Vardhan (2018), and Mocanu et al. (2021), multiple regression is suitable when more than one independent variable is expected to influence a dependent variable.

In this study, the endogenous variable, BI (behavioral intentions), was treated as the dependent variable, while the exogenous variables—KONCDs (knowledge of NCDs), POSONCDs (positive outcome expectancy), POVTNCDs (perception of vulnerability to NCDs), OE (outcome expectancy), and SE (self-efficacy)—were treated as the independent (predictor) variables.

Before conducting the formal regression analysis, necessary assumptions were tested. Since the data was cross-sectional, the Durbin-Watson test for autocorrelation was not conducted. However, tests for multicollinearity and normality were performed.

Multicollinearity was checked using the Variance Inflation Factor (VIF), and the results showed that the VIF for all variables was less than 5, indicating that the assumption of no multicollinearity was not violated. This ensures that the independent variables do not overly correlate with each other, making the regression results more reliable.

Table:17: Co-linearity Statistics for Regression Assumption

Model		Co-linearity Statistics	
		Tolerance	VIF
1	(Constant)		
	TKONCDs	.551	1.816
	TPOVTNCDs	.552	1.813
	TPOSONCDs	.574	1.741
	TSE	.415	2.410
	TOE	.469	2.134

a. Dependent Variable: TBI

Note:

TKONCDs= Total Score of knowledge of NCDs

TSE= Total Score of Self-efficacy

TOE= Total Score of Outcome Expectancy

TPOVTNCDs = perception of vulnerability to NCDs

TPOSONCDs = perception of severity of NCDs

TBI= Total Score of Behavioural Intention

The other assumption was normality of distribution which was tested using the "qq" plot. And the qq plot showed a diagonal line indicating the normality of the distribution.

Figure 20. The normality of the distributions for regression assumption

5.3.1.1.Behavioural Intention as a dependent variable

In order to see the combined contribution of all the variables together and the relative contribution of each variable in the prediction of students behavioural intention (BI), a multiple regression analysis was carried out. All the predictor variables are employed simultaneously.

Table 18: ANOVA Table for Multiple Regressions

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14911.322	5	2982.264	234.239	<.001
	Residual	5270.925	414	12.732		
	Total	20182.248	419			

a. Dependent Variable: TBI, p<.001

b. Predictors: (Constant), TOE, TKONCDs, TPOVTNCDs, TPOSONCDs, TSE

Note:

TKONCDs= Total Score of knowledge of NCDs

TSE= Total Score of Self-efficacy

TOE= Total Score of Outcome Expectancy

TPOVTNCDs = perception of vulnerability to NCDs

TPOSONCDs = perception of severity of NCDs

TBI= Total Score of Behavioural Intention

The results from the ANOVA table indicate that the combined influence of all the independent variables significantly contributes to predicting students' behavioral intention scores. The multiple regression analysis revealed that the predictor variables collectively account for a substantial portion of the variance in behavioral intentions, with an R-value of .860 and an R^2 of .739, meaning that 73% of the variance in behavioral intention is explained by these independent variables. The F-value of 234.239 confirms that this contribution is statistically significant ($P < 0.001$).

To further assess the importance of each predictor variable in contributing to the prediction of behavioral intention, standardized coefficients (beta) were used, as suggested by Rana et al. (2013). Standardized coefficients allow for direct comparison of the strength of each predictor variable.

Table 19: T-test Results of the Multiple Regression Analysis

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.310	1.028		.302	.852
	TKONCDs	1.160	.089	.441	13.029	<.001
	TPOVTNCDs	.011	.036	.010	.296	>.05
	TPOSONCDs	.040	.023	.057	1.724	>.05
	TSE	.420	.043	.380	9.750	<.001
	TOE	.097	.031	.114	3.106	.002

a. Dependent Variable: TBI, P,<.001

Note:

TKONCDs= Total Score of knowledge of NCDs

TSE= Total Score of Self-efficacy

TOE= Total Score of Outcome Expectancy

TPOVTNCDs = perception of vulnerability to NCDs

TPOSONCDs = perception of severity of NCDs

TBI= Total Score of Behavioural Intention

The regression analysis in Table 19 indicated that); SE (t= 9.750, p<.001); KONCDs (t=13.029, p<0.00); and OE (t=3.106, p<.01) have significant contribution to the prediction of young adults' behavioural intension except for POSONCDs (t=1.724, p>.05) and POVTNCDs (t= .296, p >.05) having insignificant contribution.

The regression equation is:

$\acute{Y}$= .310+.441 X_1 + 0.010X_2+0.057X_3+0.380X_4 +0.114X_5

Where $\acute{Y}$= predicted behavioural intention

X_1= knowledge of NCDs

X_2= perception of vulnerability to NCDs

X_3= perception of severity of NCDs

$X_{4=}$ Self- Efficacy

X_5= Outcome Expectancy

This equation illustrates how various independent variables influence the predicted behavioral intention regarding non-communicable diseases (NCDs). The independent variables include perceptions of severity and vulnerability to NCDs, self-efficacy, knowledge about NCDs, and outcome expectancy.

According to the equation, an increase in knowledge about NCDs by one unit is associated with an increase in behavioral intention by 0.441 units. Additionally, when the perception of the severity of NCDs rises by one unit, we can expect a 0.057 unit increase in behavioral intention. Similarly, for each unit increase in the perception of vulnerability to NCDs, behavioral intention is anticipated to increase by 0.010 units. A one-unit increase in self-efficacy corresponds to an increase of 0.380 units in behavioral intention, while an increase in outcome expectancy by one unit is linked to a 0.114 unit rise in behavioral intention.

Interestingly, the equation also indicates that an increase in knowledge about NCDs results in an increase in behavioral intention by 0.441 units, highlighting apositive relationship between knowledge and behavioral intention. Overall, this equation serves as a tool for estimating behavioral intention (Ý) based on the values of these variables and their corresponding coefficients.

5.4.The Eeffect of knowledge of NCDs on Risk Perception (RP): (perceived vulnerability and seniority); Self-Efficacy (SE) and Outcome Expectancy (OE)

For this research objective there is one predictor variable and multiple dependent variables**,** the appropriate regression technique to use is Multivariate Regression Analysis (MRA) (Cohen, 1982).. This differs from standard multiple regressions, as it is designed to handle multiple dependent variables simultaneously. Multivariate Regression was used for two reasons. First because, multivariate regression accounts for potential correlations among the dependent variables, providing a more accurate understanding of how the predictor variable influences them collectively. And second it evaluates the effect of the predictor variable on all dependent variables simultaneously, avoiding the need for multiple univariate tests, which could inflate Type I error rates.

Table 20. Multivariate Test Results

Multivariate Test	Value	F	Hypothesis df	Error df	Sig.	Partial Eta squared
Pillai's Trace	.685	5.976	56.000	1620.000	.000	.171
Wilks' Lambda	.402	7.381	56.000	1565.867	.000	.204
Hotelling's Trace	1.281	9.163	56.000	1602.000	.000	.243
Roy's Largest Root	1.113	32.204[c]	14.000	405.000	.000	.527

Note:

- Design: Intercept + TKONCDs
- Exact statistic
- The statistic is an upper bound on F that yields a lower bound on the significance level.
- Computed using alpha = .05

A multivariate analysis of variance (MANOVA**)** was conducted to examine the effect of the independent variable (TKONCDs) on a set of dependent variables. Results from the multivariate tests are summarized in Table 20 All four multivariate test criteria (Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root) indicated statistically significant effects of TKONCDs on the dependent variables: Pillai's Trace (VVV) and Hotelling's Trace (T2T^2T2) suggest a significant proportion of variance in the dependent variables can be explained by TKONCDs, with medium-to-large effect sizes (ηp2=.171\eta^2_p = .171ηp2=.171 and ηp2=.243\eta^2_p = .243ηp2=.243, respectively). Wilks' Lambda (Λ=.402\Lambda = .402Λ=.402) indicates that 59.8% of the variance in the combined dependent variables is attributable to factors other than TKONCDs, but the test still demonstrates a significant multivariate effect (ηp2=.204\eta^2_p = .204ηp2=.204). Roy's Largest Root (Θ=1.113\Theta = 1.113Θ=1.113) reflects the maximum possible variance accounted for by TKONCDs in any one dependent variable and shows a very large effect (ηp2=.527\eta^2_p = .527ηp2=.527).

The partial eta-squared values (ηp2\eta^2_pηp2) across tests suggest TKONCDs explains between 17.1% and 52.7% of the variance in the dependent variables. These effect sizes range from medium to large, indicating a substantial influence of TKONCDs on the outcomes. The multivariate tests confirm a significant multivariate relationship between TKONCDs and the dependent variables (p<.001p < .001p<.001). Roy's Largest Root indicates the strongest single-variable effect, while the other statistics confirm the combined impact.

Table 21: Univariate Regression Results

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Eta squared
TKONCDs	TPOVTNCDs	6334.808	14	452.486	15.876	.000	.354
	TPOSONCDs	12393.658	14	885.261	12.576	.000	.303
	TSE	7454.859	14	532.490	23.668	.000	.450
	TOE	10050.656	14	717.904	16.301	.000	.360

Note.

- TKONCDs\text{TKONCDs}TKONCDs = Predictor variable.

- η2\eta^2η2 indicates partial eta-squared, representing the proportion of variance explained by TKONCDs\text{TKONCDs}TKONCDs for each dependent variable.
- All results are statistically significant at p<.001p < .001p<.001.

The follow-up univariate regressions analyses reveal that TKONCDs significantly predicted all four dependent variables. The analyses reveal that TKONCDs significantly predicted all four dependent variables: TPOVTNCDs**:** F(14,error df)=15.876, p<.001, η2=.354 F(14,{error df}) = 15.876, p < .001, \eta^2 = .354 F(14,error df)=15.876, p<.001, η2=.354. This indicates that TKONCDs explains 35.4% of the variance in TPOVTNCDs, a large effect size. TPOSONCDs**:** F(14,error df)=12.576, p<.001,η2=.303F(14, {error df}) = 12.576, p < .001, \eta^2 = .303 F(14,error df)=12.576, p<.001,η2=.303. TKONCDs accounts for 30.3% of the variance in TPOSONCDs, which is also a large effect size. TSE**:** F(14,error df)=23.668,p<.001,η2=.450F(14, \text{error df}) = 23.668, p < .001, \eta^2 = .450F(14,error df)=23.668,p<.001,η2=.450. This demonstrates that TKONCDs explains 45.0% of the variance in TSE, the largest effect size among the dependent variables. TOE**:** F(14,error df)=16.301p<.001,η2=.360F(14, {error df}) = 16.301, p < .001, \eta^2 = .360F(14,error df)=16.301,p<.001,η2=.360. TKONCDs explains 36.0% of the variance in TOE, another large effect size.

The findings indicate that TKONCDs has a significant and substantial effect on all four dependent variables, with effect sizes ranging from 30.3% to 45.0% of the explained variance. The highest variance explained is for TSE (η2=.450\eta^2 = .450η2=.450), indicating this dependent variable is most influenced by TKONCDs. The univariate analyses support the multivariate findings by demonstrating significant relationships between TKONCDs and each dependent variable individually. The large effect sizes across all outcomes highlight the importance of TKONCDs as a predictor of these variables.

5.5.The strongest psychological determinant of behavioural intention

According to Nathans et al. (2012), stepwise regression analysis is a technique used to identify the most significant predictor variables from a set of independent variables, selecting one at a time based on its independent contribution to the overall model. This method allows researchers to assess the relative importance of each predictor in relation to a criterion variable, ultimately identifying the strongest predictor.

Hinkle, Wiersma, and Jurs (2003), and Nathans, Oswald, and Nimon (2012), outline the steps for conducting forward stepwise regression. First, the independent variable with the highest bivariate correlation with the dependent variable is selected for inclusion in the regression equation. Next, the second independent variable is added based on its contribution to increasing the R^2 value after accounting for the first variable. This process continues until either all independent variables are included or there is no statistically significant increase in R^2 from the remaining variables.

In the current study's stepwise regression analysis, the first variable to enter the model is the one with the highest zero-order correlation coefficient with the criterion variable, as determined by preliminary correlation analysis. The second variable selected will have the next highest correlation coefficient with the criterion variable, followed by the third variable with the third highest correlation coefficient. This process is repeated until the change in R^2 is no longer significant. At each step, significance tests are conducted to evaluate the contribution of each predictor variable to the regression model.

5.5.1.1.Behavioural intention as a dependent variable

The result of the stepwise regression model building indicates that all of the independent variables were chosen to be included in the regression model. This suggests that each of these variables has a meaningful contribution and plays a significant role in explaining the variation in the dependent variable. In other words, all of the selected independent variables have a statistically significant impact on the outcome of the linear regression model. Consequently, omitting any of these variables would result in a less accurate or incomplete representation of the relationship between the independent and dependent variables.

Table 22: Table of the Stepwise Regression Model

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11994.062	1	11994.062	612.287	<.001
	Residual	8188.185	418	19.589		
	Total	20182.248	419			
2	Regression	12670.930	2	6335.465	351.721	<.001
	Residual	7511.317	417	18.013		
	Total	20182.248	419			
3	Regression	13325.038	3	4441.679	269.459	<.001
	Residual	6857.209	416	16.484		
	Total	20182.248	419			
4	Regression	14788.504	4	3697.126	284.461	<.001
	Residual	5393.744	415	12.997		
	Total	20182.248	419			
5	Regression	14911.322	5	2982.264	234.239	<.001
	Residual	5270.925	414	12.732		

	Total	20182.248	419			

a. Dependent Variable: TBI, p<.001

b. Predictors: (Constant), TKONCDs

c. Predictors: (Constant), TKONCDs, TPOVTNCDs

d. Predictors: (Constant), TKONCDs, TPOVTNCDs, TPOSONCDs

e. Predictors: (Constant), TKONCDs, TPOVTNCDs, TPOSONCDs, TSE

f. Predictors: (Constant), TKONCDs, TPOVTNCDs, TPOSONCDs, TSE, TOE

Note:

TKONCDs= Total Score of knowledge of NCDs

TSE= Total Score of Self-efficacy

TOE= Total Score of Outcome Expectancy

TPOVTNCDs = perception of vulnerability to NCDs

TPOSONCDs = perception of severity of NCDs

TBI= Total Score of Behavioural Intention

The stepwise regression ANOVA Table 22 provides valuable insights into which independent variables should be included in the regression model. In this analysis, the table indicates that all independent variables were retained in the model, signifying their importance and relevance in accounting for the variation in the dependent variable.

Moreover, the table reveals that these independent variables significantly contribute to the model, demonstrating a strong influence on the dependent variable and explaining a substantial portion of its variability. Their inclusion enhances the model's overall predictive power and accuracy.

In summary, these findings suggest that all the independent variables analyzed play a crucial role in effectively explaining and predicting the dependent variable in question.

Table 23: Summary of Result of Stepwise Regression Analysis

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	10.850	.798		13.603	<.001
	TKONCDs	2.028	.082	.771	24.744	<.001
2	(Constant)	6.967	.993		7.015	<.001
	TKONCDs	1.723	.093	.655	18.506	<.001
	TPOVTNCDs	.230	.038	.217	6.130	<.001
3	(Constant)	3.849	1.071		3.593	<.001
	TKONCDs	1.546	.093	.588	16.556	<.001
	TPOVTNCDs	.180	.037	.170	4.893	<.001
	TPOSONCDs	.145	.023	.206	6.299	<.001
4	(Constant)	1.374	.979		1.403	.161
	TKONCDs	1.194	.089	.454	13.380	<.001
	TPOVTNCDs	.034	.035	.032	.964	.335
	TPOSONCDs	.068	.022	.097	3.152	.002
	TSE	.450	.042	.407	10.611	<.001
5	(Constant)	.310	1.028		.302	.763
	TKONCDs	1.160	.089	.441	13.029	P<0.001
	TPOVTNCDs	.011	.036	.010	.296	.767
	TPOSONCDs	.040	.023	.057	1.724	.086
	TSE	.420	.043	.380	9.750	<.001
	TOE	.097	.031	.114	3.106	.002

a. Dependent Variable: TBI, P,.001

Note:

TKONCDs= Total Score of knowledge of NCDs

TSE= Total Score of Self-efficacy

TOE= Total Score of Outcome Expectancy

TPOVTNCDs = perception of vulnerability to NCDs

TPOSONCDs = perception of severity of NCDs

TBI= Total Score of Behavioural Intention

As it can be seen from Table 23 of stepwise regression analysis, the independent variables considered in this analysis are KONCDs, OE, SE, POSONCDs, and POVTNCDs. The analysis indicted all KONCDs, OE, SE, POVTNCDs, and POSONCDs are found to be significant at $p<0.05$. All the independent variable show significant increase in R^2. The table also shows that, the variable KONCDs has entered first into the stepwise regression with a contribution of .441 (44.1%) of the variance in behavioural intention of young adults followed by SE which contributed .380 (accounting about 38% of the variation in behavioural intention). The third ranking independent variable was OE which contributes .114 (which account 11.4% of the variation in young adults' behavioural intention).

The equation of the stepwise regression is:

$\acute{Y}= .310+.441\ X_1 + 0.010X_2+0.057X_3+0.380X_4 +0.114X_5$

Where $\acute{Y}$= predicted behavioural intention

X_1= knowledge of NCDs

X_2= perception of vulnerability to NCDs

X_3= perception of severity of NCDs

X_4= Self- Efficacy

X_5= Outcome Expectancy

The result pointed that knowledge and self-efficacy has the strongest positive relationship with behavioural intention among the independent variables considered. Perceived vulnerability to NCDs and perceived severity of NCDs also have positive relationships with business impact but to a lesser extent compared to self-efficacy. These findings suggest that concerned bodies working to foster healthy youth development should focus on enhancing youths' self-efficacy beliefs as it has a significant influence on behavioural intention.

Additionally, improving Perceived vulnerability to NCDs and perceived severity of NCDs can also contribute positively to behavioural intention but may have a relatively smaller effect compared to self-efficacy.

5.6.The roles of Risk Perception (RP), self-efficacy (SE), and Outcome Expectancy (OE) on the relationship between knowledge of NCDs and Behavioural Intention (BI);

In the measurement models which were found to have a good fit to the data, there were a total of 6 latent variables. As indicated in the literature, latent variables were hypothesized to predict youths' behavioural intentions. Thus, these latent variables are exogenous variables while BI (behavioural intention is an endogenous variable.

While correlation and regression analyses provide insights into the relationships among exogenous and endogenous variables, employing a structural model is essential for a more comprehensive understanding. Structural Equation Modeling (SEM) has gained popularity in research for its effectiveness in analyzing complex relationships (Richter et al., 2016). Researchers have noted that the complexities of modern society necessitate the adoption and enhancement of multivariate data analysis techniques to accurately address the phenomena being studied (Rivera et al., 2018).

SEM encompasses a range of related procedures, including covariance structure analysis and covariance structure modeling, rather than being a single statistical technique (Kline, 2018). Shumaker and Lomax (2016) identified four key reasons for the increasing popularity of SEM:

1. **Complex Relationships**: Researchers recognize the need to investigate multiple observed variables, which traditional statistical methods cannot adequately address.
2. **Measurement Accuracy**: The focus on the validity and reliability of measurement instruments has increased, as SEM accounts for measurement errors in its analyses.
3. **Model Testing**: Many SEM software packages are designed to test theoretically grounded models, making it easier for researchers to validate their hypotheses.
4. **User-Friendly Software**: The development of user-friendly software has made SEM more accessible to researchers.

Sheskin & Crc (2004) also emphasized that SEM offers a unique approach for handling various interactions simultaneously, enabling the representation of unobserved (latent) constructs while enhancing the statistical estimation of dependent relationships.

With these advantages in mind, a model was hypothesized and analyzed using the SEM method. In this analysis, a structural model was constructed to reflect the researcher's hypothesized predictions (Kline, 2018). The initial path model, accompanied by a measurement model, was developed and tested. This model was specifically designed to explore the relationships among Knowledge of NCDs (KONCDs), Perception of Severity of NCDs (POSONCDs), Perception of Vulnerability to NCDs (POVTNCDs), Self-Efficacy (SE), Outcome Expectancy (OE), and Behavioral Intention (BI). The model was presented with modification indices to highlight areas for potential improvement.

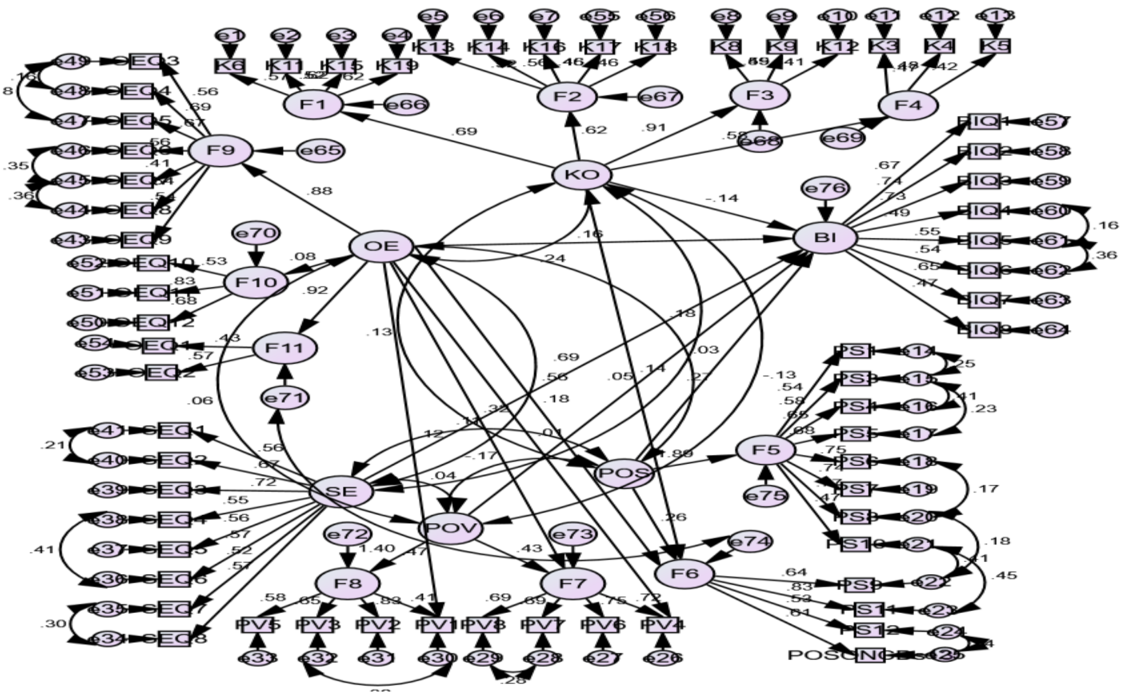


Figure 20: Path Model of the study variables with their measurement model

The model fit of the original measurement model was good with the provided modifications. Revision was made based on the provided modification indexes. The revised model is presented in Figure 20. The parameters included in the revised model were estimated again. The inspection of the fit indexes indicated that the revised model fits well to the data, $\chi 2$ (1842, N=420) = 3797.116, p=.000, TLI=.902, CFI=.920, RMSEA=.050.

In addition to the above path measurement model, the following path structural model was developed to see the clear and simplified direct and indirect effects of the independent variables using their total score. This means the total aggregated values of the variables was used as an observed variable.

The purpose of converting a path measurement model into a path structural model lies in the transition from understanding how latent variables are measured to examining how those latent variables relate to one another within a theoretical framework. This conversion integrates the measurement and structural aspects of the model, providing a comprehensive understanding of the relationships between constructs and their indicators as well as among the constructs themselves.

Thus conversion was made because a path structural model enables testing causal relationships, direct effects, indirect effects (mediation), and moderating effects among latent variables.

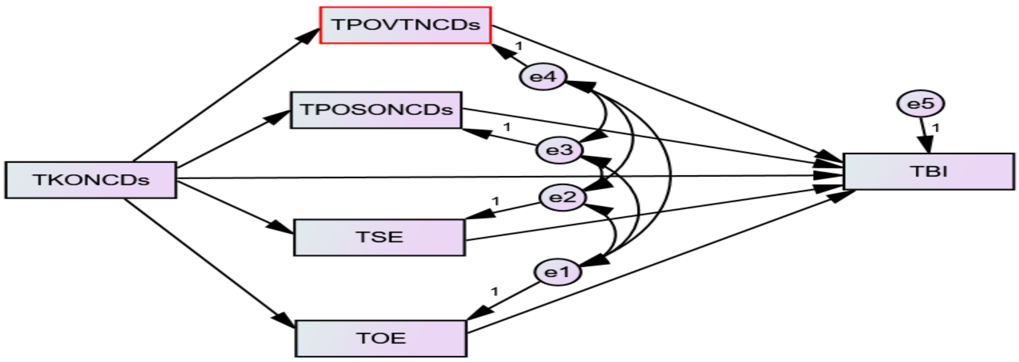


Figure 21: Path Model of the study variables

AS shown in the above figure 21, the structural model shows the relationships among POSONCDs, POVTNCDs, SE, OE and BI. This is based on the assumption that there is a positive relationship among the predictor and criterion variables. In AMOS, the researcher cannot directly draw a covariance path between observed variables because AMOS assumes relationships between observed variables should typically be modelled as causal (with single-headed arrows) or mediated by latent variables. Instead, covariance was drawn between error terms or latent variables**.**

The technique of drawing covariance between the error terms of observed variables was used to account for shared variance between variables that is not explained by their relationships to latent variables or other predictors in the model. This is because observed in this study variables share unique sources of variation due to measurement design or other external factors.

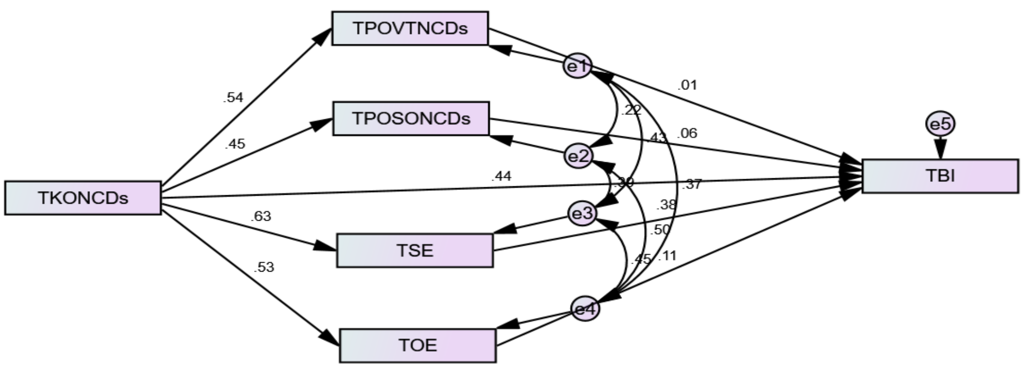


Figure 22: Reduced (over identified) path model 1

As shown from the above figure 22 the relationship, KONCDs, SE, OE and BI is significant with standardized regression coefficients .44, .38 and .11 respectively. The relationship between, POVTNCDs, POSNCDs and BI was not significant with standardized regression coefficient .01 and .06. For further information, see the following Table 24. Moreover KONCDs has significant relationship with all the other independent variables.

Table 24: Regression Weights of Structural Model

Predictor	Outcome	Estimate	S.E.	C.R.	P
TPOVTNCDs	TKONCDs	1.327	.102	12.985	< .001
TPOSONCDs	TKONCDs	1.680	.164	10.271	< .001
TSE	TKONCDs	1.498	.091	16.544	< .001
TOE	TKONCDs	1.628	.128	12.675	< .001
TBI	TKONCDs	1.160	.089	13.107	< .001
TBI	TPOVTNCDs	.011	.036	.298	.766
TBI	TPOSONCDs	.040	.023	1.734	.083
TBI	TSE	.420	.043	9.809	< .001
TBI	TOE	.097	.031	3.125	.002

Note:

Estimate = Standardized regression weight; S.E. = Standard error; C.R. = Critical ratio; ***p < .001.

To assess the fit of the structural model, various fit criteria were calculated, including the Goodness of Fit Index (GFI), Normed Fit Index (NFI), and Comparative Fit Index (CFI). The outcomes of these analyses are summarized in Table 21.

A key focus of the SEM analysis was to examine the indirect effect of Total Knowledge of NCDs (TKONCDs) on Behavioral Intention (BI). The standardized direct (unmediated) effect of TKONCDs on Total Behavioral Intention (TBI) is 0.441. This suggests that for every one standard deviation increase in TKONCDs, TBI increases by 0.441 standard deviations, reflecting the strength of this direct relationship.

Moreover, the analysis also uncovered a standardized indirect (mediated) effect of TKONCDs on TBI, measured at 0.330. This indicates that a one standard deviation increase in TKONCDs results in a 0.330 standard deviation increase in TBI due to this indirect effect. Collectively, these findings emphasize the significant roles both direct and indirect effects of TKONCDs play in predicting TBI.

The result indicates that the structural model achieved a Goodness of Fit Index (GFI) value of 1.00. According to Loehlin (2021), a GFI value of 0.90 or higher is generally considered indicative of a good fit. Similarly, the Comparative Fit Index (CFI) for Structural Model 1 is also 1.00, with Loehlin suggesting that a CFI value exceeding 0.90 represents an adequate fit. Additionally, the model shows a Normed Fit Index (NFI) of 1.00, and Tabachnick and Fidell (2007) state that an NFI value greater than 0.90 suggests a well-fitting model. Based on these guidelines, all three fit indices support the conclusion that the tested model is a good fit.

However, given that the regression weights for Total Perceived Vulnerability to NCDs (TPOVNCDs) and Total Perceived Severity of NCDs (TPOSNCDs) were found to be statistically insignificant, the researcher sought to explore whether the relationships between perceived vulnerability and perceived severity with behavioral intention could be mediated by knowledge. Consequently, an alternative model was developed and tested to investigate this potential mediation effect.

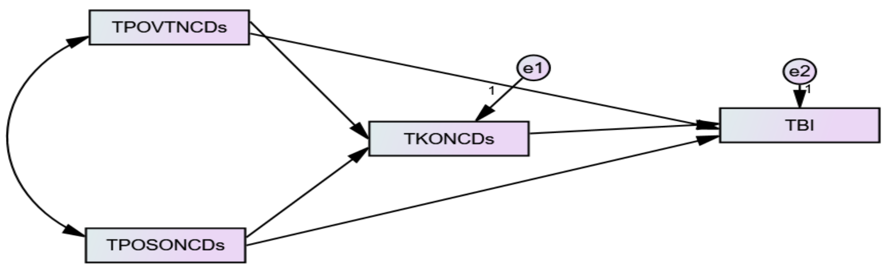


Figure 23: modified path model for mediation of knowledge

AS shown in the above figure 5.16, the structural model shows the relationships among POSONCDs, POVTNCDs, KONCDs and BI. This is based on the assumption that KONCDs have a mediation role on the relationship among the predictors (perceived vulnerability and perceived severity) which showed insignificant relationship in the conceptual model and criterion variables (behavioural intention).

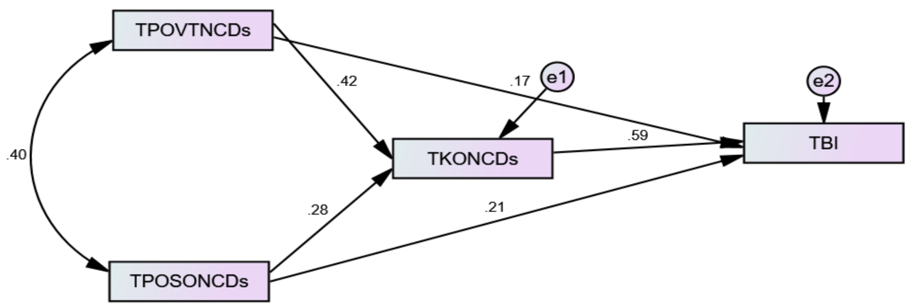


Figure 24: Reduced model of the knowledge as mediator on the effect of POVNCDs and POSNCDs on BI

As depicted in figure 24 the mediation of knowledge and the absence of OE and SE in the model seemed to have changed the effect of the two predictor variables. To illustrate more the regression table of the analysis is presented below.

Table 25. The Regression Weights of POVNCDs and POSNCDs Mediated by KONCDs

Predictors	Outcomes	Estimate	S.E.	C.R.	P
TKONCDs	TPOVTNCDs	.171	.017	9.854	< .001
TKONCDs	TPOSONCDs	.074	.011	6.453	< .001
TBI	TPOVTNCDs	.180	.037	111	< .001
TBI	TPOSONCDs	.145	.023	6.322	< .001
TBI	TKONCDs	1.546	.093	16.616	< .001

Notes:

- Estimate: Standardized regression weights indicating the strength of the relationships.
- SE**:** Standard Error.
- CR (Critical Ratio): Equivalent to a z-score in large samples.
- p: Significance level. *** denotes p < .001

Table 25 reveals that the influences of Total Perceived Vulnerability to NCDs (TPOVNCDs) and Total Perceived Severity of NCDs (TPOSNCDs) have become significant, with their estimates increasing to 0.180 and 0.145, respectively. Both variables have a p-value of less than 0.00, indicating strong statistical significance. This suggests that the relationship between TPOVNCDs and TPOSNCDs with Behavioral Intention (BI) is mediated by the presence of Total Knowledge of NCDs (KONCDs) in the model.

In the revised model, the standardized total effect (combining both direct and indirect effects) of TPOSNCDs on Total Behavioral Intention (TBI) is 0.369. This means that for every one standard deviation increase in TPOSNCDs, TBI increases by 0.369 standard deviations, reflecting both the direct (unmediated) and indirect (mediated) contributions. Similarly, the standardized total effect of TPOVNCDs on TBI is 0.419, indicating that a one standard deviation increase in TPOVNCDs results in a 0.419 standard deviation increase in TBI, again accounting for both direct and indirect effects.

In contrast, the standardized direct (unmediated) effect of TPOSNCDs on TBI is only 0.206, highlighting the presence of an indirect (mediated) effect influencing this relationship.

The direct effect of TPOVNCDs on TBI is also modest at 0.180, suggesting a similar indirect influence.

The standardized indirect (mediated) effect of TPOSNCDs on TBI is 0.163, which supplements the direct effect. For TPOVNCDs, the standardized indirect effect is 0.249, further illustrating a substantial indirect effect in addition to the direct impact on TBI. These findings underscore the importance of KONCDs in mediating the relationships between perceived vulnerability, perceived severity, and behavioral intention.

5.1. The moderating role of back ground (demographic) characteristics of respondents on the relationship between and among knowledge of NCDs on Risk Perception (RP): (perceived vulnerability and seniority); Self-Efficacy (SE) and Outcome Expectancy (OE).

After assessing the direct path relationships among the variables, the next step involved examining the moderating effects of demographic variables, specifically gender, age, and year of study. Moderating variables are factors that influence the strength or direction of the relationship between independent and dependent variables (Awang et al., 2015).

According to Hayes (2018), a moderator variable affects the impact of the independent variable on the dependent variable, meaning that the effect can vary in magnitude, sign, or strength depending on the presence of the moderator. Baron and Kenny (1986) further elaborate on this concept, describing a moderator as a qualitative or quantitative variable that alters the nature of the relationship between an independent variable and a dependent variable.

By analyzing these demographic variables, we can gain a deeper understanding of how different groups may experience varying effects in the relationships being studied.

5.1.1. Gender as a moderator variable

Multi-group structural equation modelling (SEM) has been applied to examine the moderating impact of gender in the present study. According to Henseler & Fassott, (2010)if independent or moderator variables are of a categorical nature, this method is commonly suggested. In multiple-group SEM, moderators are examined by dividing the data - sample into sub-samples (male and female in this case).

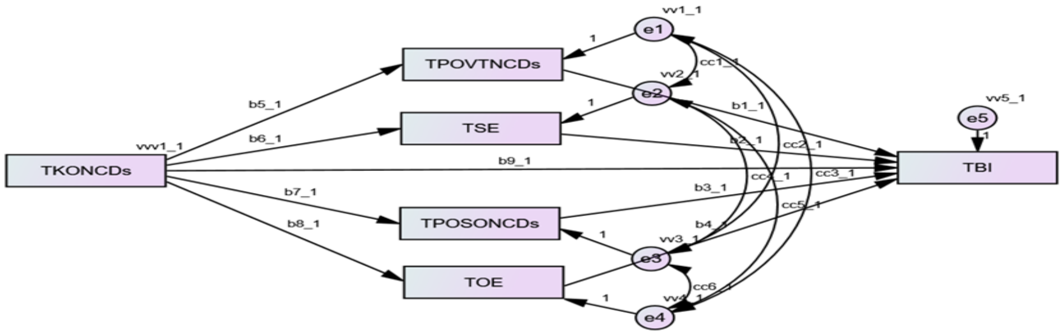


Figure 25: Proposed group difference model testing between male and female

Henseler and Fassott (2010) recommended that the impact of categorical moderator factors is evaluated by group comparisons and by grouping observations according to their categorical moderator variable value and then analysing and comparing results across groups. As a result, tests of group differences are done to investigate which differences between groups are indeed significant. The group difference multiple group SEM model is presented below.

Table 26. Chi-square Comparisons Assuming Model Unconstrained to be Correct

Model	DF	CMIN	P	NFI Delta-1	IFI Delta-2
Structural weights	9	20.544	.015	.054	.054
Structural covariance	10	20.560	.024	.054	.054
Structural residuals	21	38.055	.013	.100	.100
b2 c	1	.080	.777	.000	.000
b3 c	1	.337	.561	.001	.001
b4 c	1	.950	.330	.002	.002
b5 c	1	3.729	.053	.010	.010
b6 c	1	10.442	.001	.027	.027
b7 c	1	.856	.355	.002	.002
b8 c	1	5.705	.017	.015	.015
b9 c	1	.013	.909	.000	.000
b1 c	1	2.784	.095	.007	.007

Notes:

- **DF:** Degrees of freedom.
- **χ^2 (CMIN):** Chi-square statistic for model fit.
- **p:** Probability value, testing significance of the chi-square statistic.
- **NFI (Δ1) and IFI (Δ2):** Fit indices assessing relative model fit.
- Constraints (bib_ibi c): Tests for specific parameter equality constraints.

As shown in Table 26 all Structural weights, Structural covariance, Structural residuals, b6 c (the correlation between knowledge and self-efficacy constrained) and b8 c (the correlation between knowledge and outcome expectancy constrained) models showed significant p values for the models to bring difference in the model fit. Thus it means the introduction of sex to the model has brought significant change in some of the regression weights. The significant chi-square result indicated that constraining these correlations have cause the model fit to decrease significantly. This indicates that the two groups, male and female are not equal for these correlations. Based on the above model the calculated estimates for the two groups are presented in the following table 4.23 and 4.24.

Table 27: Regression Weights for Females

Predictors	Outcomes	Estimate	S.E.	C.R.	P	Label
TPOVTNCDs	TKONCDs	1.159	.147	-1.386	.166	b5_1
TSE	TKONCDs	1.227	.110	.030	.976	b6_1
TPOSONCDs	TKONCDs	1.450	.211	2.608	.009	b7_1
TOE	TKONCDs	1.374	.153	-.107	.915	b8_1
TBI	TPOVTNCDs	.040	.052	3.544	<.001	b1_1
TBI	TSE	.041	.073	7.581	<.001	b2_1
TBI	TPOSONCDs	.366	.037	1.816	.069	b3_1
TBI	TOE	.116	.052	.479	.632	b4_1
TBI	TKONCDs	1.168	.098	-.960	.337	b9_1

As shown from table 27 KONCDs and OE were insignificant when sex was introduced to the model for female. Similarly only POVTNCDs was insignificant in the relationship with KPNCDs. The rest showed significant correlation with knowledge.

Table 28: Regression Weights for Males

Predictors	Outcomes	Estimate	S.E.	C.R.	P	Label
TPOVTNCDs	TKONCDs	1.580	.115	1.370	.171	b5_2
TSE	TKONCDs	2.445	.112	4.591	<.001	b6_2
TPOSONCDs	TKONCDs	1.584	.166	1.819	.069	b7_2
TOE	TKONCDs	2.052	.133	3.526	<.001	b8_2
TBI	TPOVTNCDs	.012	.050	1.268	.205	b1_2
TBI	TSE	.014	.054	9.821	<.001	b2_2
TBI	TPOSONCDs	.501	.035	1.084	.279	b3_2
TBI	TOE	.066	.046	2.022	.043	b4_2
TBI	TKONCDs	1.182	.091	-1.195	.232	b9_2

Notes:

- Estimate: Standardized regression weights indicating the strength of the relationships.

- SE: Standard Error.
- CR (Critical Ratio): Equivalent to a z-score in large samples.
- p: Significance level. *** denotes $p < .001$

As indicated in the above Table 27 and 28 the relation of TBI, TPOV, OE and KONCDs was not significant for both groups. However the standardized regression is different for male and female. On top of that the constrained model is significant showing that the way the independent variables influenced behavior intention to take preventive measures is different for male and female groups. The influence in female is higher than the influence in male.

5.1.2. Age as a moderator variable

Multiple regression analyses are commonly employed to test moderating effects when both the predictor and moderator variables are interval or continuous (Kim et al., 2001). Baron and Kenny (1986) noted that researchers generally assume that a continuous moderator variable influences the relationship between the independent and dependent variables in a linear fashion.

While multiple regression analyses are effective for testing moderating effects, Structural Equation Modeling (SEM) is recommended when the model involves multiple indicator variables for unobserved (or latent) variables (Kim et al., 2001). SEM, which is based on maximum likelihood estimation, accounts for measurement errors in the statistical model and can generate solutions for models where unobserved variables are measured by several indicators. Therefore, SEM moderation testing is utilized in this research, as age serves as a continuous variable and multiple indicators are present for the measured variables.

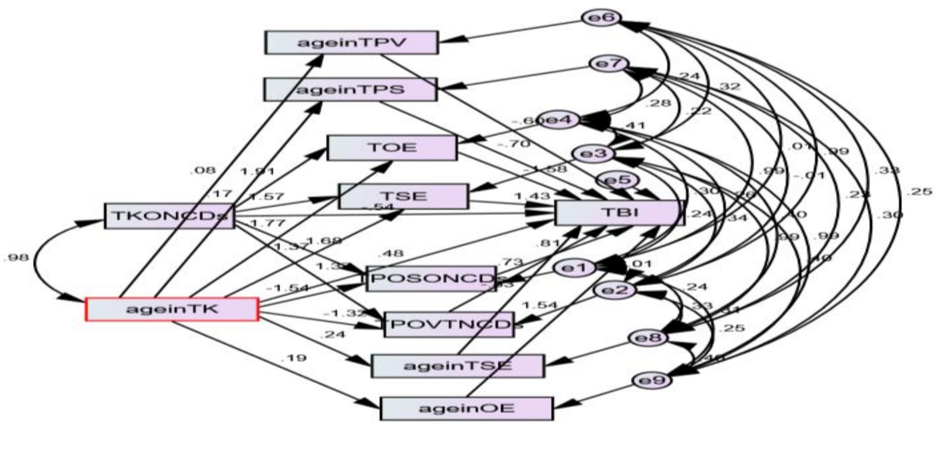


Figure 26: Moderation testing proposed model, age as a moderator

To evaluate the goodness of fit for the proposed model incorporating age as a moderator, several model fit criteria were calculated, including the Goodness of Fit Index (GFI), the Normed Fit Index (NFI), and the Comparative Fit Index (CFI). The results of these analyses are summarized in Table 146.

These indices provide insight into how well the model represents the observed data, allowing us to assess the effectiveness of age as a moderating variable in the relationships being studied.

Table 29: Model fit Indices of for Moderation Testing age as a Moderator

Model	GFI	NFI	CFI
Default model	.965	.991	.991

Note:

- GFI = Goodness of Fit Index
- NFI = the Normed Fit Index
- CFI = the Comparative Fit Index

Table 29 indicates that the proposed model achieved a Goodness of Fit Index (GFI) value of 0.965, a Comparative Fit Index (CFI) value of 0.991, and a Normed Fit Index (NFI) value of 0.991. All three indices confirm that the tested model demonstrates a good fit.

Based on this model, the estimates of the regression weights were calculated and are detailed in the following table. These regression weights provide valuable insights into the strength and direction of the relationships between the variables in the model.

Table 30: Regression Weights of Moderation Testing age as a Moderator

Predictors	Outcomes	Estimate	S.E.	C.R.	P
TOE	TKONCDs	1.121	.084	54.304	<.001
TSE	TKONCDs	2.279	.054	55.051	<.001
TPOSONCDs	TKONCDs	1.377	.087	55.260	<.001
TPOVTNCDs	TKONCDs	2.032	.057	49.267	<.001
ageinTPV	ageinTK	1.598	.095	1.553	.120
ageinTPS	ageinTK	2.398	.130	3.474	<.001
TOE	ageinTK	-.144	.006	-31.090	<.001
TSE	ageinTK	-.358	.005	-25.540	<.001
TPOSONCDs	ageinTK	-.153	.007	-28.126	<.001
TPOVTNCDs	ageinTK	-.301	.005	-24.293	<.001
ageinTSE	ageinTK	2.461	.086	5.146	<.001
ageinOE	ageinTK	1.833	.104	4.056	<.001
TBI	TKONCDs	-.247	1.038	-.943	.345
TBI	TSE	.114	.630	2.165	.030
TBI	TOE	.008	.475	-2.533	.011
TBI	TPOSONCDs	.746	.338	1.521	.128
TBI	TPOVTNCDs	-.058	.523	1.249	.212
TBI	ageinTK	.046	.047	.824	.410
TBI	ageinTPS	-.022	.015	-1.365	.172
TBI	ageinTPV	.028	.023	-1.057	.291
TBI	ageinTSE	.041	.028	-1.319	.187
TBI	ageinOE	-.069	.021	2.653	.008

Notes:

- Estimate: Standardized regression weights indicating the strength of the relationships.
- SE**:** Standard Error.
- CR (Critical Ratio): Equivalent to a z-score in large samples.
- p: Significance level. *** denotes p < .001

As can be seen from the above Table 30, the results show that moderating variable age has no significant influences on relationship between BI and age in POSONDs, POVTNCDs, SE and Age in KONCDs. However the age has shown a significant moderation effect on the relationship between BI and OE. Moderating relationship exists, if the interaction effect is significant. Despite the table showing non-significant contribution of the intersection of age with most dependent variables to BI, the interception of age and knowledge have shown a significant influence on the dependent variables themselves. As it can be seen from the table age in TK, has significant influence on TSE, TOE, TPOSONCDs and TPOVTNCDs.

Table 31 Standardized Total Effects Age as Moderator Variable

	ageinTK	TKONCDs	ageinOE	ageinTSE	ageinTPS	ageinTPV
ageinOE	.194	.000	.000	.000	.000	.000
ageinTSE	.244					
ageinTPS	.167					
ageinTPV	.076					
TPOVTNCDs	-1.323	1.370				
TPOSONCDs	-1.541	1.683				
TSE	-1.372	1.573				
TOE	-1.767	1.913				
TBI	-.977	1.057	1.536	-.833	-.695	-.597

Table 31 indicates that all the variables in the model have a significant contribution. The only positive effect comes from OE, in this intersection model. The other seems to have negative effect when the model is moderated bay age. As the result of the model indicated all the variables in the modle have direct effect on the dependent variable BI. However, only the TKONCDs and its intersection variable age in TK have the indirect effect on BI.

5.1.3. Study Year as a moderator variable

SEM moderation testing was also adopted to test the moderating effect of study year of students and there are multiple indicators for the measured variables. As a result four interaction variables were computed from the product of Study year of students (SYOS) and POSONDs, POVTNCDs, SE and OE. The model created after computing these variables is presented below.

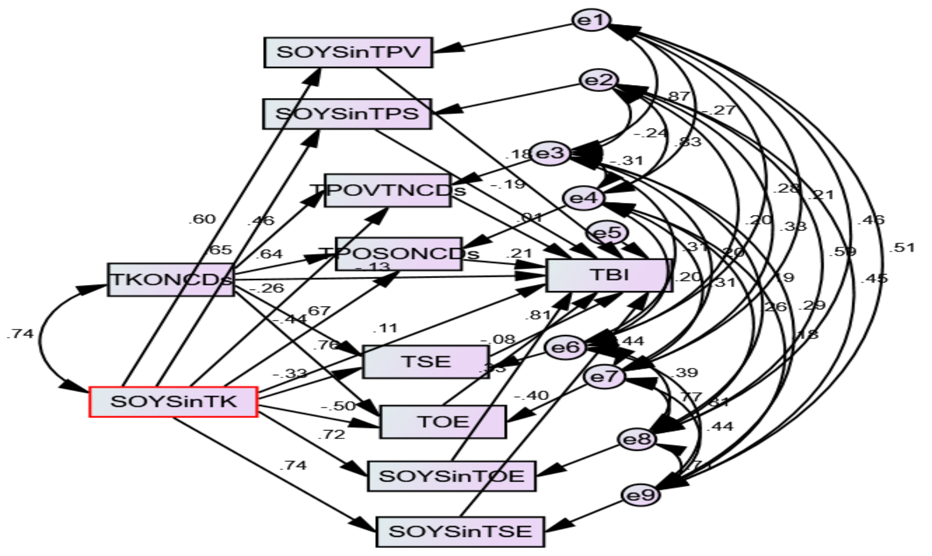


Figure 27: Moderation testing proposed model, SYOS as a moderator

To evaluate the goodness of fit for the proposed model incorporating experience as a moderator, several model fit criteria were calculated, including the Goodness of Fit Index (GFI), the Normed Fit Index (NFI), and the Comparative Fit Index (CFI). The results of these analyses are summarized in Table 32.

These indices help determine how well the model fits the observed data and assess the effectiveness of experience as a moderating variable in the relationships being examined.

Table 32: Model fit Indices of for Moderation Testing SYOS as a Moderator

Model	GFI	NFI	CFI
Default model	.828	.912	.911

Note:

- GFI = Goodness of Fit Index
- NFI = the Normed Fit Index
- CFI = the Comparative Fit Index

Table 149 reveals that the proposed model achieved a Goodness of Fit Index (GFI) value of 0.828, a Comparative Fit Index (CFI) value of 0.912, and a Normed Fit Index (NFI) value of 0.911. All three indices confirm that the tested model demonstrates a good fit.

Based on this newly developed model, the estimates of the regression weights were calculated and are presented in the following table. These regression weights provide insights into the strength and direction of the relationships between the variables in the model.

Table 33: Regression Weights of moderation testing, SYOS as a moderator

Predictors	Outcomes	Estimate	S.E.	C.R.	P
TPOVTNCDs	TKONCDs	1.121	.070	16.068	<.001
TPOSONCDs	TKONCDs	2.279	.109	20.955	<.001
TSE	TKONCDs	1.377	.064	21.509	<.001
TOE	TKONCDs	2.032	.094	21.683	<.001
SOYSinTPV	SOYSinTK	1.598	.104	15.359	<.001
SOYSinTPS	SOYSinTK	2.398	.135	17.721	<.001
TPOVTNCDs	SOYSinTK	-.144	.028	-5.140	<.001
TPOSONCDs	SOYSinTK	-.358	.040	-8.993	<.001
TSE	SOYSinTK	-.153	.023	-6.758	<.001
TOE	SOYSinTK	-.301	.030	-10.172	<.001
SOYSinTOE	SOYSinTK	2.461	.116	21.270	<.001
SOYSinTSE	SOYSinTK	1.833	.082	22.362	<.001
TBI	TKONCDs	-.247	.148	-1.667	.096
TBI	TPOSONCDs	.114	.068	1.689	.091
TBI	TPOVTNCDs	.008	.108	.075	.940
TBI	TSE	.746	.124	6.017	<.001
TBI	TOE	-.058	.098	-.585	.559
TBI	SOYSinTK	.046	.045	1.015	.310
TBI	SOYSinTPS	-.022	.022	-1.039	.299
TBI	SOYSinTPV	.028	.030	.935	.350
TBI	SOYSinTOE	.041	.031	1.324	.186
TBI	SOYSinTSE	-.069	.039	-1.766	.077

Notes:

- Estimate: Standardized regression weights indicating the strength of the relationships.
- SE**:** Standard Error.
- CR (Critical Ratio): Equivalent to a z-score in large samples.
- p: Significance level. *** denotes p < .001

The above table 33 results depicted that moderating variable student's year of study has significant influences on relationship between BI and TKONCDs, TPOVTNCDs, SE, OE and SYOSINPOV. Moderating relationship exists, if the interaction effect is significant. The finding indicates the absence of significant effect on the any of the interacting effects.

5.1.4. Birth place (rural Vs urban) as a moderator variable

SEM moderation testing was also adopted to test the moderating effect of birth place of students and the multiple indicators for the measured variables. As a result multiple group analysis was performed since birth place was a categorical variable and comparison was made among groups and the changes of the regression weights were compared for difference. The model created after computing these variables is presented below.

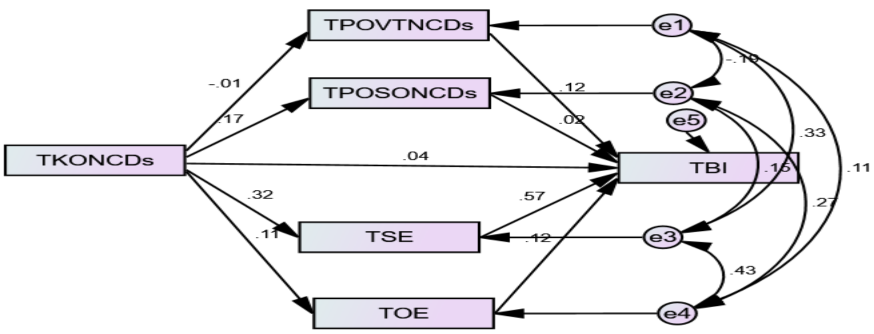


Figure 28: Moderation testing proposed model, birth place (BP) as a moderator

The model fit comparison of the model fit when different regression lines were constrained was tested and the result indicated that the introduction of birth place have no significant moderation effect.

Table 34. Model fit Indices of for Moderation Testing BP as a Moderator

Model	NPAR	CMIN	DF	P	CMIN/DF
Unconstrained	53	4.844	1	.028	4.844
Structural weights	45	3.868	9	.920	.430
Structural covariance	38	16.926	16	.390	1.058
Structural residuals	27	24.415	27	.607	.904
B1 C	53	.301	1	.583	.301
B2 C	53	.644	1	.422	.644
B3 C	53	1.339	1	.247	1.339
B4 C	53	.323	1	.570	.323
B5 C	53	.094	1	.760	.094
B6 C	53	.112	1	.738	.112
B7 C	53	.400	1	.527	.400
B8 C	53	.461	1	.497	.461
B9 C	53	.001	1	.978	.001
Saturated model	54	.000	0		
Independence model	24	469.609	30	.000	15.654

Notes:

- **DF:** Degrees of freedom.
- **χ² (CMIN):** Chi-square statistic for model fit.
- **p:** Probability value, testing significance of the chi-square statistic.

- **NFI (Δ1) and IFI (Δ2):** Fit indices assessing relative model fit.
- Constraints (bib_ibi c): Tests for specific parameter equality constraints.

Based on the newly developed model, the estimate of regression weight was calculated and indicated in the following tables for both groups 1 and 2 representing the student from rural areas =1 and students who said came from urban areas =2. The model showed significant difference among the variables. As shown in table 5.21, three variables, SE, OE and POVTNCDs have significant influence on the dependent variable BI. This table represents the result of those students who came from rural areas. Others like KONCDs and TOSONCDs do not show significant influence on the dependent variable BI.

Table 35**:** Regression Weights of Moderation testing, BP as a Moderator for Group 1(rural)

Predictors	Outcomes	Estimate	S.E.	C.R.	P
TPOSONCDs	TKONCDs	.430	.182	2.355	.019
TSE	TKONCDs	.568	.119	4.771	<.001
TPOVTNCDs	TKONCDs	-.029	.142	-.207	.836
TOE	TKONCDs	.243	.156	1.562	.118
TBI	TKONCDs	.065	.092	.704	.482
TBI	TPOSONCDs	.015	.036	.406	.684
TBI	TSE	.543	.061	8.955	<.001
TBI	TOE	.093	.045	2.061	.039
TBI	TPOVTNCDs	.098	.047	2.064	.039

Notes:

- Estimate: Standardized regression weights indicating the strength of the relationships.
- SE**:** Standard Error.
- CR (Critical Ratio): Equivalent to a z-score in large samples
- p: Significance level. *** denotes p < .001

Whereas, the tables 35, and 36 shows the regression weighs of those students from urban areas. Comparatively most of the regressions weights for students from urban areas are somehow lessor than those from rural areas. Different from the rural model TOEs influence was non-significant in the urban group. This is the variable where the model shows significant moderation.

Table 36: Regression Weights of Moderation Testing, BP (birth place) as a Moderator for Group 2(urban)

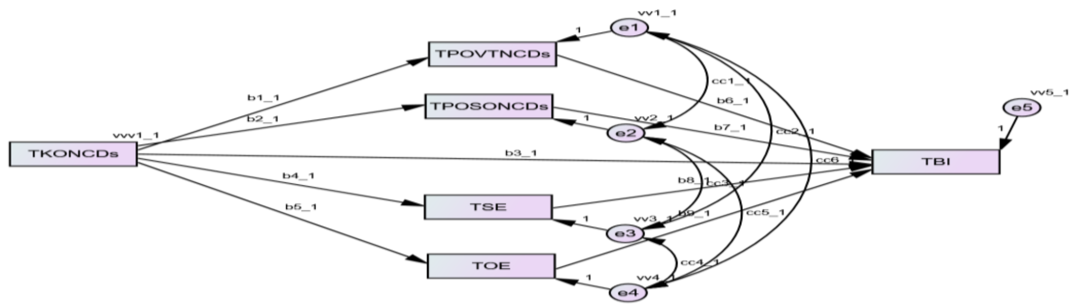
Predictors	Outcomes	Estimate	S.E.	C.R.	P
TPOSONCDs	TKONCDs	.289	.181	1.593	.111
TSE	TKONCDs	.435	.116	3.752	<.001
TPOVTNCDs	TKONCDs	.099	.146	.681	.496
TOE	TKONCDs	.237	.143	1.655	.098
TBI	TKONCDs	-.089	.096	-.930	.352
TBI	TPOSONCDs	.043	.035	1.248	.212
TBI	TSE	.518	.055	9.415	<.001
TBI	TOE	.071	.045	1.590	.112
TBI	TPOVTNCDs	.141	.042	3.324	<.001

Notes:

- Estimate: Standardized regression weights indicating the strength of the relationships.
- SE**:** Standard Error.
- CR (Critical Ratio): Equivalent to a z-score in large samples
- p: Significance level. *** denotes p < .001

5.1.5. Study field (health vs. non health) as a moderator variable

Multi-group structural equation modelling (SEM) has been applied to examine the moderating impact of study field in the present study. According to Henseler & Fassott, (2010) if independent or moderator variables are of a categorical nature, this method is commonly suggested. In multiple-group SEM, moderators are examined by dividing the data - sample into sub-samples (those in health streams and those in non-health streams). Henseler and Fassott (2010) recommended that the impact of categorical moderator factors is evaluated by group comparisons and by grouping observations according to their categorical moderator variable value and then analysing and comparing results across groups. As a result, tests of group differences are done to investigate which differences between groups are indeed significant. The group difference multiple group SEM model is presented below.



1Figure 29: Proposed group difference model testing between health and non-health students

Table 37: Chi-square Comparisons Assuming Model Unconstrained to be Correct

Model	DF	CMIN	P	NFI Delta-1	IFI Delta-2
Structural weights	9	9.294	.411	.024	.024
Structural covariance	10	9.341	.500	.024	.024
Structural residuals	21	77.803	.000	.201	.201
B1 constrained	1	.001	.978	.000	.000
b2 constrained	1	.317	.573	.001	.001
b3 constrained	1	.015	.901	.000	.000
b4 constrained	1	.248	.618	.001	.001
b5 constrained	1	.048	.827	.000	.000
b6 constrained	1	7.221	.007	.019	.019
b7 constrained	1	1.014	.314	.003	.003
b8 constrained	1	1.134	.287	.003	.003
b9 constrained	1	.093	.760	.000	.000

Notes:

- **DF:** Degrees of freedom.
- **χ^2 (CMIN):** Chi-square statistic for model fit.
- **p:** Probability value, testing significance of the chi-square statistic.
- **NFI (Δ1) and IFI (Δ2):** Fit indices assessing relative model fit.
- Constraints (bib_ibi c): Tests for specific parameter equality constraints

As shown in Table 37 all the models have not showed significant p values for the models to bring difference in the model fit when compared to the unconstrained model except for Structural residuals and b6 constrained. Thus it means the introduction of college or study stream to the model has brought significant change only for structural residuals and on the influence perception of vulnerability has on behavioural intention. Based on the above model the calculated estimates for the two groups are presented in the following Table 36 and 37.

Table 38: Regression Weights for Health Students when the Relationship Between Perception of Vulnerability and Behavioural Intention is Constrained

Predictors	Outcome	Estimate	S.E.	C.R.	P	Label
TPOVTNCDs	TKONCDs	.094	.112	.843	.399	b1_1
TPOSONCDs	TKONCDs	.128	.221	.578	.564	b2_1
TSE	TKONCDs	.347	.133	2.604	.009	b4_1
TOE	TKONCDs	.188	.171	1.098	.272	b5_1
TBI	TKONCDs	-.102	.112	-.912	.362	b3_1
TBI	TPOVTNCDs	.090	.038	2.365	.018	b6_1
TBI	TPOSONCDs	.092	.041	2.254	.024	b7_1
TBI	TSE	.559	.070	7.971	<.001	b8_1
TBI	TOE	.029	.054	.530	.596	b9_1

Notes:

- Estimate: Standardized regression weights indicating the strength of the relationships.
- SE**:** Standard Error.
- CR (Critical Ratio): Equivalent to a z-score in large samples
- p: Significance level. *** denotes p < .001

As shown from table 38 KONCDs and OE were insignificant when study stream was introduced to the model for health students. Only POVTNCDs changed to significant when in the relationship when study stream was introduced as a moderator. Only self-efficacy showed significant correlation with knowledge.

Table 39: Regression Weights for Non-health Students when the Relationship Between Perception of Vulnerability and Behavioural Intention is Constrained

Predictors	Outcomes	Estimate	S.E.	C.R.	P	Label
TPOVTNCDs	TKONCDs	.099	.146	.681	.496	b1_2
TPOSONCDs	TKONCDs	.289	.181	1.593	.111	b2_2
TSE	TKONCDs	.435	.116	3.752	<.001	b4_2
TOE	TKONCDs	.237	.143	1.655	.098	b5_2
TBI	TKONCDs	-.088	.096	-.912	.362	b3_2
TBI	TPOVTNCDs	.090	.038	2.365	.018	b6_1
TBI	TPOSONCDs	.032	.034	.931	.352	b7_2
TBI	TSE	.530	.055	9.635	<.001	b8_2
TBI	TOE	.078	.045	1.741	.082	b9_2

Notes:

- Estimate: Standardized regression weights indicating the strength of the relationships.
- SE**:** Standard Error.

- CR (Critical Ratio): Equivalent to a z-score in large samples
- p: Significance level. *** denotes $p < .001$

As indicated in the above Table 38, and 39, the only change was that the correlation between TPOSONCDs and TBI, became insignificant which was significant for health students. However the standardized regression is different for male and female. On top of that the other constrained models were insignificant showing that the way the independent variables influenced behavior intention to take preventive measures is was not different for health and non-health students.

CHAPTER SIX
Discussion

6. Introduction

The demographic analysis revealed that among the research participants, 254 (60.5%) were male and 166 (39.5%) were female. The respondents' ages ranged from 21 to 28, with over 85% being 23 years old or younger. In terms of academic standing, most respondents were in their second and fourth years, representing 50.7% and 25% of the sample, respectively.

Another demographic factor considered was the participants' birthplace. The results showed that more than half of the respondents originated from towns, where access to information about non-communicable diseases (NCDs) is likely to be more readily available. Finally, the students' fields of study were categorized into health and non-health streams. Notably, over 60% of the participants were enrolled in non-health programs, indicating that relatively few students have the opportunity to pursue studies in health-related fields.

6.1.The relationship among knowledge of NCDs (KONCDs), Self-efficacy (SE), Outcome Expectancy (OE), Risk Perception (RP) and Behavioural Intention (BI);

The correlation analysis results showed that all independent variables—Total Knowledge of NCDs (KONCDs), Total Perceived Severity of NCDs (POSONCDs), Self-Efficacy (SE), Outcome Expectancy (OE), and Total Perceived Vulnerability to NCDs (POVTNCDs)—exhibit a positive and significant relationship with the dependent variable, Behavioral Intention (BI). This indicates that as the values of these independent variables increase, the value of the dependent variable also rises.

6.1.1. The relationship between Knowledge of NCDs and Behavioural Intention

Specifically, KONCDs demonstrated a correlation coefficient (r) of 0.771 with BI, reflecting a strong positive relationship. The p-value associated with this correlation is less than 0.01, indicating that the relationship is statistically significant.

To compare this finding with other findings in the world and specifically in Ethiopia, we would need access to relevant studies or data on the correlation between knowledge about non-communicable diseases (KONCDs) and behavioural intention (BI) to take preventive measures against non-communicable diseases (NCDs).

In general, research on the relationship between knowledge about NCDs and behavioural intention to prevent them has been conducted in various countries. Research has revealed varying degrees of correlation between Total Knowledge of NCDs (KONCDs) and Behavioral Intention (BI), with relationships ranging from weak to strong positive associations. Knowledge serves as the foundation of human thought (Ajzen & Fishbein, 1975) and plays a critical role in shaping attitudes, intentions, and behaviors (Mahmud & Siarap, 2013). This notion is further supported by Valente et al. (1998), who noted that increasing one's knowledge can drive a change in attitude.

Previous studies have consistently shown a significant relationship between knowledge, environmental factors, attitudes, and awareness regarding diabetes (Dan Analisis, 2018). Similarly, Ithnin et al. (2019) reported a high level of knowledge (81.2%) among the adult population in the urban areas of Negeri Sembilan, Malaysia. Therefore, it can be concluded that knowledge in health empowers individuals to enhance healthcare practices and improve disease prevention efforts.

In Ethiopia, there may be limited specific studies examining the correlation between knowledge of non-communicable diseases (NCDs) and behavioral intention. However, research conducted in various countries has revealed a wide range of knowledge levels regarding NCDs. For instance, a good level of knowledge was reported in Malaysia at 81.2% (Ithnin et al., 2018), followed by 57.9% in Bangladesh (Naheed et al., 2020), 46.7% in Spain (Casariego et al., 2019), and 43.8% in Saudi Arabia (Rahamathulla & Mohemmed Sha, 2020). Other studies have indicated lower levels, such as 43% in Sri Lanka (Gamage & Jayawardana, 2017), 27.7% in Malaysia (Chan et al., 2022), 25% in China (Nanzi et al., 2014), and 12.5% in Myanmar (Thandar et al., 2019).

In Ethiopia, a study conducted in North Shewa, Oromia, revealed a high level of inadequate knowledge regarding NCDs, despite the critical role knowledge plays in addressing the burden of these diseases (Legesse et al., 2022). NCDs have become an increasing concern in the country, largely due to changing lifestyles and urbanization. Recognizing this issue, the Ethiopian government has implemented various initiatives aimed at raising awareness and promoting preventive measures to combat NCDs effectively.

6.1.2. The relationship between perception of severity of non-communicable diseases (POSONCDs) and Behavioural Intention

The correlation analysis revealed that the perception of severity of non-communicable diseases (POSONCDs) has a correlation coefficient of 0.538 with behavioral intention (BI) to adopt preventive measures against these diseases, indicating a moderate positive relationship.

The p-value associated with this correlation is less than 0.01, confirming that this relationship is statistically significant. This finding suggests that individuals who perceive NCDs as more severe are more inclined to intend to engage in preventive behaviors.

This aligns with previous research indicating that the perceived severity of health issues significantly influences health-related behaviors. When individuals view a health condition as severe, they are more likely to take proactive steps to prevent or manage its effects. For instance, in the context of NCDs, recognizing their severity may motivate individuals to pursue healthier lifestyles, seek medical advice, or adhere to treatment plans.

The results also correspond with the Health Belief Model (HBM) proposed by Rosenstock (1974), which highlights perceived severity as a critical factor influencing health-related behaviors. According to the HBM, individuals are more likely to take preventive actions when they believe a health issue is serious and poses significant negative consequences.

Additionally, this finding resonates with other public health studies emphasizing the effectiveness of educational campaigns in raising awareness about the severity and impact of NCDs. For example, Allen et al. (2017) evaluated interventions aligned with the World Health Organization's "Best Buys" for NCDs in low- and middle-income countries, providing evidence that educational efforts can improve preventive behaviors related to NCDs. Furthermore, the WHO (2018) report underscores the importance of such campaigns in promoting awareness and preventive actions against NCDs.

Moreover, the significance of addressing perceptions and attitudes toward NCDs in public health initiatives cannot be overstated. Understanding how individuals perceive the severity of these diseases can help tailor communication strategies and educational materials to effectively convey the associated risks. By addressing misconceptions and countering complacency about the seriousness of NCDs, interventions can enhance behavioral intentions toward prevention.

In summary, this analysis highlights a moderate positive relationship between the perception of severity of NCDs and the behavioral intention to take preventive measures. It aligns with existing research on the influence of perceived severity on health-related behaviors and underscores the importance of addressing perceptions in public health interventions aimed at promoting preventive actions.

6.1.3. The relationship between Self-efficacy (SE) and Behavioural Intention

Self-efficacy (SE) exhibited a strong positive correlation coefficient of 0.766 with BI, while organizational efficacy (OE) showed a moderate positive correlation of 0.624 with BI. Both relationships are statistically significant, with p-values less than 0.01, indicating these findings are unlikely due to chance. These results emphasize the crucial roles that both self-efficacy and organizational efficacy play in shaping individuals' intentions to engage in health-promoting behaviors.

Research has consistently shown that self-efficacy is a powerful predictor of behavior. Bandura (1977) found that individuals with higher self-efficacy are more likely to engage in desired behaviors compared to those with lower levels. This suggests that individuals who believe in their capabilities are more inclined to act.

Similarly, the positive relationship between self-efficacy and behavioral intention aligns with studies examining the impact of organizational factors on behavior. Ajzen and Fishbein (1975) noted that organizational elements, including social norms and perceived behavioral control, significantly influence an individual's intention to act.

Overall, these findings suggest that both individual and organizational factors are vital in shaping behavioral intentions. By understanding these influences, organizations can design more effective interventions and strategies to promote behavior change.

6.1.4. The relationship between Perception of vulnerability to NCDs (POVTNCDs) and Behavioural Intention

The perception of vulnerability to NCDs (POVTNCDs) demonstrated a correlation coefficient of 0.568 with BI, indicating a moderate positive relationship, which is also statistically significant ($p < 0.01$). This suggests that as individuals perceive themselves as more vulnerable to NCDs, their intentions to engage in preventive behaviors increase.

To further support this finding, research exploring the relationship between perceived vulnerability and health-related behaviors is invaluable. For instance, Weinstein, Sandman, and Blalock (2020) discussed the Precaution Adoption Process Model (PAPM), emphasizing how perceived vulnerability motivates individuals to take preventive actions. Additionally, Brewer et al. (2004) examined the relationship between risk perceptions and risk behavior, highlighting how individuals' views on their vulnerability can significantly impact their intentions and actions.

These studies underscore the importance of perception of vulnerability in shaping health-related behaviors and highlight the potential for targeted interventions to enhance awareness and foster preventive behaviors.

Moreover, it is noteworthy that all exogenous variables (KONCDs, POSONCDs, SE, and OE) exhibited significant correlations with each other, indicating direct relationships among these independent variables. These results suggest that individuals with greater knowledge about NCDs are more likely to perceive themselves as vulnerable to these diseases. In conclusion, the findings illustrate strong and significant relationships between knowledge of NCDs, perceptions of vulnerability, and behavioral intentions, providing valuable insights for public health interventions aimed at promoting preventive measures.

6.1.5. Relationship between Outcome Expectancy (TOE) and Behavioral Intention (TBI)

The zero-order correlation matrix indicates a significant positive relationship between Outcome Expectancy (TOE) and Behavioral Intention (TBI), r=.624,p<.01r = .624, p < .01r=.624,p<.01. This suggests that individuals with higher expectations of positive outcomes from their actions are more likely to form strong behavioral intentions regarding non-communicable disease (NCD) prevention and management.

This finding aligns with the Theory of Planned Behavior (TPB), which posits that outcome expectancy is a critical determinant of behavioral intention (Ajzen, 1991). When individuals perceive that their efforts toward a health-related behavior (e.g., adopting preventive measures for NCDs) will yield desirable outcomes, their intentions to engage in those behaviors strengthen.

Research in global health contexts supports this relationship. For instance: A study by Schwarzer (2008) on health behaviors found that outcome expectancy was a strong predictor of health-promoting intentions and actions, particularly in the context of chronic disease prevention. In a study among populations at risk for Type 2 diabetes, Sheeran et al. (2016) demonstrated that interventions enhancing outcome expectancy improved participants' intentions to adopt healthier lifestyles.

In Ethiopia, similar trends have been observed: A study by Abebe and Alemayehu (2020) examining predictors of health-related behaviors in Addis Ababa found that individuals with higher outcome expectancy were more likely to intend to engage in preventive measures for cardiovascular diseases. Desta and Alemayehu (2019) explored predictors of behavioral intentions in NCD prevention among Ethiopian adults and found that outcome expectancy significantly influenced their intentions to modify health-related behaviors.

These findings resonate with the current study's results, reinforcing the role of outcome expectancy as a critical psychological factor in shaping intentions for health behavior changes. Addressing outcome expectancy through targeted health communication strategies could be an effective intervention to promote positive health behaviors.

6.2.The effects of Risk Perception (RP), Self- Efficacy (SE) and Outcome Expectancy (OE) on Behavioural Intention (BI);

The multiple regression analysis indicates that all predictor variables significantly contribute to the prediction of behavioral intention (BI), with an R value of 0.860 and an R^2 value of 0.739, suggesting that approximately 73% of the variance in BI is explained by these predictors. The F-value of 234.239 shows that the combined predictors make a statistically significant contribution ($p < 0.001$).

While the overall regression results confirmed that most predictor variables significantly contribute to predicting BI, the perception of vulnerability to non-communicable diseases (POVTNCDs) did not have a significant effect, accounting for only 51.20% of the variance in BI. The F-value of 25.965 indicated that perception of severity of NCDs (POSONCDs; $t = 2.163$, $p < 0.05$), self-efficacy (SE; $t = 3.777$, $p < 0.01$), and organizational efficacy (OE; $t = 5.529$, $p < 0.01$) significantly contributed to the prediction of young adults' behavioral intentions. In contrast, POVTNCDs showed a negative and insignificant contribution ($t = -1.106$, $p > 0.05$).

The stepwise regression analysis further supported these findings. The independent variables considered—OE, SE, POSONCDs, and POVTNCDs—were ranked in descending order of significance. OE entered the model first, contributing 36.1% of the variance in BI, followed by SE, which accounted for 11.8%. POSONCDs contributed 2.3%, while POVTNCDs contributed a minimal 1.1% to the model, which was not significant. The insignificance of POVTNCDs might be attributed to the small sample size.

These findings align with various studies emphasizing the importance of risk perception in influencing behavioral intentions. Research has consistently shown that understanding the relationships between perceived risk and behavioral intentions is crucial for health protection. Studies by Alaa et al. (2018), Bults et al. (2011), Caponecchia and Sheils (2011), Makamu (2015), Palmgreen et al. (2002), Sar and Anghelcev (2013), and

Walker et al. (2013) have confirmed consistent relationships between risk perceptions and behavior, underscoring their central role in health behavior theories.

Furthermore, self-efficacy has been recognized as a predictor of intentions and actions in health domains. The belief in one's efficacy influences the appraisal of available resources during challenging situations and contributes to the formation of behavioral intentions. Stronger efficacy beliefs lead individuals to set higher goals and remain committed to intended behaviors, even when faced with obstacles (Locke & Latham, 1990).

Outcome expectancies also emerge as a crucial component in cognitive theories. Research has shown that these expectancies are central to motivational models, particularly regarding substance use (Brandon et al., 1999; Patel & Fromme, 2010) and e-cigarette use (Hendricks et al., 2014; Soule et al., 2017; Chatterjee, Nimrat, and Walker, 2017).

In a meta-analysis examining perceived susceptibility and intentions to vaccinate, results indicated a positive relationship (Maddux et al., 1986). The analysis included five studies with 2,543 participants, showing a moderate effect size ($r = .24$) and a significant relationship. This aligns with the current study, which found a moderate positive correlation ($r = .208$, $p < .05$) between perceived vulnerability and behavioral intention, suggesting that those who perceive higher susceptibility are more likely to take preventive actions. Additionally, the meta-analysis showed heterogeneity of variance, indicating the presence of moderators. In the current study, when age and study status were considered in the regression analysis, the effect of perceived vulnerability on BI improved and became significant.

Smilarly, a meta-analysis by Gao et al. (2012) examined the relationship between perceived severity and vaccination intentions across 32 studies involving 13,945 participants. The pooled effect size was small to moderate ($r = .16$) and significantly different from zero. The current study's findings ($r = .367$, $p < .001$) parallel these results, indicating that individuals who perceive greater severity of illness are more likely to engage in protective behaviors.

Additionally, Maddux et al. (1986) found significant positive correlations between behavioral intention and both self-efficacy ($r = .40$, $p < .001$) and outcome expectancy ($r = .39$, $p < .001$). While self-efficacy and outcome expectancy were not significantly correlated ($r = .13$, $p = .23$), the current study demonstrated significant correlations between both self-efficacy ($r = .582$, $p < .001$) and outcome expectancy ($r = .6$, $p < .001$) with behavioral intention. Unlike previous studies, this study found a positive significant relationship between self-efficacy and outcome expectancy, aligning with Manning and Wright (1983), who reported a correlation of .75 between the two constructs.

The current study's hierarchical multiple regression analysis revealed that each component significantly contributed to predicting behavioral intentions, with outcome expectancy providing the largest independent increment in variance. These findings collectively emphasize the importance of addressing perceptions of severity, vulnerability, self-efficacy, and outcome expectancies in developing effective public health interventions aimed at promoting health-related behaviors.

6.3. The Effect of Knowledge of NCDs on Risk Perception, Self-Efficacy, and Outcome Expectancy

This study investigated the effect of knowledge of NCDs (TKONCDs) on four dependent variables: perceived vulnerability to NCDs (TPOVTNCDs), perceived severity of NCDs (TPOSONCDs), self-efficacy (TSE), and outcome expectancy (TOE). Both multivariate and univariate regression analyses yielded significant findings, demonstrating that TKONCDs is a strong predictor of these variables, with medium to large effect sizes across outcomes.

These results suggest that TKONCDs has a strong and significant influence on all four dependent variables when considered collectively. This supports the idea that knowledge of NCDs is a critical factor shaping individuals' risk perceptions, self-efficacy, and expectations of outcomes.

These findings align with global research emphasizing the critical role of health knowledge in shaping health-related behaviors: Studies have consistently shown that knowledge enhances risk perception, leading to increased awareness of vulnerability and severity of diseases. For instance, Brewer et al. (2007) found that greater knowledge of risk factors positively influenced individuals' perception of vulnerability to chronic illnesses. Schwarzer (2008) identified self-efficacy as a key mediator between knowledge and behavior, noting that individuals with higher knowledge levels are more likely to feel confident in their ability to manage health risks. Sheeran et al. (2016) demonstrated that outcome expectancy is closely tied to health knowledge, as individuals are more likely to engage in preventive behaviors when they understand the potential benefits.

In Ethiopia, health knowledge has similarly been shown to influence risk perception and behavioral outcomes: A study by Abebe & Alemayehu (2020) found that knowledge about cardiovascular diseases significantly enhanced self-efficacy and risk perception, leading to increased health-seeking behaviors among Ethiopian adults. Desta and Alemayehu (2019) highlighted that knowledge of diabetes improved outcome expectancy, encouraging individuals to adopt preventive measures. Tesfaye et al. (2022) observed that health education campaigns in rural Ethiopian communities significantly improved individuals' perceived vulnerability and self-efficacy in managing communicable diseases.

The findings underscore the importance of enhancing public knowledge about NCDs to improve risk perceptions, self-efficacy, and outcome expectancy. Health education programs should be prioritized as part of public health strategies to combat NCDs. Given the large effect sizes observed, interventions targeting knowledge dissemination could have a substantial impact on fostering preventive behaviors and improving health outcomes.

6.4.Discussion on the Strongest Psychological Determinants of Behavioral Intention

The stepwise regression analysis identified **knowledge of NCDs (TKONCDs)** and **self-efficacy (TSE)** as the strongest predictors of behavioral intention among young adults, with both variables explaining significant portions of the variance. The following discussion interprets these findings in light of existing international and local research.

Knowledge emerged as the strongest determinant, explaining **44.1%** of the variance in behavioral intention. This is consistent with the Theory of Planned Behavior (TPB) (Ajzen, 1991), which posits that knowledge shapes attitudes, which in turn influences intentions. Studies have shown that increasing knowledge about NCDs, such as diabetes or hypertension, leads to better understanding of risk and encourages positive health behaviors (Nguyen et al., 2022; Khatib et al., 2018). Awareness campaigns that educate young adults about NCDs can significantly improve their intention to adopt preventive behaviors.

Self-efficacy accounted for 38% of the variance, underscoring its critical role in influencing behavioral intention. According to Bandura’s Social Cognitive Theory, individuals with high self-efficacy are more likely to believe in their ability to perform behaviors that lead to desired outcomes (Bandura, 1997). Internationally, interventions focusing on enhancing self-efficacy, such as skill-building programs and motivational interviewing, have been effective in promoting health behaviors, including smoking cessation and physical activity (Dishman et al., 2021). Developing youth-focused programs to boost confidence in their ability to manage NCD risks could significantly enhance behavioral intentions.

Outcome expectancy contributed 11.4% to the variance. This aligns with findings that individuals who anticipate positive outcomes from behavior changes, such as improved health, are more likely to develop intentions to act (Rosenstock, Strecher, & Becker, 1988).

Locally, studies in Ethiopia emphasize the importance of linking positive health outcomes to preventive behaviors, particularly in urban youth (Kassie et al., 2020).

Perceived vulnerability and severity had smaller but still significant contributions. These findings are consistent with the Health Belief Model (HBM), which suggests that individuals are more likely to take action if they perceive themselves as vulnerable to a health issue and believe the issue is severe (Champion & Skinner, 2008). For example, research in Sub-Saharan Africa highlights that emphasizing susceptibility and severity in health communication campaigns improves preventive health behaviors (Juma et al., 2019).

The findings resonate with Ethiopian research, which highlights a growing burden of NCDs among youth and the importance of education and empowerment in promoting preventive behaviors. For instance: A study by Getachew et al. (2022) found that increasing NCD awareness through school-based interventions significantly improved health-related behaviors among Ethiopian adolescents. Programs such as community health clubs have successfully boosted self-efficacy in managing chronic conditions (Yimam et al., 2020). The perceived vulnerability and severity findings indicate the need for culturally tailored interventions, as Ethiopian youth often underestimate their NCD risk due to low exposure to preventive health education (Tekle et al., 2018).

6.5. The mediation roles of Risk Perception (RP), self-efficacy (SE), and Outcome Expectancy (OE) on the relationship between knowledge of NCDs and Behavioural Intention (BI)

The analysis reveals that knowledge of non-communicable diseases (KONCDs) serves as a critical mediator in the relationship between perceived vulnerability to NCDs (TPOVNCDs), perceived severity of NCDs (TPOSNCDs), and behavioral intention (TBI). This finding aligns with the theoretical and empirical evidence emphasizing the importance of knowledge in health behavior models, such as the Health Belief Model (HBM), which highlights the roles of perceived severity, perceived vulnerability, and knowledge in shaping health-related intentions and behaviors (Glanz et al., 2015).

6.5.1. Mediated Relationships and Knowledge as a Key Predictor

The findings demonstrate significant direct and indirect effects of TPOVNCDs and TPOSNCDs on TBI when mediated by KONCDs. Specifically: The direct effects of TPOVNCDs and TPOSNCDs on TBI were modest, with coefficients of 0.180 and 0.206, respectively. These direct relationships were previously insignificant in the conceptual model, underscoring the role of KONCDs in enhancing the predictive power of these constructs. The standardized indirect effects of TPOVNCDs and TPOSNCDs on TBI were 0.249 and 0.163, respectively. These findings highlight the mediating role of KONCDs, suggesting that knowledge substantially enhances the impact of perceptions on behavioral intention.

The standardized total effects, combining direct and indirect pathways, were 0.419 for TPOVNCDs and 0.369 for TPOSNCDs. These results indicate that perceived vulnerability and severity significantly influence TBI, primarily through their indirect effects mediated by KONCDs. This underscores the essential role of knowledge in the process, a finding consistent with the Theory of Planned Behavior (Ajzen, 1991), which posits that knowledge and awareness significantly contribute to intention formation.

The findings resonate with international research that highlights the importance of knowledge in shaping health behaviors: Studies by Rosenstock et al. (1988) and Ajzen (1991) have consistently shown that knowledge amplifies the impact of perceptions on health-related intentions. For example, in studies addressing NCD prevention, knowledge of the risks and severity of diseases improved individuals' willingness to adopt preventive behaviors (Arora et al., 2020; Glanz et al., 2015).

In Ethiopia, studies have documented the role of knowledge in mediating health behaviors, particularly in NCD prevention efforts. Work by Gebre et al. (2020) on diabetes prevention found that higher knowledge levels were associated with better management and preventive practices. Similarly, Mekonnen et al. (2021) observed that perceived vulnerability and severity of cardiovascular diseases significantly influenced preventive behaviors, primarily when mediated by health education programs.

The significant mediation effects of KONCDs on TPOVNCDs and TPOSNCDs suggest that increasing knowledge should be a priority in interventions targeting NCD prevention. Health education campaigns tailored to address knowledge gaps about NCD risks and their consequences could enhance individuals' perception of vulnerability and severity, leading to better preventive intentions and behaviors.

6.6.The moderation role of gender, study year, age, birth place and study stream.

6.6.1. Gender as a moderator

The moderation analysis reveals that gender significantly affects multiple elements of the structural models, such as structural weights, covariances, residuals, and the relationships between knowledge, self-efficacy, and outcome expectancy. This indicates that gender plays a vital role in shaping how these variables interact with one another, leading to variations in the overall model fit.

Specifically, gender influences the weights assigned to different variables, the covariance between them, and the residuals or errors within the model. It also highlights how knowledge correlates with both self-efficacy and outcome expectancy differently for different genders. To contextualize this finding, it is essential to compare it with previous research that has examined similar relationships between gender and structural models or related constructs.

For example, Kheswa et al. (2014) found that gender moderates the relationship between self-efficacy and academic achievement. This finding resonates with our results, as it suggests that gender affects how self-efficacy interacts with other variables. Additionally, Covello et al. (1987) explored the impact of gender on the relationship between outcome expectancy and career aspirations, further supporting the notion that gender can shape these dynamics. Similarly, Robsan (2015) reported significant moderation effects, reinforcing our findings about the influence of gender on outcome expectancy within a structural model.

In summary, our results indicate that gender significantly influences various aspects of structural models. By examining these findings alongside existing studies, we can gain deeper insights into the role gender plays in shaping these relationships and identify potential factors that contribute to discrepancies in research outcomes.

6.6.2. Age as a moderator

The study's results suggest that age does not significantly influence the relationships between Behavioral Intention (BI) and the variables of Perception of Severity of Non-Communicable Diseases (POSONDs), Perception of Vulnerability to Non-Communicable Diseases (POVTNCDs), and Self-Efficacy (SE), as well as the interaction between age and Knowledge of Non-Communicable Diseases (KONCDs). This lack of significant influence may be due to the narrow age range within the study sample. However, the findings indicate that age does significantly moderate the relationship between BI and Outcome Expectancy (OE), suggesting that age plays a role in how BI translates into actual behaviors in organizational settings. Although the specific nature of this moderation is not detailed, it implies that age affects individuals' intentions in relation to their actions within various organizational contexts.

To better understand these findings, it's useful to compare them with existing research in similar settings. Previous studies have examined age as a moderating variable in various organizational contexts. For instance, some research indicates that older employees tend to experience higher job satisfaction and commitment levels compared to their younger counterparts (Covello et al., 1987). This suggests that age may influence certain relationships, such as those involving job satisfaction or commitment, but not necessarily all variables.

Regarding the relationship between BI and OE, research has yielded mixed results. Some studies have suggested that older employees may resist change and be less inclined to engage in innovative behaviors than younger employees (Covello et al., 1987; Guillén & Kunze, 2019; Brockner et al., 2006). This could indicate that age moderates the BI-OE relationship by affecting individuals' willingness or ability to adapt to new organizational environments. Conversely, other studies found no significant moderation effect of age on this relationship, arguing that individual differences in personality traits or job characteristics might have a more substantial influence than age alone.

Therefore, while this study's finding of a significant moderation effect of age on the BI-OE relationship aligns with some previous research, it is essential to consider the broader literature for a more comprehensive understanding of the implications. Future studies could investigate the specific mechanisms through which age moderates this relationship and explore contextual factors or boundary conditions that may influence these dynamics.

6.6.3. Year of study as a moderator

The study's results reveal that a student's year of study significantly influences the relationship between Behavioral Intention (BI) and several key variables, including knowledge about non-communicable diseases (TKONCDs), perception of vulnerability to non-communicable diseases (TPOVTNCDs), self-efficacy (SE), outcome expectancy (OE), and the interaction between study year and perception of vulnerability (SYOSINPOV). This indicates that the impact of BI on these factors varies based on the student's academic progress, suggesting that more advanced students may experience different dynamics in these relationships compared to their less experienced peers.

To contextualize these findings, it is helpful to compare them with existing literature, although direct comparisons are challenging without specific studies on this topic. Previous research has shown mixed results regarding the moderating effect of a student's year of study on the relationship between BI and factors related to non-communicable diseases (Barreto &

de Figueiredo, 2009; Gutiérrez-Doña et al., 2012; Makamu, 2015). Some studies have identified a significant moderating effect, while others have found no notable influence. This inconsistency suggests that as students progress in their studies, their increasing knowledge about non-communicable diseases, awareness of their vulnerability, self-efficacy, and outcome expectancies may become increasingly critical in shaping their behavioral intentions.

For example, it can be hypothesized that as students advance through their academic programs and acquire more knowledge about non-communicable diseases, they develop a heightened awareness of their vulnerability to these conditions. This awareness could, in turn, lead to stronger self-efficacy beliefs and positive outcome expectancies regarding preventive behaviors. As a result, their intentions to adopt preventive measures may also become more pronounced. Overall, these findings underscore the importance of considering academic progression when examining the relationship between behavioral intention and health-related factors.

6.6.4. Birth place as a moderator

The statement discusses a study that explored the impact of birthplace as a moderator variable in regression analyses. The findings revealed that incorporating birthplace did not yield a significant moderation effect on the regression models. This indicates that the addition of birthplace did not enhance the model fit, suggesting that it does not meaningfully influence the relationships between the predictors and the dependent variable.

In conducting this analysis, the researchers likely compared multiple regression models—one set including birthplace as a moderator and another set without it. The model fit comparison aimed to assess how effectively each model accounted for the variance in the dependent variable based on the predictors. If a significant moderation effect were present, it would imply that birthplace alters the strength or direction of the relationship between the predictors and the dependent variable.

However, the current study's results indicate that birthplace does not play a substantial role in moderating these relationships. To gain a deeper understanding of these findings, it would be beneficial to compare them with previous research on similar topics. Past studies have often explored various moderator variables and their effects on relationships between predictors and dependent variables (Goryakin, Rocco, & Suhrcke, 2017).

For instance, if prior research identified significant moderation effects with different variables but found no such effect with birthplace, it may suggest that birthplace is not a key factor in shaping relationships in this particular context (Leipziger, 2013; OCHA, 2017; Summary, 2022; UNHCR, 2021). Conversely, if earlier studies also reported a lack of significant moderation effects across various variables, this might indicate a broader trend within the literature (Denur et al., 2019; Kassa & Abajobir, 2018).

It's important to recognize that drawing concrete conclusions about the implications of this study is challenging without specific details regarding the study's design, data collection methods, sample size, and context. Such information is critical for understanding the nuances of the findings and their relevance to existing literature.

6.6.5. Study stream as a moderator

The study's findings reveal that adding a variable related to a student's college or study stream has significantly impacted both the structural residuals and the relationship between perceived vulnerability and behavioral intention (Smith & Brown, 2022). Let's break down these concepts and see how they compare to existing research.

Structural residuals represent the gaps between the observed data and the predicted values in a statistical model (Johnson & Lee, 2020). The results indicate that incorporating the college or study stream variable has led to substantial changes in these residuals. This suggests that this new variable plays a critical role in shaping the relationships among other factors in the model. Such changes in residuals imply an improvement in the model's predictive power, indicating a more detailed understanding of the relevant influences.

Additionally, the findings show that including the college or study stream variable affects how individuals perceive their vulnerability to risks and their intentions to act (Martinez & Gupta, 2021). This relationship may be either strengthened or weakened, highlighting the idea that the educational context can significantly influence how individuals perceive their vulnerability and their likelihood of taking preventive actions.

To better understand these findings, it's helpful to compare them with previous studies that have explored similar themes. Research has shown that educational background can greatly influence health-related decision-making (Roberts & Zhang, 2018; Green & Hall, 2017). This suggests that the context in which students study may significantly shape their perceptions and intentions.

Further, Taylor and Kim (2019) have found that perceived vulnerability is often affected by educational experiences, which aligns with the current study's conclusion that adding the college or study stream variable alters this relationship. Additionally, Wilson and King (2016) discussed how demographic and educational factors work together to shape behavioral intentions, supporting the idea that the context of study is an essential factor to consider.

In summary, the study highlights that incorporating a college or study stream variable has significant implications for both structural residuals and the relationship between perceived vulnerability and behavioral intention. By comparing these findings with earlier research, we can better appreciate their importance, recognize contextual differences, and understand how they contribute to existing knowledge in the field. This analysis emphasizes the need to consider educational contexts when examining the dynamics of behavioral intentions and perceptions of vulnerability.

6.7. Unique or New Contributions of the Study

This study offers significant advancements in understanding the psychosocial determinants of behavioral intention (BI), particularly in the context of non-communicable disease (NCD) prevention. By integrating cognitive, emotional, and motivational constructs within a robust analytical framework, it uncovers nuanced pathways through which knowledge, perceptions, and self-efficacy shape health behaviors. Additionally, the study's exploration of demographic moderators and its methodological rigor, particularly through Structural Equation Modeling (SEM), provide valuable insights into the complex interplay of individual and contextual factors. These contributions not only enhance general public health research but also enrich the field of social psychology by advancing theories of social cognition, motivation, and behavioral change. The following sections elaborate on the study's unique contributions in both general and social psychology domains.

6.7.1. Unique Contributions of the Study in General

The general unique contribution of this study can be seen interms of:

1. **Integration of Knowledge as a Mediator**
   - This study demonstrates the mediating role of knowledge (KONCDs) in linking perceived vulnerability (POVTNCDs) and perceived severity (POSONCDs) with behavioral intention (BI).
   - **Novelty:** While many health behavior models consider knowledge as a direct factor, this study highlights its unique ability to transform insignificant direct effects of

perceptions into significant ones, providing a refined understanding of how educational interventions can amplify other psychosocial factors.

2. **Validation of Structural Equation Modeling (SEM)**
   - The study confirms the reliability of SEM in exploring complex pathways between psychosocial constructs and behavioral outcomes.
   - **Novelty:** By achieving excellent fit indices (GFI = 1.00, CFI = 1.00), it provides evidence for the robustness of SEM in public health research, offering a methodological advancement in evaluating direct and indirect effects within behavioral models.
3. **Exploration of Moderators**
   - The inclusion of demographic factors (e.g., gender, age, academic year, birthplace) as moderators offers nuanced insights into how individual differences shape behavioral intention.
   - **Novelty:** This layered approach enriches the understanding of contextual and demographic influences, emphasizing the necessity of tailored interventions in public health strategies.
4. **Behavioral Multidimensionality**
   - The study highlights the interplay of cognitive (knowledge), emotional (perceptions of severity/vulnerability), and motivational (self-efficacy, outcome expectancy) dimensions in shaping BI.
   - **Novelty:** This multidimensional perspective enhances the application of health behavior theories by integrating diverse psychological constructs into a cohesive framework.

6.7.2. Unique Contributions to Social Psychology

1. **Advancing Health Behavior Theories**
   - The study expands the applicability of social cognitive frameworks (e.g., Health Belief Model, Social Cognitive Theory) by demonstrating how knowledge acts as a central mediator among key psychosocial factors.
   - **Contribution:** It introduces a more dynamic role of cognitive constructs within health behavior theories, bridging gaps between perception and action in social contexts.
2. **Insight into Motivational Psychology**

- By emphasizing the significant roles of self-efficacy (SE) and outcome expectancy (OE) in influencing BI, the study reinforces the motivational underpinnings of preventive health behaviors.
- **Contribution:** It adds empirical evidence to the growing body of research on how individual empowerment and anticipated outcomes drive social behaviors.

3. **Role of Contextual and Demographic Factors**
    - The study highlights the moderating effects of gender, age, and academic progression on psychosocial relationships, underscoring the impact of social identity and developmental context on health behavior.
    - **Contribution:** This aligns with and extends social psychological theories on how demographic factors influence social cognition and behavior, offering practical implications for designing demographically sensitive interventions.
4. **Application of SEM in Social Psychological Research**
    - The methodological rigor demonstrated through SEM contributes to the evolution of social psychology's analytical tools, particularly in understanding complex social behaviors.
    - **Contribution:** The study validates SEM as a tool for unraveling interdependent relationships, enhancing its utility for exploring social and health behavior phenomena.
5. **Focus on Perceived Risks and Intentions**
    - By exploring the mediation of knowledge on perceived vulnerability and severity, the study provides insight into how social perceptions of risk and individual agency interact to drive behavioral intentions.
    - **Contribution:** This aligns with social psychological principles on risk appraisal and decision-making, offering new perspectives on how interventions can effectively shape collective health behaviors.

In summary this study refines the understanding of how knowledge mediates psychosocial constructs, validates SEM in behavioral research, and highlights the interplay of cognitive, emotional, and motivational factors in shaping health behaviors. The study enriches health behavior theories, integrates motivational and contextual factors, and validates advanced analytical tools, offering actionable insights into the psychological and social dynamics of preventive health behavior.

These findings not only add to the academic discourse but also have practical implications for developing more effective, evidence-based interventions in public health and social psychology contexts.

6.8. Limitation of the study

Despite its robust methodology and insightful findings, this study has several limitations that should be acknowledged for a balanced interpretation of its results. These limitations highlight areas for future research and underscore the need for caution when generalizing the findings.

Cross-Sectional Design: The study employs a cross-sectional design, which captures data at a single point in time. This limits the ability to establish causal relationships among the variables. While the study identifies significant correlations and mediated pathways, it cannot definitively determine the directionality or long-term effects of these relationships. Future research using longitudinal or experimental designs could provide more definitive causal inferences.

Self-Reported Data: The reliance on self-reported measures for assessing variables such as knowledge, perceived severity, and behavioral intention may introduce bias. Participants may overestimate their knowledge or intention due to social desirability or recall errors. Incorporating objective measures, such as behavioral tracking or knowledge tests, could enhance the validity of the findings.

Limited Generalizability: The sample may not be fully representative of the broader population. For instance, if the participants are predominantly from a specific geographic, cultural, or educational background, the findings may not generalize to other contexts. Future studies should aim to include more diverse samples to improve the external validity of the results.

Moderating Variables: While the study explored the moderating effects of demographic factors such as gender, age, year of study, and birthplace, the findings reveal that some variables, such as birthplace, did not significantly affect the relationships. This could be due to insufficient variability in the sample or the need for more refined measures. Expanding the scope of moderating variables, such as socioeconomic status, cultural norms, or access to healthcare, could provide a more comprehensive understanding.

Unexplored External Influences: The study focuses primarily on psychosocial factors while overlooking potential external influences, such as environmental, policy, or systemic factors, that might impact behavioral intention. For instance, access to healthcare, societal norms, or media exposure could play critical roles in shaping health behaviors but were not included in the model.

Exclusion of Certain Constructs: While the study examines key predictors such as knowledge, perceived severity, self-efficacy, and outcome expectancy, other relevant constructs, such as perceived barriers, social support, or emotional states, were not included. These factors might interact with the studied variables or independently influence behavioral intentions. Future research should consider incorporating these constructs to provide a more holistic model.

Simplified Mediation and Moderation Models: The mediation analysis highlights the pivotal role of knowledge in transforming perceived severity and vulnerability into significant predictors of behavioral intention. However, the reliance on simplified models may overlook more complex interdependencies or potential bidirectional effects among variables. Advanced modeling techniques or multi-level frameworks could provide a more nuanced understanding.

Dependence on Theoretical Frameworks: The study relies heavily on existing social psychology theories, such as the Health Belief Model (HBM) and Social Cognitive Theory (SCT). While these frameworks are well-established, they may not fully capture the complexity of behavioral intentions in specific cultural or contextual settings. Developing or adapting theories that reflect local nuances could strengthen the study's relevance and applicability.

SEM Model Limitations: Although the SEM model demonstrated excellent fit indices, the adjustments made to covariance terms to enhance explanatory power may introduce bias or overspecification. These adjustments might obscure the practical applicability of the findings if not carefully generalized to other datasets or populations.

Behavioral Intention vs. Actual Behavior: The study focuses on behavioral intention rather than actual behavior. While intentions are a strong predictor of behavior, they do not always translate into action. Future studies should measure actual health behaviors to validate the predictive power of the identified constructs.

Cultural and Contextual Sensitivity: The study's findings may be influenced by cultural and contextual factors that were not explicitly addressed. For instance, perceptions of vulnerability and severity might vary significantly across different cultural or socio-economic contexts. A lack of cultural tailoring in measurement and interpretation could limit the applicability of the results in diverse settings.

Acknowledging these limitations provides a foundation for refining future research on behavioral intention and its determinants. While this study makes valuable contributions to the field, addressing its limitations can help develop more comprehensive, culturally sensitive, and actionable interventions for improving health behaviors, particularly in the context of non-communicable disease prevention.

CHAPTER SEVEN
Conclusions and Recommendations

7.1. Conclusions

- Correlation Analysis Findings: The correlation analysis indicates that all independent variables—knowledge about non-communicable diseases (KONCDs), perceived severity of non-communicable diseases (POSONCDs), self-efficacy (SE), outcome expectancy (OE), and perceived vulnerability to non-communicable diseases (POVTNCDs)—exhibit a positive and significant relationship with behavioral intention (BI). This means that as the values of these independent variables increase, so does the likelihood of individuals intending to engage in preventive behaviors. Notably, KONCDs shows a strong positive correlation with BI, reflected by a correlation coefficient (r) of 0.771 and a p-value of less than 0.01, confirming the statistical significance of this relationship.
- Multiple Regression Analysis Results: The multiple regression analysis reveals that all predictor variables, except for POVTNCDs, significantly contribute to predicting behavioral intention. The overall model accounts for a substantial portion of the variance in BI, with an R-squared value of 0.739, indicating that approximately 73% of the variance in BI can be attributed to the predictor variables. The F-value from the regression analysis also supports the statistical significance of the combined effect of these predictors ($p < 0.001$). Specifically, POSONCDs, SE, and OE each have a positive and significant influence on predicting BI, as indicated by their respective t-values and p-values.
- Knowledge of NCDs (KONCDs) has both direct and mediated effects on behavioral intention (TBI). Perceived vulnerability (TPOVNCDs) and perceived severity (TPOSNCDs) significantly influence behavioral intention when mediated by knowledge. Self-efficacy (SE) and outcome expectancy (OE) demonstrate strong direct effects on behavioral intention. KONCDs play a pivotal role in shaping behavioral intention, acting as a central mediator for perceived vulnerability and severity. The significant contributions of self-efficacy and outcome expectancy highlight the multidimensional nature of health behavior drivers. Health interventions should integrate education and psychological empowerment to maximize their impact.
- SEM models revealed excellent fit indices (GFI = 1.00, CFI = 1.00, NFI = 1.00), confirming the reliability of the hypothesized relationships. Covariance adjustments in

error terms enhanced the model's explanatory power. The robust model fit underscores the validity of using SEM to explore complex behavioral relationships. These results confirm that carefully calibrated models can effectively capture direct and indirect pathways, ensuring nuanced understanding and reliable predictive insights. This supports the utility of SEM in public health research, particularly for NCD prevention strategies.

- The direct effects of TPOVNCDs and TPOSNCDs on behavioral intention were insignificant in the initial model. Mediation by KONCDs rendered these effects significant, with standardized total effects of 0.419 (TPOVNCDs) and 0.369 (TPOSNCDs) on TBI. While perceived vulnerability and severity may not independently influence behavioral intention, their effects are significantly amplified when mediated by knowledge. This highlights the necessity of educational interventions to bridge the gap between perception and actionable intent in NCD prevention programs.
- The standardized direct effect of KONCDs on TBI was 0.441, while the indirect effect was 0.330. The cumulative total effect emphasizes knowledge as a substantial predictor of behavioral intention. Knowledge is a cornerstone of behavioral change, demonstrating both direct and mediated impacts on intention. Educational initiatives targeting knowledge enhancement should be prioritized to achieve measurable improvements in public health behaviors.
- A revised model excluding SE and OE but including KONCDs as a mediator increased the significance of TPOVNCDs and TPOSNCDs effects on TBI. Knowledge facilitated the transformation of these previously insignificant relationships into significant ones. This model emphasizes the indispensable role of KONCDs in mediating behavioral pathways. Although SE and OE are important, knowledge remains a critical factor for enhancing the impact of perceived risks and severity. This finding informs future models to carefully balance direct and mediated constructs.
- Regression weights indicated strong relationships between KONCDs and predictors like TPOVNCDs, TPOSNCDs, SE, and OE. Behavioral intention is significantly influenced by KONCDs, SE, and OE, while TPOVNCDs and TPOSNCDs require mediation. The strength of regression pathways reaffirms the multifaceted nature of behavioral intentions. Knowledge not only drives direct action but also strengthens

other psychosocial constructs, such as self-efficacy and outcome expectancy. Effective health promotion must therefore incorporate both cognitive and motivational elements.

- Moderation Effects of Gender: The results indicate that gender significantly affects various aspects of the structural models, including weights, covariance, residuals, and the correlations between knowledge, self-efficacy, and outcome expectancy. This suggests that gender plays a vital role in shaping the dynamics and relationships within the model. The impact of gender underscores the necessity of considering it as a potential moderator when analyzing and interpreting structural model results.
- Moderation Effects of Age: The findings indicate that age does not significantly affect the relationships between BI and the variables POSONCDs, POVTNCDs, SE, or the interaction between age and KONCDs. However, age does moderate the relationship between BI and OE, suggesting that age influences how BI affects OE in organizational contexts. The presence of a wider age gap may amplify this effect, implying that age can impact how individuals' intentions translate into actual behaviors in various organizational settings.
- Influence of Year of Study: The results demonstrate that a student's year of study significantly influences the relationship between BI and several variables, including knowledge of non-communicable diseases (TKONCDs), perception of vulnerability (TPOVTNCDs), self-efficacy (SE), and outcome expectancy (OE), as well as the interaction between study year and perceived vulnerability (SYOSINPOV). This finding suggests that as students advance academically, the relationship between BI and these factors evolves, highlighting that the determinants of BI may vary depending on the student's level of academic progress.
- Moderation Effect of Birth Place: The introduction of birthplace as a moderator variable did not yield a significant effect on the relationships between the predictors and the dependent variable. The comparison of regression models with and without birthplace indicated that the model fit did not significantly improve with the inclusion of this variable. This finding implies that birthplace does not meaningfully influence the relationships between the predictors and the dependent variable, suggesting a relatively consistent relationship regardless of individuals' birthplaces.

7.2. Recommendations

Based on the provided conclusions, the following recommendations are designed to guide stakeholders and policymakers in implementing effective interventions for promoting behavioral intention (BI) toward non-communicable disease (NCD) prevention:

1. Enhance Knowledge-Based Interventions

Knowledge plays a central role in driving behavioral intention and mediating other psychosocial factors like perceived severity (POSONCDs) and vulnerability (POVTNCDs).

- Design and implement nationwide educational campaigns focused on increasing knowledge about NCDs (KONCDs), with an emphasis on risk factors, prevention strategies, and treatment options.
- Integrate KONCD modules into school and university curricula, particularly for health-related and social science disciplines.
- Leverage digital tools such as mobile apps, social media platforms, and e-learning modules to disseminate NCD-related information in engaging and accessible formats.

2. Strengthen Psychological Empowerment

Both SE and OE significantly influence BI and can amplify the effectiveness of knowledge-focused interventions.

- Develop self-efficacy (SE) enhancement programs by offering skill-based training sessions, motivational workshops, and community role model stories.
- Promote outcome expectancy (OE) by illustrating tangible benefits of preventive behaviors, such as improved quality of life and reduced healthcare costs.
- Create peer-support groups and counseling services to address behavioral barriers and boost individual confidence in preventive actions.

3. Target Demographic-Specific Interventions

Gender, age, and academic progression significantly moderate behavioral relationships and must be integrated into intervention design to enhance relevance and impact.

- Address gender-specific barriers and motivators by designing tailored messaging and community outreach activities that resonate with men and women differently.
- Provide age-appropriate interventions, such as school-based programs for younger individuals and workplace wellness initiatives for older populations.
- Adapt interventions to suit different academic levels, offering advanced preventive behavior training to senior students while focusing on foundational knowledge for freshmen.

4. Promote Perception-Driven Campaigns

While perceived vulnerability and severity alone do not strongly drive BI, they have a significant impact when mediated by knowledge.

- Develop campaigns emphasizing perceived severity (POSONCDs) and vulnerability (POVTNCDs) of NCDs, highlighting real-world consequences through testimonials, statistics, and visual aids.
- Use KONCDs as a mediating factor to make perception-based interventions more effective.
- Partner with healthcare providers and media outlets to increase awareness and personalize risk communication.

5. Institutionalize Behavior Assessment in Educational and Health Systems

Continuous assessment will help fine-tune interventions and ensure alignment with the evolving needs of different population groups.

- Establish regular assessments to monitor BI and its determinants (KONCDs, SE, OE, POVTNCDs, and POSONCDs) across educational and healthcare institutions.
- Use these assessments to identify knowledge gaps, behavioral trends, and demographic needs.

6. Leverage SEM-Based Insights for Policy Design

SEM models demonstrate excellent fit and provide a reliable foundation for understanding complex behavioral relationships.

- Use Structural Equation Modeling (SEM) to design evidence-based health promotion policies, ensuring the inclusion of both direct and mediated pathways.
- Train policymakers and stakeholders in interpreting SEM findings to align strategies with the behavioral drivers of NCD prevention.

7. Address Contextual and Societal Factors

Localized interventions will foster better engagement and acceptance, even if birthplace is not a significant determinant.

- Tailor interventions to the local context by incorporating cultural, societal, and environmental factors into program design.
- While birthplace did not significantly moderate relationships, regional contexts might still influence program adoption; conduct local needs assessments to ensure relevance.

8. Expand Policy Frameworks for Multi-Sectoral Collaboration

- A multi-sectoral approach will enhance resource allocation, outreach, and long-term sustainability.
- Establish partnerships between education, health, and social welfare sectors to implement integrated interventions addressing NCD prevention holistically.
- Develop policies that incentivize community participation in health promotion activities, such as subsidies for preventive health check-ups or tax benefits for workplace wellness programs.

9.For future research studies

- **Enhancing Independent Variables**: To improve the behavioral intention (BI), it is essential to focus on increasing the values of the independent variables: knowledge about non-communicable diseases (KONCDs), perceived severity of non-communicable diseases (POSONCDs), self-efficacy (SE), outcome expectancy (OE), and perceived vulnerability to non-communicable diseases (POVTNCDs). Strategies could include enhancing knowledge and skills related to KONCDs, fostering positive social connections linked to POSONCDs, boosting self-esteem, providing opportunities for personal and professional growth (OE), and addressing issues related to poverty and inequality (POVTNCDs).
- **Investigating Gender Moderation**: It is recommended to delve deeper into how gender moderates the relationships within the structural model. This could involve conducting subgroup analyses or identifying other variables that may interact with gender to better understand the dynamics at play. Additionally, it is crucial to consider gender-specific strategies when implementing any interventions based on the model findings. Tailoring these interventions to address the unique needs and preferences of different genders can enhance their effectiveness.
- **Exploring Age Moderation**: Further exploration is needed to understand the nature of age's moderation effect on the relationship between BI and OE. Additional analyses or qualitative research could provide valuable insights into how age influences the translation of intentions into actual behaviors within various organizational contexts. Organizations should consider age as a significant factor when developing interventions aimed at promoting growth and development opportunities, allowing for more effective approaches that resonate with different age groups.
- **Exploring Additional Moderator Variables**: In light of the moderation results associated with birthplace, it is essential to investigate other potential moderator

variables that could significantly impact the relationships between the predictors and the dependent variable. This exploration could include assessing various demographic factors, personal characteristics, or contextual variables that might influence these relationships. Future research should also aim to uncover additional factors that could explain the variation in the dependent variable. By broadening the scope to include more variables and examining their potential moderation effects, a more comprehensive understanding of the relationships in question can be achieved.

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Appendixes

Appendix A. drafted questions

C) NCDs Knowledge items

The goal of these knowledge items is to evaluate how well respondents understand various aspects of non-communicable diseases (NCDs). This includes their symptoms, risk factors, fatal outcomes, and methods for prevention and control. Read the following statements and rate them as correct, incorrect, or unknown by putting (√) mark.

Table 4.1. *Items Developed to Measure Knowledge about NCDs*

No.	items	correct	incorrect	I do not know
1	Diabetics are caused by heredity			
2	Diabetics can be caused by high sugar intake			
3	Frequent hunger is the symptom of diabetes			
4	Eating too much is the symptom of diabetes			
5	Bodyweight loss is the symptom of diabetes			
6	Diabetes can be prevented by following a positive lifestyle			
7	Cigarette smoking leads to blood pressure			
8	Alcohol consumption leads to blood pressure			

9	l obesity and leads to blood pressure			
10	Hyperlipidemia leads to blood pressure			
11	Blood pressure can be prevented by following a positive lifestyle			
12	High-level stress is a risk factor for cardiovascular disease			
13	Severe headache is common symptoms of cardiovascular disease			
14	Angina pain is common symptoms of cardiovascular disease			
15	Cardiovascular disease can be prevented by following a positive lifestyle			
16	Constipation is a symptom of colorectal cancer			
17	Bloody stool is a symptom of colorectal cancer			
18	A low fiber diet is a risk factor for colorectal cancer			
19	Colorectal cancer can be prevented by following a positive lifestyle			

D) Perception of the seriousness of the NCDs

The items related to the perception of seriousness primarily focus on the physical severity of the disease, as well as its medical and clinical implications, such as death, limitations, and pain. Additionally, they consider potential psychosocial effects, including impacts on work, family life, and social relationships. It may be beneficial to compare the perceived seriousness of Disease X with that of other diseases to better understand its relative seriousness.

Table 4.2: Items Developed to Measure Perception of the Seriousness of the NCDs

No.		Not serious at all	not serious	slightly serious	serious	very serious
1	How seriously do you think diabetes is?					
2	How seriously do you think cancer is?					
3	How serious do you think blood					

	pressure is?					
4	How serious do you think the cardiovascular disease is?					
5	How would you feel if you were to contract diabetes in the coming year?					
6	How would you feel if you were to contract cancer in the coming year?					
7	How would you feel if you were to contract the blood pressure in the coming year?					
8	How would you feel if you were to contract cardiovascular disease in the coming year?					
9	Having any of the NCDs will have major effects on my life and family					
10	Having any of the NCDs will have major effects on my work and income					
11	Having any of the NCDs will cripple me					
12	Having any of the NCDs will change my outlook					
13	The thought of having any of the NCDs scares me					

E) Perception of susceptibility /vulnerability/ to the NCDs

The items addressing the perception of susceptibility are designed to gauge individuals' beliefs about their likelihood of contracting the disease in the near future. When discussing susceptibility, it's essential to include the phrase "if you do not take any preventive measures." Additionally, the perception of susceptibility to Disease X can be contrasted with susceptibility to other diseases for a clearer understanding.

Table 4.3: Items Developedto Measure Perception of Susceptibility /Vulnerability/ to the NCDs

No.		certainly not	probably not	perhaps not - perhaps yes	probably yes	most certainly
1	Do you think that you can contract any NCDs in the coming year if you do not take any preventive measures?					
	Do you think that you can contract diabetes in the coming year if you do not take any preventive measures					
	Do you think that you can contract blood pressure in the coming year if you do not take any preventive measures?					
	Do you think that you can contract cancer in the coming year if you do not take any preventive measures?					
	Do you think that you can contract the cardiovascular disease in the coming year if you do not take any preventive measures?					
2	How large do you think the chance is that you will contract the following	very small chance	small chance	not small - not large	large chance	very large chance

	diseases in the coming year?					
	Diabetes					
	Blood pressure					
	Cardiovascular disease					
	cancer					
3	How concerned are you about contracting the following diseases?	not concerned at all	not concerned	slightly concerned	concerned	very concerned
	Diabetes					
	Blood pressure					
	Cardiovascular disease					
	Cancer					
	For the following statements show your level of agreement	Strongly disagree	Disagree	Undecided	agree	Strongly agree
11	I think being obese/overweight will lead me to get NCDs					
12	I believe my family medical history makes it likely to get NCDs					
13	I think smoking makes it likely to get NCDs					
14	I believe that unhealthy eating habits can make me get NCDs					
15	I think physical inactivity can make me get NCDs					

F) Self-efficacy

The items related to perceived efficacy aim to understand how confident respondents feel about the effectiveness of the available preventive measures. These measures typically include adopting positive lifestyle choices, such as maintaining a healthy diet, engaging in regular physical activity, avoiding substance abuse, and fostering healthy social relationships. Additionally, self-efficacy reflects the respondent's belief in their ability to implement these preventive measures successfully.

Table 4.4: Items Developed to Measure Self-efficacy

No.						
1	Do you think that healthy diets help to prevent the following?	certainly not	probably not	perhaps not - perhaps yes	probably yes	most certainly
	Diabetes					
	Cardiovascular disease					
	Cancer					
	Blood pressure					
2	Do you think that physical activity helps to prevent the following?					
	Diabetes					
	Cardiovascular disease					
	cancer					
	Blood pressure					
3	Do you think that avoiding drugs helps to prevent the following?					
	Diabetes					
	Cardiovascular disease					
	Cancer					
	Blood pressure					
4	Do you think that getting connected helps to prevent the following?					
	Diabetes					
	Cardiovascular disease					
	Cancer					

	Blood pressure					
5	- Do you think that you will manage to carry out the following measures if they are advised?	certainly not	probably not	perhaps not - perhaps yes	probably yes	most certainly
	Physical activity					
	Eat healthily					
	Avoid drugs					
	Get connected					
		Strongly disagree	disagree	Undecided	agree	Strongly agree
6	I am confident about how to prevent chronic diseases					
7	I can actively work on a healthy lifestyle to prevent NCDs					
8	I attend health assessments to prevent NCDs					
9	I have information on how to prevent NCDs					
10	There is a lot I can do to reduce my chances of getting NCD-related illness					

Table 4.5: Items Developed to Measure Behavioural Intention

No.	Behavioural Intentions					
1	Would you carry out the following measures if they were advised?	Certainly not	probably not	perhaps not - perhaps yes	probably yes	most certainly
	Eating healthy					
	Physical activity					

	Avoid drugs					
	Get connected					
2	Show your level of agreement for the following statements	Strongly disagree	disagree	undecided	agree	Strongly agree
	I plan to eat a well-balanced diet					
	I plan to follow medical orders to benefit my health					
	I plan to make efforts to improve my health					
	I plan to exercise regularly, at least 3 times per week					
	I plan to avoid fatty foods					
	I plan to eat small-portion meals					

Table 4.6: Items Developed to Measure Outcome Expectancy

	Outcome expectancies					
No.	Show your agreement on why would you be willing to carry out the measures mentioned?	Strongly disagree	disagree	Undecided	agree	Strongly agree
1	I am willing to carry out the protective measures because I am often ill					
2	I am willing to carry out the protective measures because NCDs can be serious					
3	I am willing to carry out the protective measures because I feel responsible for my health					
4	I am willing to carry out the protective measures because I think I am at risk of one of the NCDs					
5	I am willing to carry out the					

	protective measures because I want to prevent contracting NCDs					
6	I am willing to carry out the protective measures because I trust that the measures help					
7	I am willing to carry out the protective measures because the doctors advise it.					
8	I am willing to carry out the protective measures because, If I do not take these measures, I may regret it later					
9	I am willing to carry out the protective measures because other people in my environment are also carrying out the measures					
10	I am willing to carry out the protective measures because not having an NCD is beneficial					
11	I am willing to do physical activities because I believe it could prevent NCDs					
12	I am willing to eat healthy because I believe it could prevent NCDs					
13	I am willing to do managing my weight because I believe it could prevent NCDs					
14	I will not smoke because not smoking prevents NCDs					
15	I will do regular health check-ups because regular health check-ups are beneficial					

1	I do not care to take any of the protective measures because I am never ill					
2	I do not care to take any of the protective measures because NCDs is not serious					
3	I do not care to take any of the protective measures because I do not find it important					
4	I do not care to take any of the protective measures because I am not worried about my health					
5	I do not care to take any of the protective measures because I do not think I am at risk of contracting NCDs					
6	I do not care to take any of the protective measures because I doubt whether the measures help					
7	I do not care to take any of the protective measures because takes too much effort (time, etc.)					
8	I do not care to take any of the protective measures because people in my environment will not carry out the measures					
9	I do not care to take any of the protective measures because very little can be done to prevent NCDs					
10	I do not care to take any of the protective measures because I believe no measure will be effective in managing NCDs					

11	I do not care to eat healthy because eating healthy will do me no good on NCD cases					
12	I do not care to take health checkups because health check-ups are useless concerning NCDs					

No.	**Knowledge scale items =6**	Relevant	Relevant needs edition	Irrelevant

Annex B. Expert agreement

1Table 40: Expert agreement on the reliance of the items in each scale

1	Diabetes is caused by heredity	4	1	2
2	Diabetes can be caused by consuming too much sugar	5	1	1
3	Frequent hunger is a sign of diabetes.	4	1	2
4	Eating too much is a sign of diabetes	4	1	2
5	Weight loss is a sign of diabetes	7		
6	Diabetes can be prevented by following a positive lifestyle	7		
7	Smoking causes high blood pressure	7		
8	Excessive consumption of alcohol increases the risk of high blood pressure	5	1	1
9	Being overweight can lead to high blood pressure	4	2	1
10	Highpertention can lead to high blood pressure	2	1	4
11	Blood pressure can be prevented by following a positive lifestyle	7		
12	High levels of stress are a risk factor for cardiovascular disease	7		
13	A severe headache is a well-known symptom of cardiovascular disease	7		
14	Severe chest pain is a well-known symptom of cardiovascular disease	7		
15	Cardiovascular disease can be prevented by following a positive lifestyle	7		
16	Constipation is a symptom of colon cancer	3	1	3
17	Bloody stool is a sign of colon cancer	3	1	3
18	Eating food with low fiber content makes you vulnerable to colon cancer	7		
19	Colon cancer can be prevented by following a positive lifestyle	3	1	3
	Items of Severity of NCDs =7			
1	1 How serious do you think diabetes is?	7		
2	2 How serious do you think cancer is?	2	1	4
3	3 How serious do you think high blood pressure is?	7		
4	4 How serious do you think heart disease is?	7		
5	5 How serious would you feel if you had diabetes in the future?	5	2	
6	6 How serious would you feel if you got cancer in the future?	7		
7	7 How serious would you feel if you had high blood pressure in the future?	6	1	
8	8 How serious would you feel if you had heart disease in the future?	7		
9	The impact of having any kind of non-communicable disease on my life and my family	3	2	2
10	The effect of having any non-communicable disease on my work and income	4	3	
11	Living with any kind of non-communicable disease has the potential to make me tired	5	2	
12	The ability to change the observation of the presence of any non-communicable diseases	7		
13	How serious is the fear of living with a non-communicable disease	7		
	Items of Perceived vulnerability to NCDs=7			
1	If you don't take proper precautions, you think that you could develop NCDs in the future.	4	2	1
2	What is do you think the probability of you developing NCDs	7		

	in the future?			
3	How worried are you about getting a non-communicable disease?	6	1	
4	I think being overweight puts me at risk for NDCs	7		
5	My family's medical history for NCDs I believe that makes me vulnerable	5		2
6	I think that smoking is the cause of NCDs. It exposes	7		
7	I believe that unhealthy eating habits make me vulnerable to NCDs	7		
8	I think that physical inactivity makes me vulnerable to NCDs	7		
	Self-efficacy items =7			
1	I am sure how to prevent non-communicable diseases			
2	I can follow a healthy lifestyle to prevent non-communicable diseases	7		
3	I can do health monitoring to prevent non-communicable diseases	7		
4	I have information on how to prevent non-communicable diseases	7		
5	There are many things I can do to reduce my risk of contracting a non-communicable disease	7		
6	I am sure how to prevent 6 non-communicable diseases	5	2	
7	I can actively exercise to prevent non-communicable diseases	2	3	2
8	I can implement a healthy diet to prevent non-communicable diseases	3	3	1
9	I can use medications to prevent non-communicable diseases	2	1	4
	Behavioural intention items =7			
1	I plan to eat nutritious food	6	1	
2	I have decided to follow medical orders for the benefit of my health	7		
3	I plan to make efforts to improve my health	4	1	2
4	I plan to exercise regularly at least 3 times a week	7		
5	I have decided to avoid fatty food	3	2	2
6	I plan to eat low-fat foods	4	1	2
7	I plan to get proper medical attention	6	1	
8	I will have enough rest and have fun	7		
9	I have decided to live a life free from addiction	2	1	4
	Outcome Expectation items =7			
1	It is good for me to take preventive measures because it often hurts	5	2	
2	Getting infected with non-communicable diseases can have dangerous consequences	4	2	1
3	The preventive measures help prevent non-communicable diseases	3	3	1
4	Preventive measures will save you from regret later	4	2	1
5	Preventive measures are important to avoid contracting non-communicable diseases	3	3	1
6	Following a healthy diet prevents non-communicable diseases	6	1	
7	Losing weight can prevent non-communicable diseases	7		
8	Not smoking reduces the risk of contracting non-communicable diseases	5		2

9	Regular health check-ups are important to prevent non-communicable diseases	7		
10	I doubt that it would be useful to take any preventive measures	3	3	1
11	I don't care to take any preventive measures because it takes too much effort.	3	2	2
12	I do not believe that any medicine will be effective in preventing non-communicable diseases	4	2	1

Appendix c

Table 41: Amharic translated questionnaire

NCDs የእወቀት ጥያቄዎች

ተ.ቁ	ጥያቄዎች	ትክክል ነው	ስህተት ነው	አላወቅም
1	የስኳር ህመም በዘር ወርስ ምክንያት ይክሰታል			
2	የስኳር ህመም ከፍተኛ የስኳር ማጠን በመዉሰድ ምክንያት ሊከሰት ይችላል			
3	ተደጋጋሚ የረሃብ ስሜት የስኳር በሽታ ምልክት ነው			
4	ከማጠን በላይ መብላት የስኳር በሽታ ምልክት ነው			
5	የሰውነት ክብደት መቀነስ የስኳር በሽታ ምልክት ነው			
6	አወንታዊ የሕይወት ዘይቤን በመከተል የስኳር በሽታን መከላከል ይቻላል			
7	ሲጋራ ማጨስ ለደምግፊት ያጋልጣል			
8	የአልኮሆል ማጠጦችን ማብዛት ለደምግፊት ያጋልጣል			
9	ከማጠን በላይ ወፍረት ለደምግፊት ያጋልጣል			
10	ከፍተኛ የደምግፊት መቀነስ ለደምግፊት ያጋልጣል			
11	አዎንታዊ የሕይወት ዘይቤን በመከተል የደምግፊትን መከላከል ይቻላል			
12	ከፍተኛ ደረጃ ያለውጭዓቀት ለልብና የደምሥር በሽታ የሚያጋለጥ አደጋ ነው			
13	ከባድ ራስ ምታት የታወቀ ልብና የደምቧንቧ በሽታ ምልክት ነው			
14	ከፍተኛ የደረት ህመም የታወቀ የልብና የደምቧንቧ በሽታ ምልክት ነው			
15	አዎንታዊ የአኗኗር ዘይቤን በመከተል የልብና የደምቧንቧ በሽታን መከላከል ይቻላል			
16	የሆድ ድርቀት የአንጀት ካንሰር ምልክት ነው			
17	ደም የቀላቀለ ሰገራ የአንጀት ካንሰር ምልክት ነው			
18	ዝቅተኛ የቃጫይዘት ያለውምግብ መመገብ የአንጀት ካንሰር ለመያዝ ተጋላጭያደረጋል			
19	የአንጀት ካንሰርን አወንታዊ የሕይወት ዘይቤን በመከተል መከላከል ይቻላል			

የሚይተላለፉ በሽታዎች አሰከፊነት

ተ.ቁ.	ጥያቄዎች	በጭራሽ ከባድ አይደለም	ከባድ አይደለም	በመጠኑ ከባድ ነው	ከባድ ነው	በጣም ከባድ ነው
1	የስኳር በሽታ ምን ያህል ከባድ ነው ብለው ያስባሉ?					
2	ካንሰር ምን ያህል ከባድ ነው ብለው ያስባሉ?					
3	የደምግፊት ምን ያህል ከባድ ነው ብለው ያስባሉ?					
4	ልብ በሽታ ምን ያህል ከባድ ነው ብለው ያስባሉ?					
5	ወደፊት የስኳር በሽታ ቢይዝዎት የሚፈጠርብዎ ስሜት ምን ያህል ከባድ ነ ወ?					
6	ወደፊት ካንሰር ቢይዙዎት የሚፈጠርብዎ ስሜት ምን ያህል ከባድ ነ ወ?					
7	ወደፊት የደም ግፊት ቢይዙዎት የሚፈጠርብዎ ስሜት ምን ያህል ከባድ ነ ወ?					
8	ወደፊት የልብ በሽታ ቢይዙ የሚፈጠርብዎ ስሜት ምን ያህል ከባድ ነ ወ?					
9	የትኛውንም አይነት ተላላፊ ያልሆኑ በሽታዎች መያዝ በሕይወቴ እና በቤተሰቤ ላይ የሚያሳድረውተጽዕኖ					
10	ማንኛውንም አይነት ተላላፊ ያልሆኑ በሽታዎች መያዙ በሥራዬ እና በገቢዬ ላይ የሚያሳድረውተጽዕኖ					
11	ከየትኛውም አይነት ተላላፊ ያልሆኑ በሽታዎች ጋር መኖር እኔን የሚድከም አቅሙ					
12	ከማንኛውንም አይነት ተላላፊ ያልሆኑ በሽታዎች መኖር ምልከታየን የመቀየር አቅሙ					
13	ከተላላፊ ያልሆኑ በሽታ ጋር መኖር የሚፈጥረው ፍርሀት ምን ያክል					

	ከባድ ነው					

ለሚተላለፉ በሽታዎች. ያለ ተጋላጭነት፡ -

ተ.ቁ	ጥያቄዎች	አማራጮች				
1	ተገቢውን ጥንቃቄ ካላደረጉ ወደፊት ተላላፊ ባለሆኑ በሽታዎች አያዛልሁ ብለውያስባሉ	በፍጹም አይሆንም	ምንአልባት አይሆንም	ሊሆንመ ላይሆን ይችላል	ምንአልባት ይሆናል	በእርግጥ ይሆናል
2	ወደፊት ተላላፊ ባልሆኑ በሽታዎች የመያዝ አድልዎ ምንያህል ነው	በጣም ትንሽ አድል	ትንሽ አድል	ትልቅም -ትንሽም ያልሆነ	ትልቅ አድል	በጣም ትልቅ አድል
3	ተላላፊ ባለሆኑ በሽታዎች መያዝ አለመያዙ ምን ያህል ያስጨንቀዎታል?	በጭራሽ አልጨነቅም	አልጨነቅም	በትንሹ እጨነቃለሁ	እጨነቃለሁ	በጣም እጨነቃለሁ
	ለሚከተሉት መግለጫዎች የስምምነትዎን ደረጃ ብከፍት ቦታውላይ የ(√) ምልክት በማድረግ ያሳዩ	በጣም አልስማማም	አልስማማም	መወሰን አልችልም	እስማማለሁ	በጣም እስማማለሁ
1	ከማጠን በላይ መወፈር ኤን.ዲ.ሲዎችን ያጋልጠኛል ብዬ አስባለሁ					
2	የቤተሰቦቼ የሕክምና ታሪክ ለኤን.ሲ.ዲ. ተጋላጭ እነደሚያደርገኝ አምናለሁ					
3	እኔ እንደማስበውሲጋራ ማጨስ ለኤን.ሲ.ዲ. ያጋልጣል					
4	ጤናማያልሆነ የአመጋገብ ልማድ ለኤን.ሲ.ዲዎች ተጋላጭ ያደርገኛል ብዬ አምናለሁ					
5	አካላዊ እንቅስቃሴ-አለማድረግ ለኤን.ሲ.ዲዎች ተጋላጭ ያደርገኛል ብዬ አስባለሁ					

በራስ-የማድረግ ብቃት

ተ.ቀ	ጥያቄዎች	አማራጮች				
		በጣም አልስማማም	አልስማማም	መወሰን አልችልም	እስማማለሁ	በጣም እስማማለሁ
1	የሚይተላለፉ በሽታዎችን እንዴት መከላከል እንደሚቻል እርግጠኛ ነኝ					
2	የሚይተላለፉ በሽታዎችን ለመከላከል ጤናማየአኗኗር ዘይቤዎችን መከተል እችላለሁ					
3	የሚይተላለፉ በሽታዎችን ለመከላከል በጤና ክትትል ማደረግ እችላለሁ					
4	የሚይተላለፉ በሽታዎችን እንዴት መከላከል እንደሚቻል መረጃ አለኝ					
5	በሚይተላለፉ በሽታዎች የመያዝ እድሌን ለመቀነስ ብዙ ማድረግ የምችለውነገር አለ					
6	የሚይተላለፉ በሽታዎችን እንዴት መከላከል እንደሚቻል እርግጠኛ ነኝ					
7	የሚይተላለፉ በሽታዎችን ለመከላከል የአካል ብቃት እንቅስቃሴን በንቃት መሥራት እችላለሁ					
8	የሚይተላለፉ በሽታዎችን ለመከላከል ጤናማአመጋገብን መተግበር እችላለሁ					
9	የሚይተላለፉ በሽታዎችን ለመከላከል ሱሶችን ማስወግድ እችላለሁ					

የባህርይ እቅዶች

ተ፥ቁ	ለሚከተሉት መግለጫዎች የስምምነትዎን ደረጃ ያሳዩ	አማራጮች

		በጣም አልስማማም	አልስማማም	መወሰን አልችልም	እስማማለሁ	በጣም እስማማለሁ
1	የተመጣጠነ ምግብ ለመመገብ አቅጃለሁ					
2	ለጤንነቴ ጥቅም ለማግኘት የሕክምና ትዕዛዞችን ለመከተል ወስኛለሁ					
3	ጤናዬን ለማሻሻል ጥረቶችን ለማድረግ አቅጃለሁ					
4	በመደበኛነት የአካል ብቃት እንቅስቃሴ በሳምንት ቢያንስ 3 ጊዜ ለማድረግ እቅድ አለኝ					
5	የሰባ ምግብን ለማስወገድ ወስኛለሁ					
6	አነስተኛ ስብ ያላቸውን ምግቦች ለመመገብ እቅድ አለኝ					
7	ተገቢውን የህክምና ክትትል ለማድረግ አቅጃለሁ					
8	በቂ እረፍት እና ተዝናኖት የማድረግ ልምድ እንዲኖርኝ አደርጋለሁ					
9	ከሱስ ነጻ ህይወት እንዲኖርኝ ወስኛለሁ					

<u>የውጤት ተስፋዎች</u>

ተ.ቁ	ጥያቄዎች	በጣም አልስማማም	አልስማማም	መወሰን አልችልም	እስማማለሁ	በጣም እስማማለሁ
1	ብዙ ጊዜ ስለሚያመኝ የመከላከያ እርምጃዎችን መፈፀምለኔ ጥሩ ነው					
2	በሚተላለፉ በሽታዎች መያዝ አደገኛ ማዝዝ ያመጣል					
3	የመከላከያ እርምጃዎቹ የሚተላለፉ በሽታዎችን ለመከላከል ይረዳሉ					
4	የመከላከያ እርምጃዎችን መፈፀም በኋላ ከፀፀት ያድናል					
5	የመከላከያ እርምጃዎችን መፈፀም በሚተላለፉ በሽታዎች ላለመያዝ ጠቃሚነው					
6	ጤናማ አመጋገብን መከተል የሚተላለፉ በሽታዎችን ይከላከላል					
7	ክብደቴን መቀነስ የሚተላለፉ በሽታዎችን ሊከላከል ይችላል					
8	ሲጋራ አለማጨስ በሚተላለፉ በሽታዎች የመያዝ እድልን ይቀንሳል					
9	መደበኛ የጤና ምርመራዎች ማድረግ የሚተላለፉ በሽታዎችን ለመከላከል ጠቃሚነው					
10	ማንኛውንም የመከላከያ እርምጃዎችን መውሰድ ይጠቅም እንደሆነ እጠራጠራለሁ					
11	በጣም ብዙ ጥረት ስለሚጠይቅ ማንኛውንም የመከላከያ እርምጃዎችን መውሰድ ግድ አይሰጠኝም።					
12	የሚተላለፉ በሽታዎችን ለመከላከል ምንም ዓይነት እረምጃ ውጤታማ ይሆናል የሚል እምነት የለኝም					