# PREDICTING HIGH SCHOOL STUDENTS' STEM CAREER CHOICE THROUGH SUPERVISED MACHINE LEARNING ALGORITHMS AND CHI-SQUARE ANALYSIS

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**Abstract**

PREDICTING HIGH SCHOOL STUDENTS' STEM CAREER INTEREST

THROUGH SUPERVISED MACHINE LEARNING ALGORITHMS AND

CHI-SQUARE ANALYSIS

by

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The dearth of STEM students in the United States is a growing concern for policymakers and educators alike. With the increasing reliance on technology in the global economy, a STEM-trained workforce is essential for the United States to remain competitive. However, the number of students majoring in STEM disciplines and pursuing STEM careers is not keeping pace with the demand for these skilled workers. As a result, understanding the characteristics that contribute to students' confidence in science and their desire to pursue professions in science remains a national priority. This research investigated the factors influencing the choice of STEM careers among high school graduates. To achieve this, the study analyzed data from 520 high school graduates, using machine learning models and chi-square analysis to predict their propensity for choosing STEM careers. This study evaluated the performance of four machine learning models—Logistic Regression, K-Nearest Neighbors (KNN), Decision Tree, and Neural

Network—across various metrics, including accuracy, precision, recall, and F1 Score, to determine their effectiveness in classification tasks. The Logistic Regression model has a performance with an accuracy of 83.65%, precision of 88.83%, and recall of 84.12%. This indicates a slight preference for precision over recall. On the other hand, the K-Nearest Neighbors (KNN) model shows better accuracy (87.5%) and recall (93.6%), but with a slightly lower precision (86.7%). This suggests that the KNN model is effective in identifying relevant instances but with some compromises in precision. This study also explored the impact of socioeconomic status (SES), ethnicity, and access to Advanced Placement (AP) courses on the career choices of students in STEM fields. It found that gender did not significantly affect these decisions, but disparities in SES, ethnicity, and educational opportunities played a critical role. The study recommended that educational stakeholders work together to address these disparities by providing supportive measures and equitable resource allocation to promote a more inclusive and diverse STEM workforce.

*Keywords*: STEM career, machine learning, chi-square analysis, leakage in STEM pipeline

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## Dedication

To my family, to whom I dedicate this thesis, thank you for being my steadfast support throughout this journey. You have stood by my side at every step, providing love and encouragement.

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# Chapter 1 The Problem

## Introduction

The term "STEM" is a very common term that is widely used in both educational and occupational contexts. It stands for Science, Technology, Engineering, and Mathematics. In the 1990s, the term "STEM" originated from the National Science Foundation, initially coined as "SMET" (Bejan, Miron, & Barna, 2015). Judith A. Ramaley, who was in charge of the Foundation's Education and Human Resources Division at the time, did not like the acronym SMET and changed it to STEM. She chose STEM deliberately to highlight the importance of science and mathematics, with technology and engineering providing additional real-world relevance (Christenson, 2011). Nevertheless, there is still some ambiguity regarding what subjects are included in STEM. There are differing views among various organizations and experts, with some considering areas like agriculture and health sciences as part of STEM while others do not.

Definitions of STEM are categorized into two main types: educational and occupational. The National Center for Education Statistics Classification of Instructional Programs 2000 is used for educational and academic classifications, while the Standard Occupational Classification (SOC) system is used for occupational studies (Koonce, Zhou, Anderson, Hening, and Conley, 2011). According to the SOC, there are 819 different occupations, among which 414 require a wide range of skills in STEM subjects (Noonan, 2017). According to the 2021 Census Bureau report, there are significant differences in the demographics of the American workforce, especially in STEM jobs, for those between the ages of 18 and 74. Although women make up more than half of the population at 51%, they only account for 35% of STEM jobs. Conversely, men make up less than half of the population at 49% but hold a much larger share of STEM jobs at 65%. In terms of race and ethnicity, White people are overrepresented in STEM jobs, accounting for 64% of the workforce, compared to their population percentage of 61%. Asian people, who constitute 6% of the population, have a smaller role in the overall workforce at 6% but a larger role in STEM at 10%. Hispanic or Latino people make up 18% of the population and workforce but only 15% of STEM jobs.

Similarly, Black or African American people constitute 12% of both the general population and workforce but only 9% of those in STEM. American Indians and Alaska Natives are the least represented, accounting for less than 1% in both the overall and STEM workforce. This data highlights the significant gaps and challenges in making STEM fields more diverse, as evidenced by the report from the Census Bureau in 2021, which indicates that out of the 146.4 million people employed, 34.9 million or 24% work in STEM careers. You can find the complete list of STEM and non-STEM jobs in Attachment C.

**Statement of the Problem**

In reaction to the Soviet Union's 1957 Sputnik launch, the United States intensified its efforts in the global competition for technological and engineering excellence. As a result, educational priorities shifted markedly, with a heightened focus on science education for students, resulting in a surge of funding and resources for schools (Woodruff, 2013).

Educators, administrators, and policymakers understand the crucial importance of STEM in our daily lives. The progress of STEM fields plays a vital role in fostering innovation and development, ultimately enhancing our overall quality of life. In 2020, the American Association for the Advancement of Science (AAAS) emphasized the significant impact of STEM on the

U.S. economy. It noted that STEM is responsible for two-thirds of all employment, contributes to 69% of the country's GDP, and generates $2.3 trillion in annual tax revenue for the government. So, it is crucial to keep the workforce knowledgeable and skilled in STEM to keep the United States ahead globally and maintain its economic advantage.

The Department of Labor and the U.S. Bureau of Labor Statistics projects a significant increase in demand for STEM specialists, anticipating the need for around one million more professionals in the next ten years. This expectation builds on the previous trend observed between 2009 and 2015, during which STEM jobs grew by 10.5%, notably higher than the 5.25% increase seen in non-STEM fields. Looking ahead, STEM occupations are expected to expand by 10.8% from 2022 to 2032. Furthermore, these roles are projected to offer median annual wages substantially above those in non-STEM areas, highlighting the rewarding nature of STEM careers in terms of both job security and financial benefits. This increase shows how important STEM fields are in creating new ideas and helping the economy grow. Jobs in STEM help with making new inventions and keeping the U.S. economy competitive.

In the following sections, different terms that will be used in this study are defined.

## Definition of Terms

***STEM:*** The disciplines of science, technology, engineering, and mathematics are included under the STEM umbrella of academic and career-relevant study topics (Koonce et al., 2011).

***STEM Education*****:** STEM education is an interdisciplinary approach to learning that removes the traditional barriers separating the four disciplines of science, technology, engineering, and mathematics and integrates them into the real world, creating rigorous and relevant learning experiences for students (Vasques, Sneider, & Comer, 2013).

***STEM Career****:* STEM careers require knowledge and skills in the scientific, technological, engineering, and mathematical fields. The SOC system will be utilized to identify which occupations are considered STEM careers. Attachment C classification will be utilized for STEM career choice in this study.

***STEM Identity:*** According to Kim, Sinatra, and Seyranian (2018), stem identity is a socially constructed identity in which individuals define themselves as involved in STEM fields and believe they are a part of the STEM community. In this type of stem identity, the individual also believes they are a STEM community member.

***Internal Factors:*** Internal influences include an individual's viewpoints, principles, and feelings regarding STEM fields, along with their self-perception, abilities, and sense of belonging.

***External Factors:*** External factors affecting an individual's choice to follow a career path in STEM encompass parental influence, societal and cultural norms and stereotypes, the academic environment, and early exposure to STEM fields.

# Chapter 2 Literature Review

This section will discuss the various factors that influence an individual's decision to pursue a career in STEM fields. According to the literature, several factors can impact this decision, including family support, socioeconomic status, available courses, teacher influence, educational settings, gender, ethnicity, and informal learning experiences. The purpose of this exploration is to uncover previously overlooked or underexplored aspects of the literature. Identifying these gaps will contribute to a more comprehensive understanding of the pathways to STEM careers.

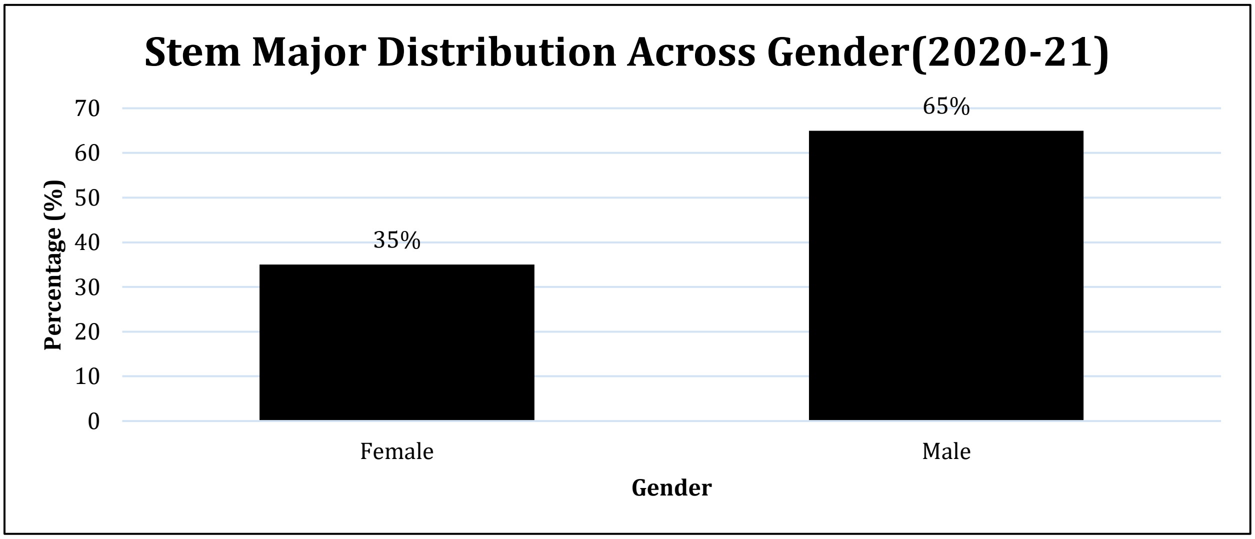
## STEM Pipeline

Berryman (1983) first introduced the concept of the "STEM pipeline," a term that describes the educational trajectory students follow from elementary school through various stages, culminating in a career in one of the STEM fields. Despite recognizing the significance of STEM and extensive efforts to foster interest in these areas, producing graduates ready for STEM careers remains challenging.

As technology and scientific progress continue to advance, there is a growing demand for skilled professionals in STEM fields. Despite this, there has been a noticeable decrease in the proportion of U.S. students obtaining STEM degrees in recent years. According to Hagemann (2015), nearly 16 percent of students complete a degree in a STEM field. Every year, the need for STEM jobs increases, resulting in the creation of millions of new job opportunities across the country. According to the National Center for Education Statistics, in the academic year 2020-2021, there were 5.2 million graduates across all fields in the United States, out of which 790,752 graduates were in STEM fields. This means that approximately 15.2% of the total graduates in that academic year were in STEM fields. In the academic year 2020-21, a total of

790,752 students graduated in the STEM field. Out of these graduates, 514,323 were male, while 276,429 were female. This means that the percentage of male graduates in STEM was approximately 65%, and the percentage of female graduates was around 35%. This gender distribution in STEM fields is significantly different from the general gender distribution in the United States, where the Census Bureau reports that approximately 50.8% of the population is female, while 49.2% is male.

Figure 1:Gender distribution among STEM majors




*Source:* National Center for Education Statistics

Table 1.1 shows a comparison between the percentages of various racial and ethnic groups in the United States' general population and their representation within STEM majors, along with the actual number of STEM major graduates. Whites (non-Hispanic or Latino) comprise 58.9% of the U.S. population and represent 57.4% of STEM majors, which translates to 385,194 individuals. Hispanic or Latino individuals make up 19.1% of the population and hold a slightly lower proportion in STEM at 15.1%, with 101,761 graduates. Black or African American people constitute 13.6% of the population but are less represented in STEM majors at 8.9%, with 59,848 graduates. Asians, who are 6.3% of the population, are significantly overrepresented in STEM majors at 14%, with 92,217 graduates. Individuals of two or more races make up 3.0% of the population and a slightly higher 4.2% of STEM majors, with 28,389 graduates. The American Indian/Alaska Native category, comprising 1.3% of the U.S. population, represents only 0.5% of STEM majors, which amounts to 4,731 graduates. This table highlights both the representation and underrepresentation of different groups within STEM education relative to their proportions in the general population.

Table 1:Comparison of Racial and Ethnic Representation in STEM Majors Versus General Population-(2020-21)

| | General Population Percentage (2020) | STEM Major Percentage(2020-21) | STEM Major Count (2020-21) |
|---|---|---|---|
| White | 58.90% | 57.40% | 385,194 |
| Hispanic or Latino | 19.10% | 15.10% | 101,761 |
| Black or African American | 13.60% | 8.90% | 59,848 |
| Asian | 6.30% | 14% | 92,217 |
| Two or more races | 3.0% | 4.20% | 28,389 |
| American Indian/Alaska Native | 1.30% | 0.5 | 3158 |

*Source:* National Center for Education Statistics and 2020 Census Bureau Data

*Notes*: Number and percentage distribution of science, technology, engineering, and mathematics (STEM) degrees/certificates conferred by postsecondary institutions, race/ ethnicity, level of degree/certificate, and sex of student: Academic years 2020-21. Numbers rounded up.

**Leaky Pipeline in STEM Career**

College students frequently display eagerness for STEM fields, but a significant number of them end up choosing non-STEM careers or do not complete their STEM degrees. This trend, referred to as the "leaky pipeline," is especially noticeable in higher education when students switch their majors, resulting in a smaller pool of potential STEM professionals (Alper, 1993).

Many high school graduates, particularly those proficient in mathematics, are not selecting STEM majors in college. It has been observed by the Business-Higher Education Forum (2011) that slightly more than a quarter of 12th graders skilled in mathematics are not pursuing STEM disciplines. Furthermore, studies indicate that nearly 50% of students initially pursuing degrees in STEM switch to majors outside of these areas for their final degree. (Chen, 2013). Notably, while 28% of college students show interest in STEM fields, about 48% eventually shift from STEM majors to non-STEM careers or decide not to complete their degrees (Ball, Huang, Cotton, & Rikard,2017).

To address this challenge, numerous academic sources have emphasized the need for enhanced STEM education to meet the increasing demand for experts in these areas, highlighting a significant concern for the future workforce (National Research Council, 2007; PCAST, 2012). Research has concentrated on identifying parameters that influence students' decisions to follow STEM majors and those that impact retention in STEM fields. The "leaky pipeline" is associated with various elements, such as gender disparities in student choices, the underrepresentation of minorities, socioeconomic status, and environmental influences (Bal et al., 2010). In the upcoming section, we will thoroughly explore the factors that influence STEM careers, aiming to gain a comprehensive understanding of their underlying dynamics.

# Factors Affecting STEM Career Interest

## *Family Influence on STEM Career Interest*

Understanding the impact of social relationships, particularly with family, is crucial for educators aiming to support STEM students in college. Young adults' well-being and career choices are significantly influenced by their closest relationships, which shape their emotional management, self-esteem, and feelings of loneliness. Bronfenbrenner (1977) described various levels of influence: the micro level (like your family), the macro level (society at large), the meso level (how different parts of your life connect, such as school and home), and the exo level (settings that affect you indirectly). For any young person, the family, particularly the relationship with parents, plays a critical role at the micro level. This emphasizes the importance of nurturing supportive social environments for young adults navigating pivotal life decisions, including choosing a college major.

Though many variables impact a child's interest in science, one of the most powerful influencers has been demonstrated to be parental and caregiver involvement. Several studies indicate that parents significantly influence their children's career choices in STEM-related fields. The concept of family involvement is multidimensional and can be defined as the actions and activities of parents that are relevant to their child's education in the school environment (Hill & Taylor, 2004).

### Parental Support Disparities Across Genders.

The type and amount of parental assistance can vary depending on the gender of the child. This disparity in support is rooted in societal norms and beliefs about gender roles, which influence how parents interact with their sons and daughters. Cridge (2015) has suggested that parents critically influence their children's career choices, especially during the early stages of their lives. However, the parental approach to career choice can indeed differ significantly between daughters and sons. According to the results of a national survey conducted by the American Society for Quality (2012), 21% of parents of girls aged 8-17 encouraged their daughters to pursue a career in the entertainment industry, while only 10% of parents encouraged their adolescent girls to pursue a career in the engineering industry. On the other hand, 31% of boys reported that their parents encouraged them to consider a career as an engineer.

Rowan-Kenyon, Swan, and Creager (2010) suggest that numerous girls report receiving help from their parents with their math homework and having high expectations set for their grades. Such support and expectations from parents are crucial for girls' success and sustained participation in mathematics as they age. According to teachers, parental encouragement and support are significant determinants of students' ability to succeed in mathematics (Rowan-Kenyon et al.,2020). Moreover, the actions of parents have a substantial impact on the attitudes held by girls and boys.

Consequently, girls find themselves at a disadvantage and require distinct approaches from parents to encourage a focus on STEM careers. Campbell (1991) suggests several ways in which parents can encourage their daughters to pursue careers in STEM fields, including: a) highlighting the importance of math and science in seventh and eighth-grade b) integrating science and math into their daily routine c) paying attention to career exposure d) being conscious of inaccurate information about women working in STEM careers e) participating actively in their child's academic environment f) assisting young women in overcoming the stereotype that people with math and science interests are "nerdy."

### Parent Education.

Parental education levels also significantly impact their children's decisions regarding careers. The education parents have received often dictates the advice and expectations they have for their children's education and future jobs, especially at the high school level. Svoboda et al. (2016) found that higher parental education positively impacts college students' enrollment in STEM courses. Research also shows that households where a parent or relative works as a professional engineer can significantly impact the career choices of the children in the family (Dorie & Cardella, 2013).

As college students move away from their families and focus more on building relationships with peers, parents remain a significant influence, as the principles and behaviors instilled during early socialization can shape their children's choices as they begin their university studies (Steinberg, 2016). This influence can also extend to parents working in other STEM fields, as they can serve as positive role models and inspire their children's selection of majors.

### Family Support at Schools.

Studies have shown that getting involved with STEM subjects in high school offers lasting benefits. Students who engage more with STEM are more likely to follow a career path in these fields in the future. This suggests that early exposure to STEM can have a significant influence on career preferences in the future (Tey, Moses, and Cheah,2020b). As such, the role of parents in encouraging science education is crucial for boosting the chances of their children choosing careers in the STEM fields. In the following paragraphs, I will discuss various methods to strengthen parental school participation to improve student interest in science courses. This, in turn, is expected to encourage more students to pursue careers in STEM fields.

The Coleman Report (Coleman et al., 1966) and the Jencks Report (Jencks et al., 1972), as well as more recent works, both in the United States, support the idea that family influences academic performance. The Coleman Report, widely considered one of the most pivotal policy documents of the twentieth century in the United States, played a crucial role in shaping educational strategies across various subjects during the civil rights era. Coleman et al. highlighted the substantial influence of family background on student academic achievement in their report. Not long after the Coleman Report, the Jencks Report came out. Jencks et al.(1972) used data collected by Coleman(1966) and the findings of additional surveys to explore whether students' cognitive abilities are significantly influenced by their families.

Lee and Bowen (2006) explored the impact of family engagement on high school students' success, focusing on how racial/ethnic backgrounds and family income levels influence parental involvement. They found that race and socio-economic status significantly affect how parents participate in their children's education, underscoring the importance of these factors in students' academic achievements. Additionally, the level of parental involvement in educational activities tends to vary with socio-economic status, with parents from higher SES backgrounds generally showing more engagement than those from lower SES backgrounds. This suggests that both educational attainment and socio-economic factors play critical roles in shaping the extent and nature of parental participation in the educational landscape (Crowley,2015).

Jeynes (2007) reviewed 52 empirical studies on urban secondary school students and parental involvement. These studies found that active parental involvement can lessen the academic performance gap between students of racial minorities and their white counterparts in secondary school children. This highlights parental engagement's role in fostering academic success and mitigating educational inequalities among students from diverse racial backgrounds. Ellington (2006) investigated the mathematical abilities of eight successful African American female undergraduates to assess their performance. Participants linked their success in math to the support they received from their parents. The female students credited their parents for sparking their early interest in mathematics and their early success.

Various models aim to enhance parental involvement in schools to foster stronger collaborations between families and educational institutions, ultimately benefiting student learning and development. These models emphasize the importance of mutual understanding and encourage the participation of parents from diverse backgrounds in their children's education. Models developed by researchers such as Hoover-Dempsey (2005), Epstein (1995), and Olivos (2016) underscore the significance of effective communication between homes and schools. Each model highlights the interrelated roles of students, parents, and schools in achieving better educational outcomes.

Olivos' approach addresses the challenges parents from different cultural backgrounds face in engaging with public schools, aiming to tackle disparities and enhance inclusivity. This model pays particular attention to the experiences of bicultural families and seeks ways to improve their interactions with educational institutions.

Conversely, the frameworks proposed by Epstein, Hoover-Dempsey, and Sandler offer a broader perspective on parental involvement, encompassing a wide range of cultural and social backgrounds. These models provide insights into how parents can contribute to their children's education and how such involvement can positively impact students' academic achievements and development.

In conclusion, the research underscores the critical influence of family and social relationships on students' interest and success in STEM fields. Bronfenbrenner's ecological systems theory highlights the pivotal role of familial support at the micro level in shaping career choices, with parental guidance and encouragement significantly affecting children's inclination towards STEM careers. While boys often receive more encouragement for careers in engineering, girls are less supported in STEM, indicating a need for increased parental support for daughters. Parents' educational background, socio-economic status, and involvement in STEM professions significantly influence students' decisions regarding careers in STEM fields. Engaging in STEM activities during high school further heightens interest in STEM careers, emphasizing the importance of parental involvement in education to foster a supportive environment for students exploring STEM fields.

***Informal Learning Effect on STEM Career Choice***

Informal learning is a learning environment that is voluntary, open-ended, and has less structure (Leblebicioglu et al., 2017). Eshach (2007) provides an alternative definition of informal learning, describing it as learning that can occur in any setting. His study further explains that an individual's informal learning is shaped by their experiences in various settings and circumstances throughout their lifetime.

According to the After-school Alliance (2015), seven million students in the United States who are enrolled in middle school participate in STEM activities outside their regular school day (i.e., informally or outside of their traditional instruction). Outside the classroom, Lachapelle and Brennan (2018) found that engineering after-school and summer programs positively influence students' attitudes toward STEM and their career aspirations. Kurz et al. (2015) noted that participation in an Engineering Expo significantly boosts students' interest and perception of STEM fields.

Informal learning, such as that offered by an OST (Out of School Time) STEM program, provides educators with the chance to answer questions posed by students, promote the academic interests of students, and enhance students' motivation to study STEM subjects. Informal science may teach knowledge regarding science and the natural world, exemplify the use of scientific inquiry, and motivate students to become prospective scientists by fostering their interest in science learning through informal learning (Brisson et al., 2010). Students have the option to become self-directed learners through the use of the informal learning approach. Brown (2016) and Holmquist (2014) found that middle school students who participated in OST STEM activities learned more STEM content. Introducing middle school students to STEM activities outside of school hours allows them to develop their interest and identity in STEM, which can motivate them to follow a STEM-related path (Hazari, Sonnert, Sadler, & Shanahan, 2010).

Informal learning emphasizes student interests and motivations, with various characteristics of these environments fostering skills like leadership, effective interaction, digital literacy, innovation, teamwork, and social and interpersonal abilities. When students are given the chance to experience the content of the curriculum in an informal setting and the context of the real world, they apply their academic knowledge in a new approach. Students can also broaden their understanding of STEM subjects by participating in informal educational activities such as excursions and after-school programs. These settings allow students to explore current topics and engage with innovative concepts. Students would have a more profound comprehension of STEM ideas by combining their previous academic education with the real-world experiences gained from participation in field excursions pertaining to STEM subjects (King and Pringle, 2019). Students exposed to these educational settings tend to develop a greater interest in STEM-related subjects and show increased enthusiasm for careers in these areas.

Additionally, a study on a cohort of young female scouts participating in an informal educational setting revealed that such experiences enhanced their interest and confidence in fields related to STEM (Burrows, Lockwood, Borowczar, & Janak, 2018). Research has shown that students who engage in extracurricular activities, such as field excursions, are better at applying STEM concepts to real-world situations. Furthermore, these students are more likely to develop and maintain an interest in careers that are related to STEM.

After-school Alliance (2015), the National Research Council (2015), and the National Research Council (2009) all found that increasing students' access to high-quality OST STEM experiences was one of the most critical factors in growing students' persistence in STEM careers. Haden et al. (2014) found that children exposed to direct teaching or information regarding STEM at a science museum showed a higher likelihood of remembering STEM-related content.

Additionally, Kirchberg (1998) pointed out that entrance fees are a significant barrier preventing people from visiting museums. This suggests that children from families of higher SES tend to have greater access to science museums and various informal learning environments throughout their childhood and teenage years compared to those from lower SES backgrounds. This difference in access could have implications for their educational and developmental experiences. Therefore, researchers must investigate additional predictors such as SES, parental support, and teacher encouragement in STEM to consider strategies for spreading young people's interest in science. These activities provide students with a real, hands-on learning experience using STEM tools (technology) and practices that enhance their understanding of STEM subjects and identity (Holmquist, 2014). The desire of middle school kids to grasp STEM subjects and develop a STEM identity has been experimentally associated with an individual's motivation or inherent willingness to study. Students are more motivated when they have a choice than when forced to comply (Deci, Vallerand, Pelletier, & Ryan, 1991). Therefore, assessing student engagement in OST STEM activities may contribute to understanding STEM career choices.

In conclusion, like the activities in OST STEM programs, informal learning is essential for helping middle school students get excited about and feel connected to STEM careers. These programs, which can include after-school clubs and field trips, let students see and use STEM ideas in the real world, helping them understand their lessons better. Studies show that being part of these activities makes students more confident and interested in STEM and teaches them essential skills like how to work well with others and solve problems creatively. Access to real-world OST STEM experiences is vital for keeping students interested in STEM careers as they grow up. However, only some get the same chance to join these activities, often because of differences in where they live or how much money their families have. This means we must find ways to ensure all students can get involved and benefit from these experiences. Doing STEM activities outside of regular school hours can inspire students to learn more independently and think about working in STEM fields one day by making learning fun and hands-on, sparking their curiosity and drive to discover new things.

### *Educational Influences on STEM Career Choice*

Education is crucial in promoting interest and developing a positive mindset towards STEM. Students build a solid foundation by engaging in interactive lessons and practical experiments, sparking their curiosity and passion for STEM. This section will examine the impact of academic coursework and the school environment in guiding students toward pursuing careers within the STEM fields.

Most students are interested in science until they are approximately 10 years old, after which many students' interests tend to decline, particularly among girls, suggesting that the trajectory of early scientific interest may be particularly crucial to study (Lindahl, 2007). The Royal Society (2006) reported that in a survey conducted among STEM professionals in England, one-third of the respondents indicated that they had begun considering a STEM field by the age of 11, and an additional one-third had started contemplating this career path by the age of 14. According to researchers who examined gifted children, by the age of nine, they had already decided whether or not they liked science (Joyce & Farenga, 1999).

Lamb et al. (2015) compared kindergarten, second, and fifth-grade students in schools with and without a STEM-focused curriculum. The study, involving 254 students, showed that those in the STEM-integrated curriculum had more positive cognitive and affective outcomes in STEM fields, indicating the beneficial impact of STEM experiences in the classroom.

Aschbacher and Ina (2017) conducted a study with fifth graders in California to examine their perceptions of learning opportunities in school science, their self-view as science learners, and their aspirations for taking more science courses, hoping to inspire STEM careers. The study surveyed 690 students and discovered a significant link between the science education opportunities offered in schools, the student's inclination to take additional science classes, and their positive self-view regarding careers in science.

In conclusion, early engagement in STEM disciplines is critical, as early exposure to STEM can influence career paths, with many STEM professionals deciding on their career direction by early adolescence. Studies involving younger students in STEM-focused curriculums show more favorable outcomes, underscoring the impact of early STEM experiences.

In the upcoming section, having provided a general overview of education, I will concentrate on the specific impact teachers have within educational environments on guiding students toward careers in STEM.

**Teacher Influence.**

Teachers, in addition to parents, are key figures in students' lives who considerably influence their views on science. Effective scientific education primarily relies on instructors' efforts regardless of grade level. Teachers are important in promoting students' interest, perseverance, and curiosity in class subjects by arranging lessons and adjusting the difficulty of the content (NRC, 2007). Young et al. (1997) found that a teacher who shows enthusiasm for their topic can significantly develop students' interest in STEM fields.

In addition to impacting students' enthusiasm for science, teachers' support may significantly affect students' career selections and expectations for their professional outcomes (Metheny, McWhirter, & O'Neil, 2008). These researchers emphasized the importance of teachers in increasing primary school science interest. Dick and Rallis' (1991) research states that teachers have a significant impact on students when it comes to making career decisions. It is also essential that some other various factors can negatively impact students' decision to pursue STEM fields. These factors may include insufficient preparation of teachers, inadequate comprehension of the subject matter, ineffective teaching methods, and poor relationships with students (Jensen & Sjausted, 2014). This is especially important for underrepresented groups since environments that foster or pose a risk for stereotypes can have a negative impact on students (Makarova, Aeschlimann & Herzog, 2016). Multiple research projects have investigated how different elements influence pupils' desire to pursue STEM careers. These studies have found that the influence of educators is among the most significant factors determining whether students opt to pursue careers in STEM. It was also worth noticing that teachers significantly impacted females' decisions more than males.

**STEM Programs at Schools.**

Recent investigations have demonstrated the influential role of STEM-oriented high schools in steering students toward educational and career pathways in STEM. A significant insight from these studies is that the combination of academic courses and extracurricular activities within these schools motivates students to pursue STEM degrees at higher educational institutions (Sahin, Ekmekci, & Waxman, 2017). This educational strategy fosters a strong interest in STEM fields and provides a robust foundation for advanced studies.

Further inquiry into the effectiveness of STEM-focused education reveals that students from these specialized schools are better prepared for the academic challenges of college STEM programs than their peers from traditional high schools. This preparation underscores the ability of STEM-focused schools to equip students with the necessary skills and knowledge for success in higher education (Means, Wang, Young, Peters, & Lynch, 2016).

Moreover, student involvement in STEM-centric educational settings increases participation in STEM-related courses and activities. This enhanced engagement promotes a more profound interest in STEM careers, establishing a clear connection between secondary education and future professional objectives (Bottia, Stearns, Mickelson, & Moller, 2018). Studies consistently indicate that students who have been part of a STEM-focused learning environment are more likely to pursue careers in STEM fields than those who have received a general education.

The influence of high school engineering and engineering technology (E&ET) courses on students' decisions to attend two- or four-year colleges for STEM degrees has also been examined. These studies conclude that enrollment in E&ET courses positively impacts students' intentions to pursue further education in STEM, emphasizing the vital role these courses play in students' academic and career planning (Phelps, Camburn, & Min, 2018).

In summary, evidence suggests that STEM-focused high schools are pivotal in encouraging students to follow paths leading to higher education and careers in STEM disciplines. By providing an immersive and comprehensive STEM education, these schools prepare students for the rigors of college STEM programs and nurture a lasting interest in STEM professions.

**STEM Related Courses.**

Taking advanced math and science classes in high school deepens students' understanding of intricate mathematical ideas and nurtures an increasing enthusiasm for careers in STEM. Starting with Algebra 1 in middle school lays a strong foundation for success. Middle school students who complete Algebra 1 often perform better academically, preparing them for the challenges of more sophisticated math and science classes in their later years. Their educational path typically includes demanding courses like Geometry, Algebra II, Pre-Calculus, and Advanced Placement (AP) Calculus. Exposure to such advanced courses plays a crucial role in steering students toward STEM careers, greatly enhancing their interest and ambitions in these fields (Wang, 2013; Bayard, 2013).

As mentioned earlier, AP courses play an indispensable role in the academic journey of high school students, particularly those aspiring to careers in the STEM field. These courses are designed to challenge students with college-level material, providing them with a solid foundation in subjects critical to STEM fields. Completing AP courses can significantly influence a student's decision to pursue a career in STEM, as it equips them with essential academic knowledge in the subject area.

Concurrently, courses in engineering and technology are equally crucial for students aiming for success in STEM fields. These courses offer practical, hands-on experiences vital for understanding real-world applications of STEM principles. They foster innovative thinking, problem-solving skills, and creativity—attributes that are as essential as theoretical knowledge for anyone looking to enhance STEM careers. However, a notable challenge arises from the heavy workload demanded by AP courses, which often leaves students with little flexibility in their schedules to explore engineering and technology electives. This imbalance can lead to a gap in the comprehensive education necessary for a successful career in STEM. Students might excel in theoretical knowledge and exam preparation but need more practical skills and an innovative mindset that are increasingly valued in the STEM industry (Jang,2016).

To address this issue, there should be a concerted effort to balance the inclusion of AP and engineering/technology courses in students' schedules. Educational institutions and advisors must guide students in creating a balanced curriculum that allows for exploring both theoretical and applied STEM subjects. Encouraging a balanced approach ensures that students take advantage of the critical hands-on learning experiences provided by engineering and technology courses while benefiting from the rigorous academic preparation offered by AP courses. This balanced educational pathway is essential for developing the next generation of innovators, problem solvers, and leaders in STEM fields.

### *Individual Difference Effect on STEM Career Choice*

Individuals' character traits can significantly impact their choice of profession. This is especially true for careers that require specific personality traits and characteristics. Just as the arts, including music, require special skills and talents, careers in STEM also demand specific traits. However, it is also important to understand the common traits among individuals who choose science-related professions. Studies have been conducted to identify common personality traits for science-oriented individuals. One such study administered the 16-factor Personality Questionnaire to individuals involved in chemistry and biology, revealing that they exhibit higher confidence and dominance than others. Interestingly, this difference is more pronounced among females than males. Females tend to show higher levels of confidence and dominance (Feist,1998)

Another study by Lounsbery et al. (2012) used the Personal Style Inventory (PSI) to measure five personality aspects: Agreeableness, Conscientiousness, Emotional Stability, Extraversion, and Openness. This study supports the previous findings and suggests that scientists excel in intrinsic motivation, such as challenge, purpose, autonomy, and diversity. Traits like openness, conscientiousness, dominance, and confidence are more prevalent in scientists than non-scientists. This highlights the importance of personality in career choice, particularly in science-related professions. It also suggests that certain innate qualities may predispose individuals to pursue and excel in scientific endeavors.

To sum up, personality traits play a crucial role in determining career paths, especially in professions that demand specific attributes. Investigating the shared characteristics of individuals ***w***ho pursue careers in science is equally important.

### ***Persistence Effect on STEM Career Choice***

Perseverance has been studied in various contexts, including task-oriented definitions and definitions that view persistence as an intrinsic trait. The two definitions of persistence that are most frequently encountered are "an objective feature of deliberate conduct" (Hebb, 1989) and "a goal-directed activity" (McDougall, 1908). STEM persistence is described as a student's capacity to continue STEM learning and pursue a logical STEM-based route (Sithole et al., 2017).

Maintaining persistence in STEM fields is essential for the global STEM industry. The future workforce (Sithole et al., 2017) and the lack of significant STEM persistence toward a STEM degree in the U.S. is becoming an issue due to a rise in demand for STEM jobs in the USA (Carnevale, Smith, & Melton, 2011.). According to information provided by the Bureau of Labor Statistics (BLS) of the United States of America, positions related to the STEM fields are "projected to expand to more than 10 million between 2022 and 2032. Soldner, Rowan-Kenyon, Inkelas, Garvey, and Robbins (2012) reported that one out of seven U.S. students get a degree in science or engineering, compared to one out of two in China and two in three in Singapore.

Another serious problem that must be taken into consideration is the high dropout rate among students majoring in STEM fields (Ingersoll & May 2012). Over the past twenty years, there has been a fifty percent decline in the percentage of high school students opting for STEM fields in college. Furthermore, about fifty percent of students who enroll in STEM programs end up transferring to another institution before completing their degree. (Chen, 2013; Daempfle, 2003). The physical sciences and engineering are particularly at risk due to a significant drop in bachelor's degrees and doctorates awarded in these subjects over the last decade (National Science Foundation, 2013; Xie & Achen, 2009). It has also been shown that many college students change their majors throughout their time in school, especially those pursuing STEM degrees (Daempfle, 2003). Furthermore, studies also show that minority students and women are more prone than their male and white counterparts to switch majors or leave STEM programs (National Science Board, 2007). In the United States, this lower persistence is related to a variety of factors, such as negative stereotypes towards women and minority groups (Beasley & Fischer, 2012), lack of high performance in math and science courses (Sadler, Sonnert, Hazari, & Tai, 2014) and lack of early access to STEM learning.

Students' persistence in STEM fields can be impacted by factors such as the quality of the curriculum, a sense of intrigue in STEM fields, prior experience, easy access to STEM education at a young age, and academic achievement in STEM classes (Anderson & Ward, 2014). Research on the issue of STEM persistence has been undertaken retrospectively by investigating STEM college students' academic readiness in high school, particularly their performance on math and science examinations and in AP courses (Sadler et al., 2014).

The K-12 school system must support students' persistence in STEM fields (Houssain & Robinson, 2010). Prospective STEM employees must be able to think logically, solve problems creatively, and communicate effectively while working in a team-oriented environment. Students need to continue their studies in STEM fields if the opportunity is given to them to develop their skills and their understanding and interest in STEM-related fields. This will also help students have more positive learning experiences in mathematics and science (Maltese & Tai, 2011). Several strategies can be implemented to encourage STEM students to continue pursuing a career in engineering: a)OST (out-of-school programs), b)in-school engineering design enrichment programs, c)formal K-12 engineering curriculum, d)engineering guest speakers, and e)formal engineering teacher professional development (Reynolds, Mehalik, Lovell, & Schunn, 2009). These activities improve students' STEM knowledge and attitudes while enhancing their STEM subject and skill acquisition (Brown, 2016).

Another important approach to improve STEM persistence is to provide information about STEM careers in K-12 school settings. Activities that explicitly connect STEM learning with possible job pathways are one technique that may be used to raise awareness. These activities can assist in bridging the gap between STEM education and potential career paths in STEM (Christensen, Knezek, & Tyler-Wood, 2015). Wyss et al. (2012) discovered that exposing students to various STEM jobs and providing information about those careers enhanced their interest in STEM disciplines. In addition, research conducted by Reynolds et al. (2009) discovered that high school students who participated in engineering activities and career awareness topics had a greater interest in engineering and the occupations that are linked with it.

***Numerous Studies on Interest's Role in STEM Career Choice***

The link between interest and learning quality has been studied extensively, and many researchers have concluded that interest is associated with in-depth learning. A young person may be inspired by motivation when determining their future goals. Depending on the situation, the motivation might be internal or external. Intrinsic motivation occurs when people do things because they like them and are interested in them; extrinsic motivation, on the other hand, occurs when people do things for different reasons, such as getting a price or grade (Wigfield, Eccles, Schiefele, Roeser, & Davis-Kean, 2007).

Research indicates that participants' interests and aspirations significantly influence whether they choose to pursue STEM opportunities while still in high school. These interests and goals are critical in pursuing a STEM career (Heilbronner, 2013). Several studies have been conducted to explore student interests and ambitions in subjects heavily focused on mathematics during both high school and post-secondary education. According to these studies, some research indicates that interest does not predict career goals in mathematics-focused fields (Lent, Lopez, Lopez, & Sheu, 2008), while others suggest that interest reflects personal aspirations, particularly among high school and college engineering students (Moore, 2013). For example, in a study of 173 high school students, the researchers found that the female participants were less interested in engineering than the male participants. They linked this to the fact that few women are in post-secondary engineering programs, which fits with what they found in the more extensive literature (Riegle-Crumb & Moore, 2012).

Some post-secondary studies have investigated the relationship between one's interests and goals. Gainor and Lent (1998) conducted an early study with 164 black university students in which they used a survey instrument with a reliability coefficient of .90 to assess students' interest in math and science-related tasks, along with the effect that interest had on students' decisions to enroll in math-related classes and choosing a math-related major. The study revealed a significant correlation ($r = .37$, $p < .001$) between interests and essential decision-making, with interests having an impact on the choice of major (path coefficient of .22, $p < .05$). A survey instrument with a reliability coefficient of.82 was used in a global study that involved 579 engineering students in Spain. The purpose of the survey was to measure student interest in engaging in activities related to engineering self-efficacy of females, which is related to their interests and personal goals as well as gender and socio-economic status (Myers, Jahn, Gaillard, & Stoltzfus, 2010). Hackett et al. (1992) used an interest in engineering scale to assess 197 post-secondary engineering students' interest in 18 engineering careers in relation to self-efficacy. It was found that females had a lower interest in engineering than males (effect size = -0.3) and reported a strong correlation between interest and occupational self-efficacy ($r$ =.39, p.01).

### ***Socio-economic Status Effect on STEM Career Choice***

Social scientists have used children's socioeconomic status, abbreviated as SES, for decades as a proxy for analyzing various aspects of child development. According to the United States Department of Education (2000), low-income students are identified as those coming from households with earnings that fall below a specified threshold of the federal poverty level.

Roberts et al. (2018) analyzed the relationship between educational background and interest in pursuing a STEM profession. They discovered that students from underrepresented groups, such as students from low-income backgrounds or students from different backgrounds, had a lesser chance of entering a STEM field. This trend indicates that kids from less affluent families face more difficulties in obtaining STEM jobs. Furthermore, this problem is getting bigger as the demand for STEM workers is growing faster than the number of students being trained for these jobs. (Kitchen, Sonnert, & Sadler, 2018). Insufficient opportunities to participate in STEM-related extracurricular activities and a lack of early exposure to these subjects at home have been highlighted as two possible causes of this problem (Kitchen et al., 2018). These considerations influence ongoing efforts to expand access to informal STEM learning settings so that more students from underrepresented groups may study these subjects and enter STEM professions (Maiorca et al., 2021). On the other hand, they discovered that students from low-income families who attended specialized STEM high schools had a higher probability of entering a STEM career.

Saw et al. (2018) noted variations in STEM career choices linked to socio-economic backgrounds. Parents' impact on their children's lives extends beyond their direct actions. For example, parents might influence their child's choice of college major by linking their financial support for education to selecting a specific major. This is evidenced by 49% of college students stating that their parents play a role in decisions regarding college finances (Dickler, 2018), and almost 50% of college students' parents offer some financial support to their kids (Priceonomics, 2017).

It is possible to influence the direction that education will take in the future and create pathways for other students by listening to the stories of students who come from families with little financial resources but have decided to choose STEM-related jobs.

**Current SES situation in STEM Career.**

As previously stated, SES is another key element that affects students' choices regarding their career paths. Researchers have been exploring the number of students affected by the reality that a student's socio-economic status impacts their educational success. In 2014, 21.1% of children eligible for school were living in poverty, with their family income falling below the federal poverty level (DeNavas-Walt & Proctor, 2015). The U.S. Census Bureau reported that in

2022, the poverty rate among children under 18 in the U.S. dropped to 16.3%. Their academic performance influences school success for students from low-income families, the availability of role models, and higher stress levels compared to their wealthier peers (Levin, 2007). Skilled teachers can reduce the negative impact of socio-economic status on students. It has been shown that when teachers take the time to get to know their students on a personal level, they are better able to tailor lessons to each student's distinct needs and learning styles (U.S. Department of Education, 2000).

Students from low-income families tend to face ongoing stress and stress-related challenges due to issues like parental separation, separation from brothers and sisters, increasing incidents of crime, and general economic difficulties. This raises the chances that these students will encounter social and educational challenges during their academic journey (McKenzie, 2019). Students who come from these kinds of environments are unable to give their full attention to school; instead, they must divide their attention among a variety of responsibilities; as a result, they miss more classes, and as a direct consequence, they struggle more to maintain their academic motivation and perseverance (Jensen, 2009). Additionally, kids who originate from families with low incomes are more likely to attend schools where most of the other students also come from families with low incomes, which further contributes to a dynamic unfavorable to the educational system's efficiency (Boschma & Brownstein, 2016). This leads to a more significant obstacle for entry into STEM careers than their peers from wealthier families due to the difficulties they need to navigate and the necessary motivation.

A further challenge faced by children from lower-income families is the lack of access to resources that could improve their enthusiasm for learning. Johnson et al. (2016) found that kids from these families usually find it harder to do well in school than those from wealthier families.

This happens because kids from more affluent families can access more learning materials. They noticed that kids with lots of different things to learn from when they are young tend to know more words and talk better.

### The Impact of Testing on STEM Choice.

Due to its inability to take students' socioeconomic status into account, standardized testing was shown to discourage low-income students from pursuing careers in STEM (Reardon, 2013). Students from low-income families are more likely to be negatively impacted by standardized testing than their middle- and upper-class counterparts because they face more challenges and pressures (Jensen, 2009). Because of an existing achievement gap that results in lower GPAs, exams have emerged as an additional barrier to entering STEM fields for numerous children from economically disadvantaged families (Sherman, Darwin, Song, Li,& Satchel, 2015). Students are less likely to be college and job-ready in STEM fields when standardized testing is used as the only criterion; low-income students have always had a more challenging time succeeding academically when standardized tests were the major measure of success (Reardon, 2013). If students' test results were considered throughout the admissions process, 72 percent of those granted admission to a university in North Carolina belonged to the highest income quartile on the national scale.

Additionally, since many universities use standardized tests like the ACT and SAT as predictors of college fit, testing has a negative impact on student enthusiasm in STEM fields by functioning as a barrier. According to Soares (2015), a student's test score is a significant determinant of whether or not they are offered a place at a prestigious university.

Students from low-income families who took high-stakes tests in their STEM classes were more likely to suffer tension and anxiety, as revealed by Rozek, Ramirez, Fine, and Beilock (2019). As a result, these students had difficulty performing well on the tests, which became a significant obstacle to their advancement in STEM studies.

Students from low socio-economic situations face many challenges regarding testing, but there are multiple strategies to overcome these challenges. According to Rozek et al. (2019), when students could emotionally regulate their worries and analyze their emotional state before taking tests in their STEM courses, they performed significantly better than when they did not have this space. After implementing emotional regulation techniques, economically disadvantaged students in STEM courses experienced a 50% reduction in failure rates. (Rozek et al., 2019).

### ***Perception and Student Desire to Pursue STEM Career Choice***

Students' beliefs and attitudes significantly influence their desire to explore careers in STEM. Access to non-traditional learning spaces boosts their confidence in STEM and guides their decisions about pursuing careers in this field. A key factor influencing a student's decision to pursue a specific field is their belief in their ability to achieve their goals in that area (Eccles & Wigfield, 2002). Previous STEM experiences impact their self-efficacy and confidence in their ability. These kids were also more likely to have poor self-efficacy due to external stresses outside of school, as well as low test scores linked with academic success. Kids from low-income families were less likely to pursue STEM occupations owing to a widespread misconception that scientific programs were considerably more complex than non-STEM degrees (Cheryan, Master, & Meltzoff, 2015). Low self-efficacy reduces students' confidence that their goal of pursuing a

STEM profession is achievable, diminishing the action of choosing a STEM major that is viewed as more challenging. Sithole et al. (2017) discovered that tackling the barrier of negative STEM views by increasing student self-efficacy improved the number of students enrolled. Therefore, raising students' confidence that they will succeed in STEM fields is essential if we want them to pursue these fields. Increasing self-efficacy and encouraging students to believe in a satisfactory outcome would favorably affect achievement-related choices for kids from low-income families (Kitchen et al., 2018).

### *Peer Influences in STEM Career Choice*

Children can be encouraged or influenced to follow similar professional aspirations if they are exposed to career-minded people through living with those people or being in their immediate environment. Students might be motivated to follow these people's career paths if they see them making positive career achievements (Alika, 2012; Scholastic, 2008). According to research, their classmates might influence kids' academic success and ambitions (Kindermann, 2007). Having high-achieving close friends, for example, is linked to a higher chance of enrolling in advanced courses throughout high school (Crosnoe, Riegle-Crumb, Field, Frank, & Muller, 2008). Furthermore, this relationship appears stronger for girls taking advanced math and science courses (Riegle-Crumb et al., 2006). Compared to adolescent boys, teenage females claim their classmates are less supportive of pursuing STEM professions (Robnett & Leaper, 2013).

The network of friends and family around a person plays a crucial role in shaping their growth and development. These relationships influence their behaviors, beliefs, and choices throughout life. Students may find themselves in the wrong direction in life if they associate with the wrong people, as decisions are frequently influenced by the perspectives of others in their surroundings. Many bright individuals have been pulled away from promising jobs by gangs, drugs, and crime because individuals around them criticized or embarrassed those students into keeping away from the positive path in life. Negative attitudes and misconceptions regarding STEM careers can prevent students from pursuing them (The Institution of Engineering and Technology, 2008).

Peers are also crucial for women studying STEM in college and graduate school. Women's interest in coursework rapidly diminished when they felt alone in their struggles, under the impression that they were the only ones encountering difficulties. Several studies have found evidence to support the idea that some women who work in STEM fields experience a sense of social isolation (Zeldin & Pajares, 2000).

As a result, the authors concluded that developing strong, mutually supportive relationships with other students may be essential for increasing the number of people who remain in the area. The advantages of peer support were also emphasized by Zeldin and Pajares (2000), who revealed that women's success in STEM professions and peer support were positively correlated.

### ***Underrepresented Groups (URGs) in STEM Career Choice***

The racial and ethnic composition of the United States has shifted considerably during the last several decades. In the United States, the minority population grows faster than the white majority population. According to the 2010 census, approximately 16 percent of the population is Hispanic/Latino(a), making them the fastest-growing and biggest ethnic minority group in the United States (U.S. Department of Commerce, Census Bureau, 2011). Blacks constitute 12 percent of the population. Minorities accounted for one-third of the population in 2008 and are predicted to account for the majority of the population by 2042. By 2025, the U.S. population will be 21% Hispanic, 58% White, 13% Black, 6% Asian, 1% American Indian, 1% Pacific Islander, and 2% other races and ethnicities (U.S. Department of Commerce, Census Bureau 2008). According to predictions, ethnic and racial minorities will make up 62% of all school-aged children by 2050 (U.S. Department of Commerce, Census Bureau, 2008).

While it is clear that the minority population is growing in the U.S., minority participation in STEM areas is low and does not reflect the existing or predicted demographic trends. According to the National Science Foundation, women, African Americans, Hispanics and Latinos, Native Americans, Pacific Islanders, and Alaskan natives are among the groups that are underrepresented in STEM. In 2021, although women accounted for 51% of the U.S. population aged 18 to 74 years, they only represented about 35% of individuals employed in STEM occupations (NSF,2023). The figures for ethnic minorities are much more concerning. While blacks account for 12 percent of the population, they only account for 3 percent of the scientific and engineering fields. Hispanics account for 16 percent of the population but only 4 percent of the science and engineering fields, respectively (National Science Foundation, 2013). Diversifying the STEM workforce will allow previously underrepresented groups to contribute to solving global challenges and improve their economic standing (National Academies, 2010). Diversity is beneficial not only to businesses but also to the nation as a whole. When it comes to tackling the difficulties we confront as a society, diversity brings a variety of methods and lenses to the table (National Academies, 2010).

Despite the apparent benefits of a diversified STEM workforce, URGs do not pursue employment in STEM professions. Discrimination, poor prior academic accomplishment, lack of financial help, and absence of role models and mentors are just a few of the difficulties facing today's youth in science (National Academies, 2010).

### ***Women in STEM Career***

For the majority of history, women have typically been viewed or regarded as second-class citizens (Clabaugh, 2010). This was the case back when the United States was in its infancy and dame schools were being established within the communities. Women were only permitted to attend school when it was not in session, often during the summer or evenings ("Education of Women," 1997). Even after completing and excelling in the dame schools, females were not encouraged to continue their education by enrolling in the town schools in the city (Madigan, 2009).

The colonization and growth of new territory in the American West throughout the 19th century brought significant social and cultural changes. At the time, fewer resources were available to pay instructors and supply classrooms. Therefore, men and women could attend the same schools (Madigan, 2009). Even though more women were receiving an education, the traditional tasks of a woman in society were still seen as caring for the house and raising children (Halsall, 1996). During the 1930s, it was widely believed that the place of a white woman from a middle-class family was in the home, serving as a mother and wife. This attitude persisted even after the Great Depression (Nash & Romero, 2012). On the other hand, there was a rise in the number of women enrolling in post-secondary schools as a direct result of the need for more educated primary school teachers brought about by the development of the educational system (Clabaugh, 2010).

In 1975, legislation was passed to ensure that students of all genders received equal opportunities in all educational realms, including classroom activities, physical education, sports, and competitive events (Gelbrich, 1999). The aim was to eliminate gender-based bias, fostering significant societal and educational advancements in understanding and addressing gender discrimination. During this period, there was a notable increase in the number of women pursuing and obtaining Bachelor of Science degrees in college.

Over the last four decades, this advancement has resulted in more women than men attaining graduate degrees. Women have surpassed men when it comes to completing high school and earning a bachelor's degree. (Women in America, 2011). According to the National Center for Education Statistics, in 2021, approximately 88.6% of male students and 90.4% of female students graduated from high school.

**Women in Workforce.**

Previously, gender-based societal norms in the United States assigned specific roles to men and women. Men were expected to work outside the family farm, while women were tasked with managing household duties and caring for children. These roles were reinforced by stereotypes that labeled women as emotionally unstable, physically weak, and less inclined to take risks, which restricted their employment opportunities to roles such as educators, nurses, clerks, and house cleaners. Moreover, women who were married were discouraged from seeking employment outside the home, as nearly 80% of Americans believed it was improper (Bomarito & Hunter, 2005).

However, the late 1950s and early 1960s marked a transformative cultural shift, with increased awareness and the burgeoning women's rights movement. Women achieved great educational opportunities, and affirmative action policies were introduced. These changes collectively altered societal perceptions, significantly departing from the restrictive norms of the past and broadening the scope of work considered acceptable for women (Hall, Orzada, & Lopez-Gydosh, 2015).

**Woman in STEM Workforce.**

As highlighted earlier, societal expectations significantly influence women's career choices, leading to a notable underrepresentation in engineering and science fields. Even though women recognize the value of these disciplines and strive to overcome cultural barriers, they often end up working in more traditionally female-dominated fields, such as education and healthcare, rather than STEM-related roles. This trend is concerning because it means that women's diverse perspectives and innovative ideas, crucial for finding effective solutions to complex problems, are missing in the industry. With women accounting for half of the global population, their limited presence in STEM fields restricts their career opportunities and slows down societal progress and innovation (Fisher, 2013).

Women face distinct challenges in the STEM fields, which contribute to a higher dropout rate in STEM careers compared to their male counterparts. Notably, there is a significant underrepresentation of women in specific areas such as physics, engineering, and computer science. This disparity highlights the need for targeted interventions and support. However, it is encouraging to see that women are better represented in the life sciences, such as chemistry and biology (Dawson, Bernstein, & Bekki, 2015). The recruiting and retention efforts of programs and initiatives in computer science and engineering will probably not be able to meet the needs of women, especially the requirements of women from underrepresented groups. Consequently, women are deprived of high-quality employment prospects and the advantages associated with STEM areas. In contrast, STEM sectors lack varied workforce expertise (Corbett & Hill, 2015).

The representation of women in STEM fields decreases consistently throughout their educational and professional journeys. Even though there is evidence that more females are enrolling in higher-level STEM-related courses during high school, there is also evidence that more girls are not continuing their education in these fields during college (Wee Teo, 2014). A breakdown of precisely which girls of different ethnicities and socio-economic classes are enrolling in such courses is sometimes missed from the statistics. Furthermore, starting in middle school, females tend to opt out of STEM-related courses, and research has shown that academic success does not solely explain this phenomenon. Instead, the persistent gender gap in enrollment for advanced high school scientific courses may be attributed to students' perceptions of the societal acceptance of STEM-related subjects (Master, Cheyan, & Meltzoff, 2016).

The "leaky pipeline" phenomenon, where students disengage from STEM fields, starts in secondary school and persists through university, into their careers, and beyond. This trend is particularly evident in computer science, where the proportion of women in the workforce has significantly decreased over the past two decades (Blickenstaff, 2005). This is a challenge, considering engineering and computer science account for 80 percent of all available STEM employment (Corbett & Hill, 2015). According to Metcalf (2018), the number of women pursuing mathematics degree programs has declined. The current figures are similar to those from the 1970s. Recent statistics reveal that women comprise only 35% of all mathematics degree holders. Additionally, these women hold only 27% of jobs associated with this field and less than 16% of tenure-track faculty positions in mathematics.

**Barriers of Females in Nontraditional STEM Careers.**

According to Social Cognitive Carrier Theory (SCCT), personal characteristics such as gender significantly affect career choice. Various factors, including confidence in gender roles, education readiness, and societal stereotypes, have been proposed as possible causes for the underrepresentation of women in certain employment sectors. However, there is no single identified root cause for this phenomenon (Blickenstaff, 2005).

Alper (1993), in one of his early studies, identified several contributing causes, one of which was the inadequate mathematical education obtained by most female high school students. Culture plays a role when there are disparities in expectations for women and men regarding aptitude and professional options. Female students' low self-esteem is another early leak in STEM majors. Blickenstaff (2005) conducted a meta-analysis on the participation of women in STEM careers. He identified reasons, including a lack of female role models in STEM professions, the impact of scientific curriculum on female students, and the challenges women encounter when pursuing careers in STEM fields.

Despite various initiatives aimed at fostering girls' interest in and access to science careers, women continue to be underrepresented in STEM fields. Researchers have proposed multiple theories to elucidate the differing interests, attitudes, and perceptions of science between male and female students. Nevertheless, studies indicate that the gap in scientific interest emerges early in education, with sociocultural factors exerting a considerable influence (Jacobs, 2005).

Girls as young as five begin to receive implicit signals that math and science are just for males. As their gender identity grows and gender disparities expand between eighth and twelfth grades, an increasing number of girls say they cannot perform science (Perez-Felkner, McDonald, Schneider, & Grogan, 2012). In the male-dominated STEM fields, women often face subtle signs that their gender (and maybe their ethnicity, religion, or other identification attribute) might be a disadvantage (Walton, Logel, Peach, Spencer, & Zanna, 2015). This indicates that a woman's choice to enter and remain in a STEM field is heavily influenced by her gender and how she identifies with her gender. Additionally, if women believe their gender is a disadvantage in STEM, they are more likely to abandon these fields.

Gender identification refers to how much a person aligns with the qualities and characteristics associated with a particular gender. According to several studies, women who have a strong sense of their own female identity are statistically more inclined to choose professional routes closely aligned with their gender and are statistically more likely to be affected by stereotypes. This could explain why female students with higher gender identification tend to have lower math scores. It could also explain why girls tend to have an overly optimistic view of their scientific skills and why many high school girls develop a negative association between the female gender and math and physics classes. (Rozek et al., 2014).

Gender disparities also influence the path that women choose in STEM fields. At the high school level, male students were found to exhibit a stronger preference for math and science, enroll in more STEM courses, and achieve higher scores in math and science on standardized tests. Women enter STEM fields at a comparable rate to men, with over 50% of degrees in biology, chemistry, and mathematics awarded to women. Despite similar entry rates, women tend to enter STEM careers later in life and face challenges negotiating family, work, and cultural barriers. Work hours, social dynamics, and career misconceptions influence women's job choices (Davis, 2014).

**Summary**

According to the studies that were presented, the following were found to have a positive influence on scientific self-efficacy and the intention to pursue a career in STEM: a)early engagement, b)activities based on hands-on inquiry, c)science, technology, engineering, and mathematics role models and mentors d)learning opportunities in the field of science that are both inside and outside of the classroom e)encouragement from friends, family, and adults in the community as well as educators' parental support f)activities in the scientific field that are relevant to students' points of entry and everyday life g)mechanisms of support at each stage of the STEM education pipeline.

One obvious limitation of SCCT research in STEM is that it has primarily been done using quantitative and qualitative research methods. Alternatively, a machine learning algorithm can predict career interest or choice. Machine learning is not commonly employed in educational research, and this study intends to fill these gaps by applying various machine learning algorithms. On the other hand, few studies have studied the role of gender, SES, AP courses, GPA, and ethnicity on career development. This study also seeks to fill these gaps by examining the importance of learning experiences, contextual affordances, and personal input in STEM career development through machine learning and traditional chi-squared statistical methods.

# Chapter 3 Theoretical Framework

## Social Cognitive Career Theory (SCCT)

Social Cognitive Career Theory (SCCT) is based on the Social Cognitive Theory developed by Albert Bandura in 1980. SCCT is a well-regarded theory in career development emphasizing the significance of self-efficacy in determining career paths and results. The theory suggests that people are inclined to choose and continue in careers where they feel confident in their ability to succeed and reach their objectives. SCCT also highlights the role of personal and environmental influences in career development, including interests, values, social support, and the resources at one's disposal. The theory has been widely applied in career counseling, vocational education, and organizational development, generating a large body of research on career development. His theory explores how three fundamental elements interact: (1) environmental influences, (2) individual characteristics, and (3) behavioral tendencies.

To better recruit and retain teenagers in STEM fields, we must first understand the processes that lead someone to choose a profession. SCCT is a valuable theoretical lens for understanding what factors contribute to STEM career choices. SCCT is a comprehensive social cognition theory focusing on several cognitive-person characteristics (self-efficacy, outcome expectations, and goals) and their interactions. This concept provides a comprehensive approach to comprehending an individual's growth and conduct by considering various factors. These factors include a person's inclinations, abilities, morals, and the conditions surrounding them. Inclinations indicate the activities a person finds attractive, and abilities indicate the skills they have developed. Morals represent the fundamental values and principles a person adheres to, and the context encompasses the physical, societal, and cultural surroundings with which an individual interacts. The SCCT provides a guideline for examining how individuals develop their academic and vocational interests, make informed decisions regarding their education and career paths, and ultimately achieve success in their chosen fields. The theory also explores the origins of individual interests and preferences, examines the elements that impact decision-making in educational and career choices, and identifies the tactics that contribute to achieving success in both academic and professional environments.

This theory suggests that an individual's belief in their ability to perform a task, or self-efficacy, plays a crucial role in determining their career trajectory. Additionally, the theory highlights the significance of outcome expectations, which refer to an individual's anticipated results or consequences of their actions and personal goals in shaping their career path. By understanding and harnessing these factors, individuals can effectively navigate their professional development and achieve success in their chosen field.

***Self-Efficacy***

According to SCCT, individuals are often more attracted to and perform better in tasks where they feel confident in their abilities and have strong convictions about their success. Four primary types of information shape these self-efficacy beliefs: personal achievements, observing others' experiences, receiving encouragement from others, and considering their physiological and emotional conditions.

Self-efficacy is a belief that can change depending on circumstances, affecting one's ability to perform tasks. Bandura (1986) says that "self-efficacy" is "people's beliefs about their abilities to plan and carry out the actions needed to achieve certain types of performances. "A poor sense of self-efficacy may cause someone to abandon challenging work because they believe they will be unable to do it successfully; they may also get disheartened or overwhelmed by the task. When considering career interests and choices, it is essential to consider the kind of work involved, the people and surroundings you interact with, and how skilled you feel based on similar past experiences. How people view their skills plays a bigger role in what careers they are interested in and choose than how they rate their talents (Brown, Lent, & Gore, 2000).

### *Outcome Expectations*

The term "outcome expectations" refers to viewpoints about the impacts or outcomes of specific actions. People's decisions regarding the activities in which they will participate, as well as social effort and commitment, are influenced by their outcome expectations and their abilities' beliefs. For instance, individuals are more inclined to engage in an activity when they believe it will result in desirable outcomes for themselves and others, such as gaining social and self-approval, financial rewards, and appealing work environments.

Numerous studies have established that a person's expectations regarding the outcome of their employment play a significant role in determining their actual employment outcomes, and research has demonstrated that outcome expectancies are the most potent predictor of employment outcomes for individuals (Morrow et al., 1996). Fouad and Gillen (2006) used if-then expressions to define outcome expectancies; i.e., if one participates in a specific activity, one may anticipate certain outcomes. The difference between the action and its consequences is critical because people make decisions based on their perceptions of prospective outcomes. Outcome expectations are tied to self-efficacy beliefs because individuals feel that they have a greater chance of succeeding if they believe they can accomplish whatever goal they set for themselves. Lent et al. (1994) proposed that individuals' career choices are influenced by their expectations regarding job-related outcomes, including the anticipated salary and prestige associated with the positions.

Outcome expectations are the estimated chances of a specific result happening. Questions like "What benefits will someone see if they excel in swimming?" or "What happens if someone applies to MIT?" and "What outcome can someone expect if they seek a recommendation from Mr. G?" illustrate this concept. On the other hand, self-efficacy is about whether someone believes they can complete a task. For instance, asking, "Can someone perform well in swimming?" demonstrates a belief in self-efficacy.

As a result, outcome expectancies are concerned with what could happen, while self-efficacy estimates one's capacity to execute a task or task set. Bandura (1986, 1997, 2002) has categorized outcome expectancies such as physical, social, and self-evaluative. Getting income from employment is an example of a physical outcome expectation. In contrast, an appraisal from your father for educational success is an example of a social outcome expectation, and being happy with your performance at school is a self-evaluative outcome expectation. Bandura finds that self-efficacy generally outweighs outcome expectations when deciding on an action.

***Goals***

Personal goals may be characterized as one's intent to participate in a particular activity (for example, pursuing a specific academic major) or to achieve a specific degree of performance (e.g., to receive an A in a particular course). People choose objectives according to their perceptions of their skills and the purposes they hope to achieve by following a specific path. Whether people succeed or fail in reaching their goals, they learn lessons that affect their future. Success can boost confidence and show what one is capable of, while failure, though disheartening, teaches valuable insights for improvement. These experiences shape beliefs about one's abilities and potential for future achievements.

Individuals develop goals that assist them in organizing their behavior and guiding their behaviors throughout various periods. They could wonder, "To what extent and degree does she wish to succeed in achieving her goal?" (Lent, 2005). For instance, a student aiming to become an attorney must establish multiple goals and select specific actions that will assist in reaching those objectives. Pursuing goals serves as a significant motivation. It offers a sense of purpose and direction, and the satisfaction derived from achieving these goals can be highly fulfilling. Whether it involves completing a doctoral program, becoming an attorney, or reaching any other significant milestone, the sense of accomplishment associated with realizing aspirations is immensely rewarding.

As a result, understanding how our goals, self-belief, and anticipated outcomes play a role in career decision-making is crucial. These three elements are interconnected and affect each other. Setting goals gives us something to work toward, believing in our abilities increases the likelihood of success, and considering potential outcomes helps us decide if it is worth the effort. Our perspective on these factors is vital in determining our future careers (Blanco, 2011)

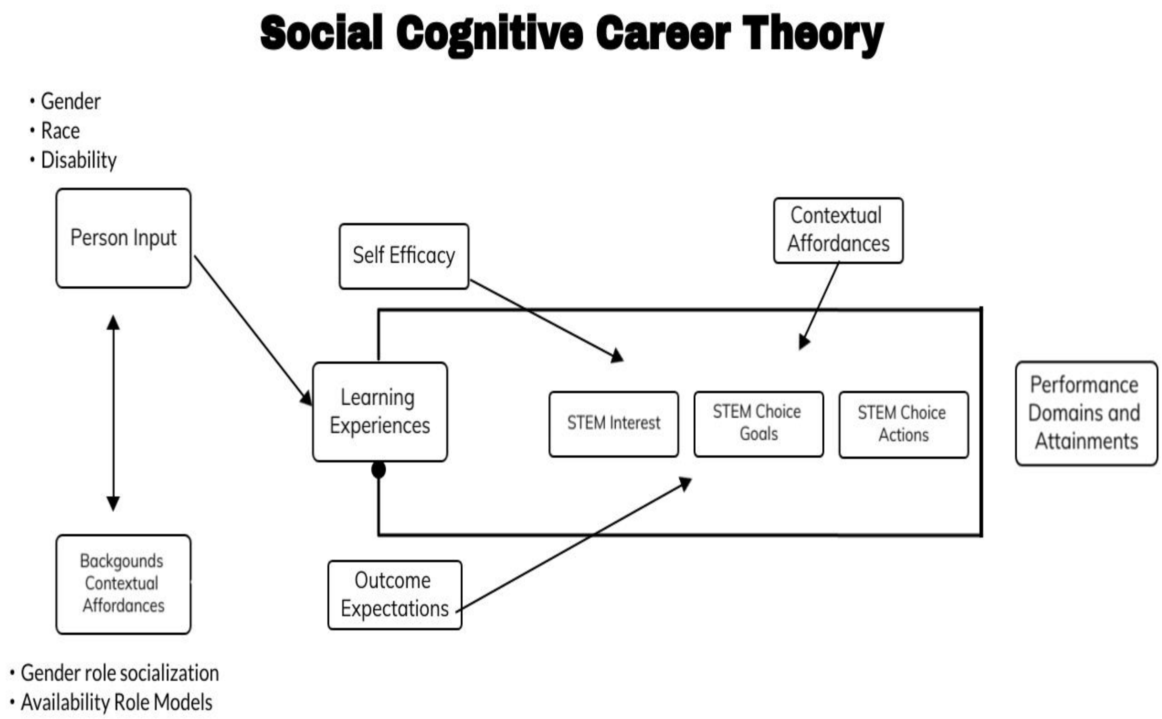
### ***Background or Contextual Factors***

Early and continuous learning experiences have been shown to alter self-efficacy, affecting interests, goals, and professional choices. According to the SCCT model, contextual variables such as environmental supports and barriers may impact job choices mediated by learning experiences. SCCT also recognizes the importance of environmental and personality factors in career success. Environmental predictors, which are supports and obstacles, are thought to directly and indirectly affect outcomes via self-efficacy, outcome expectancies, and goals (Lent, Brown & Smith, 2013).

Lent, Brown, and Hackett (2000, 2002) and Lent (2005) define two main categories of contextual components: background contextual factors and contextual influences close to choosing behavior. Background contextual elements emerge when people learn about and engage with their culture and become more aware of gender role expectations. Contextual influences proximal to choice are important at specific academic and professional decision points.

Contextual factors may support or impede an individual's choice to follow a specific career route, depending on the circumstances. Present (proximal) effects rather than contextual elements influence most supports and barriers. For instance, attempting to solve a financial issue by seeking financial help is significantly easier than overcoming the challenge of growing up in a household with little food. Support and motivation to the children from parents can be provided even in significant background contextual factor limits (such as a lack of sufficient food supplies). Aside from personal characteristics, interests, talents, and perspectives, budgetary constraints and help and motivation from teachers are essential components in choosing a career (Lent, Brown, Talleyrand, 2002). Both support and impediments can impact self-efficacy, affecting professional objectives. (Lent et al., 2003). An investigation conducted among college students found that several forms of assistance, including family and peer support, financial background, and employment prospects, all impacted their self-efficacy (Dahling & Thompson, 2010). In research on racial-ethnic minority and white engineers, social support and obstacles were shown to predict self-efficacy and other outcomes (Cardenas, 2010). In tenth to twelfth-grade adolescents, external support, encompassing job exploration and moral encouragement, was significantly connected with professional self-efficacy and outcome expectations (Conkel Ziebell, 2011).

Figure 2:Social Cognitive Career Theory




*Note:* Adopted from " Toward a unifying social cognitive theory of career and academic interest, choice, and performance " . By R.W. Lent, S. D. Brown,& G. Hackett. (1994). Journal of Vocational Behavior, 45 ,p. 93 III.

### *Social Cognitive Model of Career Choice*

Self-efficacy, outcome expectations, goals, choice, outcome, and contextual variables interact in the social cognitive model of career choice. The iterative approach implies that the ideas impact one another, whether direct or indirect, and this cycle continues throughout a person's life. The model of career choice behavior is shown in Figure 14.1, which shows the channels of interaction between the concepts. To illustrate the process of making career choices, this discussion employs the SCCT framework to examine the academic and professional challenges faced by an individual. The subsequent sections will break down and highlight the various aspects of this model. This analysis aims to uncover the critical factors social cognitive career theorists identify as essential in selecting a profession. The exploration starts with the key principles fundamental to understanding career decisions and job selection.

According to Bandura (1986), interests are generally stable over time, shaped by the belief in one's ability to succeed and the expectation that effort will lead to success. When individuals engage in new activities, such as sports, and discover a lack of skill, they may lose interest in those areas. For example, a person who believes they cannot master math might anticipate a low score on a math test. This lack of confidence and negative expectation contributes to losing interest in the subject.

Individuals' interests significantly impact their willingness to engage in certain activities and set goals related to those activities. When a person loses interest in mathematics, they no longer wish to study it and prefer to explore other interests. Suppose this individual discovers a passion for singing, particularly feeling confident as a talented soprano with positive outcomes. In that case, their interest can be further reinforced by opportunities such as being invited to perform solo in church. Consequently, their aspirations in music start to overshadow their goals in mathematics, indicating a shift in priorities based on their interests and perceived abilities.

Individuals' goals shape the actions they undertake to achieve these objectives. For instance, when someone sets their sights on improving their singing abilities, they might start taking vocal lessons and dedicate more time to practice. Conversely, suppose mathematics is no longer a primary focus for them. In that case, they might allocate significantly less time, such as only 10 minutes a day, indicating a shift in priorities where their efforts are concentrated on areas of higher interest and perceived competence. The activities individuals engage in play a crucial role in shaping their outcome expectations. For instance, when someone focuses on enhancing their singing skills through dedicated practice, they will likely see improvement in this area. However, if they neglect other areas like mathematics, their skills in that domain may decline. The outcomes of these activities influence their learning experiences, affecting their beliefs in their abilities (self-efficacy) and their expectations about future outcomes. In the case of an individual who has positive experiences participating in a choir and performing as a soloist, these successes can boost their confidence in their singing abilities and lead to an increased expectation of being offered more performance opportunities.

In contrast, her low performance on math examinations has a negative impact on her learning experience. She feels that she does not possess a strong sense of self-efficacy in mathematics, and as a result, she anticipates scoring poorly on upcoming math exams.

Outcome expectations may have a direct impact on how people view goals. If an individual cannot locate professional singing chances, her ambition of becoming a professional singer will be affected, as will her future career choices. Individual appreciates the aspiration of becoming a professional singer but does not have high hopes for success.

Individuals' belief in their capabilities significantly impacts their career ambitions, actions, and performance levels. For example, a person's self-doubt in their math skills can shape their interests, goals, and the range of career options they consider, influencing their vocational decisions. Social cognitive theorists point out that various other factors also affect learning and performance. Individual and contextual elements, including gender, disabilities, natural talents, race, and family background, play a crucial role in shaping career choices. In the scenario described, the individual's natural aptitude for music notably boosts their performance and, as a result, strengthens their belief in their singing abilities. Conversely, societal stereotypes suggesting women are less adept at math contribute to negative learning experiences for these individuals, diminishing their confidence in their mathematical skills.

An individual's career path choice is also influenced by contextual factors, which are conditions beyond their immediate control. For example, financial constraints and limited job opportunities can hinder someone's pursuit of a career in singing. Additionally, the influence of family can play a significant role. For instance, the achievements of a sibling who attends one of the nation's top universities can serve as a motivational factor. Regular discussions with a successful older sibling can encourage an individual to focus more on their academic pursuits, such as improving their math skills. This family dynamic is a motivational contextual factor that can positively impact decision-making behaviors related to career choices. As depicted in theoretical models, the decision-making process regarding career choices underscores the importance of both self-efficacy and outcome expectations. While self-efficacy and outcome expectations play crucial roles, Lent and colleagues (Lent 1994, 2002) and Lent (2005) also consider past biological, social, or environmental influences and current contextual factors in their evaluations. These authors point out that as individuals age, altering their interests, goals, and overall performance becomes increasingly challenging due to the influence of their past experiences.

### ***Social Cognitive Model of Interest Model***

The model of career choice and the interest model within social cognitive career development share significant similarities. The main distinction is that personal interest is emphasized on interest rather than a career choice. The encouragement from teachers, family, and peers to engage in various activities during childhood, along with self-efficacy and outcome expectations, leads to the formation of goals. Having goals motivates individuals to practice, leading to successful outcomes, and individuals draw on their past experiences to evaluate and pursue new opportunities. Recursive cycles occur as new opportunities and activities present themselves, as well as new interests, are explored. Adults tend to have generally focused and stable career interests (although these can change due to changing circumstances, restricted options, and experiences yielding new ideas, such as pursuing a career in student affairs). SCCT holds that shifts in interest are primarily due to changing self-efficacy beliefs and outcome expectations (Lent, 2012). Outcome expectations and self-efficacy beliefs influence interest, and interests help predict goals, which help predict behaviors associated with selecting and practicing activities (Lent,2013). The SCCT recognizes that individuals' career decisions are influenced by their environments and personal circumstances, including permanent and conditional factors such as ethnicity, disability status, socioeconomic conditions, and gender (Lent, 2012). Background and contextual variables may be interpreted as impediments or facilitators of outcome expectations. For example, a young man with a strong desire to serve others and a strong interest in medical subjects may be discouraged from pursuing a career in nursing because he believes that nursing is not a proper profession for a male.

### *Social Cognitive Model of Performance Model*

SCCT is a concept that has caught the attention of many experts who are studying careers and education. It explains how success in past activities can make people feel more confident and have certain expectations about their abilities to achieve goals. For instance, take a young woman who was good at basketball in high school. Because she did well before, she felt confident about her basketball skills and decided to try out for the basketball team at her college. After she makes the team, she sets high goals for herself, like scoring at least double-digit points in every game, based on her past success and her belief that she can do well in the future (Lent et al., 2002; Lent, 2013).

## **Summary**

Social cognitive career theory focuses on individuals' belief in their ability to accomplish specific tasks. This confidence is pivotal in shaping one's career trajectory and influencing one's interests, values, and skills. The theory examines the interplay among three key elements. Numerous external elements, such as the availability of resources, personal attributes including one's experiences, convictions, preferences, and identity, as well as behavioral tendencies, significantly influence an individual's life. Within this context, self-efficacy is recognized as a crucial component. The degree of an individual's self-efficacy can profoundly impact their capacity to set and achieve goals, overcome challenges, and ultimately lead a fulfilling and successful life.

As a result, Lent, Brown, and Hackett's SCCT sheds light on the processes that lead individuals, particularly teenagers, to choose careers in STEM fields. SCCT focuses on self-efficacy beliefs, outcome expectancies, and goals, providing a comprehensive framework for examining how interests develop, decisions are made regarding education and employment, and success is achieved in STEM careers. Understanding these processes is crucial for developing effective strategies to recruit and retain teenagers in STEM fields, which will contribute to a more diverse and skilled workforce in these critical areas of innovation and development.

In conclusion, SCCT offers valuable insights into the development of careers in STEM fields and is an essential tool for creating a brighter future for individuals and society. After exploring SCCT career theory, I would like to assess the effect of gender, GPA, math score, science score, ethnicity, parent education, and SES. The SCCT model will be the best fit for my study. Figure 14.1 helps to understand my model if SCCT is applied in my research:

Person Input: Gender, Ethnicity

Background Contextual Affordance: SES

Learning Experience: Number of STEM-related AP courses, ACT Reading, Math and Science Score, and GPA.

# Chapter 4 Methodology

This study will investigate the career development processes of high school students using the Social Cognitive Career Theory. Additionally, this investigation will examine the relationships between the variables that influence students' decisions to participate in STEM careers. This section begins with an overview of the terminology used throughout the study. This research places significant emphasis on terms related to STEM.

## Definition of Terms

***STEM:*** The disciplines of science, technology, engineering, and mathematics are included under the STEM umbrella of academic and career-relevant study topics (Koonce et al., 2011).

***STEM Career:*** STEM careers require knowledge and skills in the scientific, technological, engineering, and mathematical fields. These fields include science, technology, engineering, and mathematics. STEM careers are highly varied and can be found in a wide variety of industries and fields, such as healthcare, finance, manufacturing, education, and research, to name a few. Appendix A classification will be utilized to determine STEM career choice in this study.

***GPA:*** The grade point average will be treated as a continuous independent variable and measured on a scale from 1 to 4.

***Ethnicity:*** The following categories will be used to categorize ethnicity: In statistical analyses, ethnicity is typically treated as a categorical variable through the creation of dummy variables for each ethnic group, with one group serving as the reference category. This method involves assigning a value of '1' to indicate an individual's association with a particular ethnic group and '0' to indicate their absence from that group.

***Math, Science, Reading ACT Score:*** The results of the ACTs will be used to determine students' scores in mathematics and science; these scores will fall into a range from 1 to 36. These observations will be utilized in an analysis using a continuous independent variable.

***STEM-Related AP Score:*** The number of STEM-related AP courses will be treated as a continuous variable, representing the total count of AP exam courses a student has received.

***Socioeconomic Status:*** Students will be divided into two groups based on their parents' income. Those who receive free or reduced lunch are classified as low-income, while the rest are high-income.

The study aimed to investigate the factors influencing students to pursue STEM careers. The research utilized data collected from 520 students attending a charter school in the Henderson area. The study employed machine learning models and chi-square analysis to analyze the data.

The development of machine learning models centered on classification will be used to forecast students' intentions toward careers in STEM fields. The method of examining the various machine learning models and establishing the significance of the variables will be discussed. The following research topics and associated hypotheses will be presented in light of the demanding need for more professionals in STEM fields and the importance of addressing the depth of inequity when analyzing demographic shifts in STEM participation.

Research Question 1: Does gender, ethnicity, GPA, math, reading, and science scores (ACT), STEM-related AP courses, and socioeconomic status influence high school students' career selection?

Research Question 2: How can we predict the students' STEM career intent through various machine learning models?

Research Question 3: Does ethnicity influence the choice of a STEM career?

Research Question 4: Does socioeconomic status play a role in selecting a STEM career?

Research Question 4: Does gender affect the decision to pursue a career in STEM?

**Data Collection**

The demographic data presented here is collected from a charter school located in the Henderson area of Nevada. The school is recognized for its focus on science education. It holds a 5-star rating within the state's educational system. The data was collaboratively collected with the involvement of the school principal and central office and sourced from various channels, including counselor records, Infinite Campus, and ACT data from the school's database. The data underwent analysis utilizing Python libraries such as Keras, NumPy, Pandas, Seaborn, TensorFlow, and sci-kit-learn within Google Colab. STEM and non-STEM classifications were aligned with the Standard Occupational Classification (SOC) system, as detailed in the Bureau of Labor's Attachment C documents.

The demographic breakdown of the charter school reveals that 56% of the population is male, while 44% is female. The demographics further show that 37.14% of the population identifies as White, 24.94% as Asian, 17.63% as Hispanic, and 11.97% as Two or More Races. Smaller segments include Black (6.21%), Native Hawaiian/Pacific Islander (1.88%), and American Indian/Alaska Native (0.22%). Notably, 23% of the students are enrolled in the Free Lunch Program, with an additional 5% benefiting from the Reduced-Price Lunch Program.

Moreover, 8% of the population comprises students with disabilities. The average ACT score is 22, and a significant 42% of students are engaged in Advanced Placement (AP) courses, indicating their commitment and academic enthusiasm.

**Data Analysis**

The dataset comprises 520 student records that contain information collected between 2020 and 2023. It includes various details such as ACT scores in Math, Reading, and Science, enrollment in Advanced Placement (AP) courses related to STEM, socioeconomic background, ethnicity, gender, GPA, and the selection of a STEM career path. The dataset includes 2 Amer Ind/Alaskan Natives, 154 Asians, 26 Black/African-Americans, 93 Hispanic/Latinos, 10 Native Hawaiian/Pacific Islanders, 73 individuals of two or more races, and 162 Whites. Out of the total students, 225 identified as female, and 295 identified as male. The SES was categorized into two groups: 69 individuals were in the lower group (SES 0), and 451 were in the higher group (SES 1). A preprocessing phase was performed to prepare the data for analysis using machine learning techniques. This phase included missing entries, which were ultimately found to be absent, and verifying that all data points were correctly formatted. Specifically, academic scores were denoted as integers, while SES and STEM interests were categorized as binary variables, and ethnicity and gender were represented through one-hot encoding.

During the feature selection process, I evaluated all variables to identify those significantly impacting STEM outcomes. Because the dataset was not too large, methods such as Principal Component Analysis (PCA) that reduce dimensionality were unnecessary and skipped.

## Machine Learning

During the 1950s and 1960s, machine learning research mainly focused on developing machines that could think logically, much like how humans solve problems using reason. One of the early successes in this field was the Logic Theorist program created by A. Newell and H. Simon. This program could independently solve mathematical problems, leading people to believe that making machines intelligent made them good at reasoning. From the 1960s to the 1980s, machine learning research explored methods like neural networks and symbolic learning, leading to its recognition as a distinct field in the 1980s. This period was focused on teaching machines through examples, either by direct instruction or observation. During the 1980s and 1990s, innovations such as the backpropagation algorithm improved neural networks. As we entered the 21st century, significant enhancements in neural networks occurred due to the progress of deep learning. This was mainly due to the abundance of available data and improved computing power, which enabled applying these technologies without requiring a detailed comprehension of their inner workings (Zhou,2021).

Taking advantage of advancements in machine learning, this study will use logistic regression, which is well-suited for binary classification. We will also use the K-Nearest Neighbors (KNN) algorithm, decision trees, and neural networks to help predict the STEM career choice.

### *Logistic Regression*

Logistic regression is a valuable statistical tool utilized across many fields to understand the correlation between a binary outcome variable and one or more predictor variables (Agresti, 2015). While linear regression is better suited for continuous outcome variables, logistic regression can be employed in forecasting categorical outcomes or events that follow a binary distribution (Hosmer, Lemeshow, & Sturdivant, 2013).

This model employs a sigmoid curve to forecast classifications, starting with calculating a weighted sum of the input variables, adding an intercept, and then applying the sigmoid activation function (Young, Holland, & Weckman, 2008). Logistic regression is a highly regarded machine learning technique known for its effectiveness in classification tasks. It has yielded fewer classification mistakes than other statistical approaches (Fienberg, 2007). Given its prevalence in machine learning, logistic regression is used as a standard point of comparison in this study.

Logistic regression is a discriminative classifier that uses the maximum likelihood method to determine its parameters. The relationship between the log odds of the probability p(X) and the predictors is expressed as the natural logarithm of the ratio of p(X) over 1 minus p(X), which equals the intercept (b0) plus the sum of each predictor variable (x1, x2, ..., xk) multiplied by their respective coefficients (b1, b2, ..., bk). This formula indicates that the log odds are directly calculated from the model's dependent variable, necessitating an iterative approach rather than linear regression or ordinary least squares for optimization. The optimization process starts with an initial guess of the parameters, then refined through iteration until the likelihood of observing the given data under the model is maximized (Hosmer, Lemeshow, & Sturdivant, 2013).

Specifically, the logistic regression framework assumes that the probability of y being either 0 or 1 can be modeled as p, which equals the exponential of Z divided by 1 plus the exponential of Z. This simplifies to 1 over 1 plus the exponential of minus Z, where Z equals b0 plus b1x1 plus b2x2 plus .... This formulation allows the model to estimate the probability of different outcomes within a bounded [0, 1] range (Hosmer, Lemeshow, & Sturdivant, 2013).

The log odds of the binary outcome are modeled through the logarithm of the odds ratio, establishing a linear relationship with the predictor variables (Cox & Snell, 1989). The log of the odds ratio is a mathematical technique frequently used to create a linear connection between predictor variables and the log of the probabilities of binary outcomes.

**Steps for Logistic Regression.**

In conducting logistic regression analysis, I employed the methodology described in "An Introduction to Statistical Learning" by James, Hastie, and Tibshirani.

***1. Split the data into validation, training, and test sets.***

First, I divide my dataset into training, validation, and test sets. The training set is where I train or build my model. The validation set is where I fine-tune the model parameters and make decisions about the model, like choosing the best hyperparameters. Finally, the test set is where I evaluate the model's performance on new, unseen data to assess its effectiveness objectively.

***2. Standardize the Data.***

Data standardization involves adjusting the data to have a mean of zero and a standard deviation of one, transforming it into z-scores. This step is crucial because it ensures that all features contribute equally to the model's performance, avoiding situations where features with larger scales dominate those with more minor scales.

***3. Apply K-Fold Cross-Validation.***

In K-Fold Cross-Validation, I assess the model's performance and generalizability to an independent dataset by dividing the training data into K-equal subsets. Each subset is used once as a test set, while the rest serve as a training set. This process repeats K times, with each of the K subsets used exactly once as the test set. Opting for K=10 often balances the variance and bias in the model's estimated performance.

***4. Find the Best C Value for L2 Regularization.***

When applying L2 regularization, also known as Ridge regularization, a penalty equal to the square of the magnitude of coefficients is added to the loss function. The C parameter controls the strength of this regularization. Finding the optimal C value involves using techniques like grid search and cross-validation to balance model simplicity and predictive performance on the validation set.

***5. Find the Coefficients for the model.***

After determining the best regularization strength, I use this parameter to train my model on the entire training set. The model then provides coefficients for each feature in the dataset. These coefficients reflect the importance or influence of each feature on the prediction outcome, with higher absolute values indicating greater significance.

***6. Find the Best F1 Score and Threshold for the dataset.***

The F1 score, which considers precision and recall, measures a model's accuracy, which is especially important when dealing with imbalanced classes. To find the best F1 score, I experimented with different threshold values to classify a prediction as positive or negative. Adjusting this threshold helps me discover the value that maximizes the F1 score, thus achieving a balance between recall and precision for my dataset. Through these steps, I ensure that my model is accurate and generalizes well to new data, providing reliable predictions while avoiding the risk of overfitting.

### *K-Nearest Neighbors (KNN)*

The K-Nearest Neighbors (KNN) algorithm is a sophisticated tool for classification and prediction tasks. Due to its intuitive approach, the k-Nearest Neighbors (k-NN) algorithm is widely used in machine learning, especially in classification and regression tasks (Cover & Hart, 1967). It operates on a simple, intuitive principle: to classify a new item, KNN looks at the 'K' closest labeled items and uses their classifications to inform its decision. Despite this simplicity, KNN is effective on complex tasks.

The basic idea behind the KNN algorithm is that similar items are usually grouped in the data space, as Tobler (1970) observed. Implementing KNN involves selecting a way to measure how far apart items are, typically using Euclidean distance for its straightforward calculation and interpretation. The 'K' value, a key parameter, dictates how many neighboring items the algorithm considers in its classification process. Choosing the correct 'K' value and distance metric is crucial (Hastie, Tibshirani, & Friedman, 2009). If 'K' is too small, the algorithm can become too sensitive to random noise, which might result in wrong classifications. On the other hand, a 'K' that is too large may overwhelm the algorithm with irrelevant information, leading to confused decisions (Tobler, 1970).

#### Steps for The KNN Model.

1. ***Splitting the Data.***

To begin, it is essential to divide the dataset into three subsets: the training, validation, and test sets. This division is critical to develop a robust model. The training set enables the model to learn the patterns within the data. The validation set is then used to fine-tune the model's hyperparameters and conduct initial evaluations. Lastly, the test set assesses the model's performance on previously unseen data, objectively evaluating its predictive capabilities.

***2. Standardizing the Data.***

Standardization is a crucial preprocessing step that transforms the data into a mean of zero and a standard deviation of one. This step is significant for models such as KNN, which rely on distance calculations. Standardization guarantees that all features contribute equally to the distance computation, preventing bias towards features with larger scales (Han, Kamber, & Pei, 2011).

***3. Applying K-Fold Cross-Validation.***

One effective way to validate a model's effectiveness is through K-Fold Cross-Validation, where K is set to 10. This involves dividing the training data into ten equal parts and then training and testing the model ten times, each subset serving as the test set (James, Witten, Hastie, & Tibshirani, 2013).

***4. Finding the Best 'K' Value.***

When working with KNN, it is crucial to identify the best 'K' value. This requires testing various 'K' values and evaluating their effect on the model's effectiveness. The aim is to identify a 'K' that balances bias and variance, capturing the data without overfitting (James, Witten, Hastie, & Tibshirani, 2013). In this study, the best K was found to be 17.

### *Decision Tree*

Decision trees, or classification trees, represent a machine learning technique characterized by its visual nature, utilized for classification and regression analysis (Young, 2017). Unlike other machine learning methodologies, decision trees focus on examining variables individually.

According to Quinlan, J.R. (1986), a decision tree is a predictive model that simplifies complex decision-making into a sequence of straightforward questions. In a decision tree, every internal node corresponds to a question about the data. As we move down the branches, the answers lead to further questions until we reach a leaf node. This node contains the final decision or classification based on the chosen path through the tree. Constructing these trees involves selecting attributes that reduce uncertainty with each step to group data with similar characteristics while minimizing confusion. This process consists of maximizing "information gain" and minimizing "impurity" or "entropy."

#### Steps for Decision Tree Analysis.

##### *1-Splitting the Data:*

In the initial phase of my model development, I divide my dataset into three key sections: training, validation, and test sets. I use the training set to introduce the Decision Tree to the patterns within the data. The validation set is crucial for me to fine-tune the model's parameters, like the depth of the tree, ensuring it is straightforward enough and simple. The test set is my model's ultimate challenge, unbiasedly evaluating its predictive power (Breiman, Friedman, Olshen, & Stone, 1984).

##### *2-Standardizing the Data.*

Though decision trees can easily handle varied data scales, I did not standardize my dataset.

***3-Optimizing Clarity: Gini Coefficients.***

A central part of my methodology involves optimizing the Gini coefficients, which measure how mixed the data is within each tree node. My goal is to lower these indices, aiming for purer nodes. This means I meticulously assess potential splits in the data, choosing those that significantly lower impurity. Such precision is vital for ensuring that the decisions made by the Decision Tree are clear and well-founded (Esposito, Malerba, & Semeraro, 1997).

***Neural Network***

Neural networks are critical within machine learning. These computational models are inspired by the biological neural networks in animal brains (LeCun, Bengio, & Hinton, 2015). At the core of neural networks are interconnected nodes or "neurons," each designed to perform specific computations. The input layer receives the data, which then passes through a series of one or more hidden layers, where the actual processing takes place. Finally, the output layer delivers the model's prediction. During the training process, the connections, or "weights," between these neurons are adjusted using a mechanism known as backpropagation, which iteratively minimizes the difference between the predicted and actual outcomes (Goodfellow, Bengio, & Courville, 2016).

**Steps for Neural Network Model.**

Here are several steps that can be followed during Neural Network:

**1-Define the Neural Network Architecture:**

In my neural network design, I ensured that the input layer had as many neurons as there were features in the dataset. I started with one or two hidden layers. Based on the model's performance, I adjusted their number and the neurons within them, usually choosing a neuron count that fell between the input and output layer sizes. The output layer's configuration was tailored to my specific task; for example, I used a single neuron for classification tasks like predicting STEM career choices.

**2-Normalize the Data**:

I used StandardScaler to ensure that the features in my dataset have a mean of 0 and a standard deviation of 1.

**3-Split the Data**:

I divided the dataset into training and testing sets to evaluate the model's performance on unseen data.

**4-Compile the model and determine the best learning rate:**

I used binary_crossentropy for binary classification, used Adam as the optimizer, and measured accuracy. I also adjusted the learning rate based on the model's performance during training.

**5-Train the model**:

I fitted the model to the training data, utilizing the validation data to monitor overfitting.

**6-Evaluate the model**:

After training, I assessed the model's performance on the test set to understand its accuracy.

## Chi-Square Analysis

The Chi-square test is a method used to compare the differences between groups when the outcome is categorized. It is useful because it does not assume a specific distribution of the data. Essentially, this test works well even if the groups being compared do not have similar variances, and it can handle both yes-or-no-type questions and comparisons across several groups. What makes the chi-square test powerful is its ability to provide detailed insights into how different groups contribute to the overall outcome of the study.

One of the key characteristics of the Chi-square test is that it is non-parametric, and tests like the chi-square are preferred under certain conditions:

1. When all variables are on a nominal or ordinal scale.
2. When the sizes of the groups are not the same

### *How to Perform Chi Square Analysis?*

When conducting statistical analysis using the Chi-square test, we start by establishing two hypotheses - the Null Hypothesis (H0) and the Alternative Hypothesis (H1). The null hypothesis states that there is no significant difference between the observed frequencies and the expected frequencies, which means that there is no relationship between the variables being studied. On the other hand, the alternative hypothesis posits that there is a significant difference between these frequencies, indicating an association between the variables. To test these hypotheses, we collect data and organize it into a contingency table, which categorizes the frequency count of each variable. We then calculate the expected frequencies for each cell in the table using a specific formula. This helps us determine if the observed frequencies significantly deviate from what was expected under the assumption of no association, guiding us to either support or reject the null hypothesis.

# Chapter 5 Results

## Logistic Regression Model Performance Evaluation

The intercept value from logistic regression analysis is 0.820560, which shows the logarithm of the odds of achieving a positive outcome when all predictor variables are set to zero. This analysis explains the effects of input features on the likelihood of a positive outcome. A higher Math Score (0.634630) demonstrates a strong positive correlation, significantly increasing the chance of a positive outcome. The Reading Score (0.006538) exhibits a moderate positive effect and is less than the math scores. Conversely, the Science Score (-0.0575390) shows a negative association, indicating that higher science scores decrease the likelihood of a STEM career choice.

Participation in AP STEM courses is a highly positive predictor (1.757750), highlighting the substantial positive influence of these courses on the outcome. Socioeconomic status (SES) also shows a strong positive relationship (0.602031), suggesting that higher SES is closely linked to an increased likelihood of choosing a STEM career.

The results of the model demonstrate how ethnicity affects the predictions. People with Asian heritage (0.410921) are more likely to have positive outcomes, while those who identify as Black/African-American (-0.378317) have lower chances. White ethnicity (0.128007) slightly increases the likelihood of STEM career choice. Hispanic/Latino (-0.253157), Native Hawaiian/Pacific Islander (-0.094278), and people of multiple races (-0.181566) are less likely to have favorable outcomes.

Gender differences show a slight indication of marginal differences. The logistic regression model assigns a coefficient of 0.06 to females, which is small and insignificant. This suggests that when all other variables are kept constant, the log odds of the event occurring are approximately 0.06 units higher for females than for males. In logistic regression, typically, one category is compared to a reference category. This implies that the coefficient for males is implicitly set to 0. Therefore, the coefficient of 0.06 for females represents the difference in log odds between females and males. However, it is important to note that this coefficient is statistically insignificant.

The coefficient of GPA in a logistic regression model examining its relationship with the choice of a STEM career indicates a positive but small impact on the likelihood of selecting such a career.

The model's performance metrics underscore its predictive accuracy and reliability. The accuracy rate of 83.65% indicates a high proportion of correct predictions for both positive and negative outcomes. The precision rate of 88.83% reflects the accuracy of positive class predictions. The recall rate of 84.12% shows the model's ability to identify actual positive cases correctly. Finally, an F1 Score of 86.17% offers a balanced measure of precision and recall, confirming the model's effectiveness in predicting positive outcomes based on the examined predictors.

The model correctly identified 34 non-STEM cases as True Negatives (TN), demonstrating its ability to recognize cases that do not belong to the STEM field. However, there were 7 False Positives (FP), where non-STEM cases were mistakenly classified as STEM, indicating a slight error in over-predicting STEM outcomes. On the other hand, 10 False Negatives (FN) were observed, where actual STEM cases were misclassified as non-STEM, reflecting a challenge in capturing all genuine STEM instances.

On a positive note, the model has successfully identified 53 True Positives (TP), correctly predicting STEM cases as STEM and demonstrating a strong capability in recognizing true STEM instances. Overall, this matrix highlights the model's effectiveness and areas for improvement in distinguishing between STEM and non-STEM categories. The following confusion matrix describes the performance of a logistic regression model with Non-Stem and STEM Careers. The following confusion matrix table shows the outcome of the logistic regression.

Table 2:Confusion Matrix for Logistic Regression Model

| | Predicted-Non STEM | Predicted-STEM |
|---|---|---|
| True-Non STEM | 34 | 7 |
| True-STEM | 10 | 53 |

*Note:* The table displays the number of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions made by the classification model for STEM and Non-STEM categories.

**K-Nearest Neighbors (KNN) Model Performance Evaluation**

This study identified that the best value for K was determined to be 17. The accuracy of the model, standing at 87.5%, indicates a high level of predictive reliability. This metric signifies that, on average, the model correctly predicts the classification of approximately 87 out of every 100 instances within the test dataset. Such accuracy underscores the model's proficiency in generalizing its learned patterns to new data (American Psychological Association, 2020).

Precision, at 86.7%, reflects the model's ability to identify true positive outcomes from those it labels as positive. When the model predicts an instance to belong to the positive class, it does so with a reliability of about 86.7%. The precision metric is essential for applications where the cost of false positives is significant. Recall, or sensitivity, measured at 93.6%, reveals the model's capacity to capture most positive instances. This high recall rate indicates the model's effectiveness in minimizing false negatives, a critical aspect in scenarios failing to detect positive cases.

The F1 score, calculated at 90.07%, combines precision and recall to give a single score showing how well the model performs. Given the imbalance in the data, the F1 metric helps compare models and assess the model's performance because it provides a balanced measure of precision and recall. This is particularly important in imbalanced datasets where accuracy alone can be misleading.

Table 3:Confusion Matrix for K-Nearest Neighbors (KNN) Model

| | Predicted-NON-STEM | Predicted-STEM |
|---|---|---|
| True-NON-STEM | 32 | 9 |
| True-STEM | 4 | 59 |

*Note:* The table displays the number of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions made by the classification model for STEM and Non-STEM categories.

This KNN model correctly identified 59 STEM instances (True Positives) and 32 Non-STEM instances (True Negatives), while misclassifying 4 non-STEM instances as STEM (False Positives) and 9 STEM instances as Non-STEM (False Negatives). This breakdown highlights the model's strength in accurately identifying STEM cases. It points out the need for improvement in minimizing the misclassification of non-STEM as STEM and STEM as non-STEM.

**Decision Tree Model Performance Evaluation**

We derive precision, recall, and the F1 score from the matrix. The decision tree achieved an F1 score of 0.77, signifying a balance between precision and recall (James et al., 2013). After using K-fold cross-validation, the best ccp_alpha value found for the decision tree model is 0.016203. This helps the model balance between being too complex and accurate and avoids overfitting by removing less essential tree parts.

Table 4:Confusion Matrix for Decision Tree

| | Predicted-NON-STEM | Predicted-STEM |
|---|---|---|
| True-NON-STEM | 5 | 36 |
| True-STEM | 1 | 62 |

The confusion matrix reveals that the model accurately identified 62 instances as STEM (True Positive) while incorrectly classifying 5 non-STEM instances as STEM (False Positive). It also mistakenly identified 1 STEM instance as Non-STEM (False Negative) and correctly recognized 5 instances as Non-STEM (True Negative). The model has an overall accuracy rate of approximately 64.42%. This means that it can correctly predict both STEM and NON-STEM categories with around 64% accuracy. Specifically, when it comes to identifying STEM predictions, it has a precision rate of about 63.27%, indicating that it can accurately predict STEM cases more than 63% of the time. The model's recall rate for STEM classifications is notably high at approximately 98.41%, which means that it can correctly identify almost all of the actual STEM instances. These performance metrics highlight the model's effectiveness, particularly in accurately detecting STEM cases, while also reflecting on the precision and accuracy balance in its predictive capabilities.

**Neural Network Model Performance Evaluation**

The confusion matrix is represented as [[25 7], [16 56]], and it reveals how well the neural network model performed. The model achieved an accuracy rate of approximately 77.88%, indicating its ability to classify most instances correctly. The model also exhibits an 88.89% precision, which showcases its ability to make precise positive class predictions (e.g., STEM), and the recall is approximately 77.78%, meaning that the model correctly identifies about 78% of all actual STEM instances. The F1 Score of 82.96% confirmed the model's balanced performance, making it a dependable choice for classification tasks.

Table 5:Confusion Matrix for Neural Network

| | Predicted-NON STEM | Predicted-STEM |
|---|---|---|
| True-NON STEM | 25 | 7 |
| True-STEM | 16 | 56 |

*Note:* The table represents the confusion matrix of career path predictions, showing the number of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) instances for the STEM and Non-STEM careers.

These metrics collectively underscore the effectiveness of our neural network model in categorizing individuals into STEM and non-STEM categories. Below is the confusion matrix for the neural network, which offers a more detailed view of the model's effectiveness.

**Machine Learning Model Comparison**

We compared the performance of four machine learning models: Logistic Regression, K-Nearest Neighbors (KNN), Decision Tree, and Neural Network. Among these models, Logistic Regression showed a good performance with an accuracy rate of 83.6%, indicating its ability to predict outcomes accurately for both positive and negative classes. It also demonstrated a precision rate of 88.83%, which means it could correctly identify positive class predictions, and a recall rate of 84.1%, indicating its ability to identify actual positive cases correctly. The F1 Score of 86.17% confirmed the model's balanced performance, making it a dependable choice for classification tasks.

On the other hand, the K-Nearest Neighbors (KNN) model achieved a great accuracy rate of 87.5%, with a slightly lower precision rate of 86.7%. However, it excelled in recall, matching Logistic Regression with a rate of 93.6%, indicating its proficiency in capturing actual positive instances and minimizing false negatives. The F1 Score of 90.07% suggested a balanced trade-off between precision and recall. This makes KNN a crucial option when minimizing false negatives.

The Decision Tree model did not provide explicit accuracy metrics. Still, it achieved an F1 Score of 0.77. This indicates a balanced performance between precision and recall and suggests the potential for further optimization with varying thresholds or pruning techniques. This model was also achieved with an accuracy of around 64.42%. Its precision in identifying

STEM topics is approximately 63.27%, meaning it is accurate in these predictions over 63% of the time. Notably, its recall rate for STEM is about 98.41%, showing it almost always identifies true STEM instances correctly.

Lastly, the Neural Network model achieved an accuracy and precision rate of 77.78% and recall rates of 88.89%. Although effective, this model may require additional fine-tuning or architectural adjustments to optimize its performance fully.

In the comparison of machine learning models, Logistic Regression and KNN demonstrate strong performance across various metrics. Logistic Regression achieves an accuracy of 83.65%, with high precision (88.83%) and recall (84.12%). Similarly, KNN exhibits impressive accuracy at 87.5%, with a balanced precision of 86.7% and a notably high recall of 93.6%. However, the Decision Tree model lags with an accuracy of 64.0%, reflecting its lower performance. While it achieves relatively high recall (98.4%), its precision is substantially lower at 12.2%, indicating a higher rate of misclassification. On the other hand, the Neural Network model shows competitive accuracy (77.88%), precision (77.78%), and recall (88.89%), although slightly lower than Logistic Regression and KNN. Overall, Logistic Regression and KNN emerge as the top-performing models in terms of accuracy, precision, and recall, illustrating their effectiveness in this context.

Chi-square analysis is also utilized to explore and clarify more how different characteristics influence the choice of a career in STEM fields.

A Chi-square test of independence was used to understand the relationship between ethnicity and career choice. The results indicated a significant association, $\chi 2(6, N=520)=91.285$, *p*<.001, with a Cramer's V of 0.419, with a Cramer's V of 0.419, suggesting a moderate to a strong association between ethnicity and preference for STEM or Non-STEM careers.

A Chi-square test of independence was also employed to assess the association between gender and career choice (STEM vs. Non-STEM). The results showed no significant association, $\chi 2(1, N=520)=0.0, p=1.0$,, with a Cramer's V of 0.0. This indicates that, within the dataset, gender does not significantly influence the preference for STEM or Non-STEM careers. This result suggests that gender does not significantly influence whether a student is in a STEM field.

Lastly, a chi-square test of independence was conducted to explore the association between socioeconomic status (SES) and career preference (STEM vs. non-STEM). The analysis showed a significant effect, $\chi 2(1, N=520)=23.05, p<.001$, with a Cramer's V of 0.211, indicating a moderate association between SES and career choice in STEM versus non-STEM fields.

Table 5 summarizes the performance metrics for several models, including KNN (K-Nearest Neighbors), Decision Tree, Neural Network, and Logistic Regression, illustrating how each model fares in terms of its predictive capabilities.

Table 6:Machine Learning Model Comparison

| | Accuracy (%) | Precision (%) | Recall (%) |
|---|---|---|---|
| Logistic Regression | 83.65 | 88.83 | 84.12 |
| KNN | 87.5 | 86.7 | 93.6 |
| Decision Tree | 64.42 | 63.27 | 98.4 |
| Neural Network | 77.88 | 77.78 | 88.89 |

*Note:* This table presents a comparison of four machine-learning models

# Chapter 6 Discussion and Implications

This study has examined how gender, socioeconomic status (SES), ethnicity, and participation in Advanced Placement (AP) courses influence students' decisions to pursue STEM careers. The findings provide a detailed understanding of these dynamics, which can offer valuable insights to educators, policymakers, and researchers.

## The Role of Gender in STEM Career Choices

The findings of this study indicate that gender may not have a significant impact on the career choices of students in STEM fields. However, it is important to note that gender continues to be a crucial consideration in STEM fields overall. Although existing literature often highlights differences between male and female participation in STEM fields, this study's results suggest otherwise. One possible explanation is that the data were collected from schools with a strong emphasis on science education, where students are primarily interested in science subjects. This indicates that such schools provide an environment that encourages female students to pursue careers in STEM. Nevertheless, it is still essential to recognize that the absence of significant findings regarding gender does not diminish the importance of creating supportive environments for female participation in STEM. Further research is needed to understand these dynamics better and develop strategies for promoting STEM in females.

Moreover, recent research indicates that women are equally represented in various STEM disciplines, such as biology and chemistry. This suggests a balanced participation across these fields. In my study, I found that a significant number of female students chose biological science, which influenced both female and male students' choices within STEM fields. As a result, my research revealed no gender disparities, aligning with the broader trend of balanced representation in STEM disciplines.

### The Importance of AP Courses and SES

Participation in AP STEM courses and students' socioeconomic status emerged as significant factors affecting the likelihood of choosing a STEM career. Students who have access to and succeed in AP STEM courses are more inclined towards STEM fields, underscoring the value of these courses in preparing students for STEM careers. Additionally, a student's family income level plays a significant role, with students from wealthier families being more likely to lean toward STEM subjects. This indicates the need for targeted interventions to provide equitable access to AP STEM courses, particularly for students from lower SES backgrounds.

### Support for SES-Disadvantaged Students

Findings from this study indicate that students from SES-disadvantaged backgrounds require additional support, particularly in terms of financial resources, to pursue STEM careers. Scholarships, grants, and other financial aid programs targeted at these students could help alleviate some barriers to accessing STEM education and careers. Schools and educational institutions should also focus on creating supportive environments that encourage and facilitate the participation of SES-disadvantaged students in STEM subjects.

### Ethnic Disparities in STEM Career Choices

The research identified notable disparities in STEM career choices among different ethnic groups, with Asian and White students showing a higher inclination toward STEM fields compared to their Hispanic and Black counterparts. Given demographic projections indicating a growing Hispanic and Black population in the future, efforts must be made to encourage these groups toward STEM. This calls for policymakers and educational leaders to devise strategies that address cultural, educational, and financial barriers preventing these students from pursuing STEM careers.

### The Role of ACT Scores in STEM Career Choice

Intriguingly, science and reading scores do not serve as strong predictors of STEM career choice. According to existing literature, one would expect science scores to be indicative, but this was not the case. Upon receiving the ACT science score, it became apparent that the science section primarily focuses on comprehension rather than assessing content knowledge. Its format resembles that of the reading section. This could explain why the science score is not a reliable predictor of STEM career choice. Further exploration is necessary to delve into why this result was obtained, thus enhancing our understanding of the phenomenon.

Additionally, it is worth considering that the period during which the students took the ACT, possibly during the COVID-19 pandemic, could have influenced their science scores. The disruptions caused by the pandemic might have impacted their ability to effectively prepare for and perform on the science section of the exam. This factor could also contribute to the diminished predictive power of science scores in determining STEM career choices. Further investigation would provide valuable insights into the observed results.

### Availability of STEM-Related AP Courses

The availability of STEM-related AP courses is crucial in nurturing interest and competence in STEM fields. The study suggests that making these courses accessible, especially to underrepresented groups, could significantly impact students' career trajectories. Schools should work towards expanding their AP course offerings and ensure these opportunities are known and available to all students, regardless of their income level or ethnic background.

## The Role of GPA in STEM Career Choice

The logistic regression model indicates that the coefficient of GPA is 0.007910. This value helps us understand the relationship between a student's GPA and their likelihood of choosing a career in STEM. Although academic achievement and choosing a career in STEM fields are related, the effect of GPA is relatively small. One possible explanation for this weak effect could be the context in which the data was collected, especially during the COVID-19 pandemic. Teachers may have adopted more lenient grading practices, considering the added stress and challenges students faced. This approach, along with the possibility of inflated grades, might have contributed to a situation where GPA was not strongly correlated with career choices, as it would have been under normal circumstances.

## Limitations and Future Implications

This study is subject to certain limitations that could affect the applicability of its findings. Understanding these limitations is essential for interpreting the results and guiding future research directions.

The study has provided valuable insights into the factors that affect students' decisions to pursue STEM careers. However, it is important to note that parental education and informal education could also play significant roles in this regard. Unfortunately, due to limitations in available data, these elements were not examined. Therefore, future research that incorporates data on parental education levels and informal educational experiences could provide a more nuanced understanding of the complexities surrounding career choices in STEM fields.

A fundamental limitation of the study is having access to a limited dataset. A larger and more diverse dataset could help us better understand the effect of the STEM career choice. More data points could allow us to conduct a more detailed analysis.

Another significant limitation is the inadequate representation of all ethnic groups, particularly Black individuals and those identifying with two or more races. This underrepresentation cannot fully capture these groups' experiences or challenges with STEM career paths. The lack of sufficient data on these populations restricts the study's ability to comprehensively analyze how ethnicity intersects with educational achievement and career choices.

As the data obtained from science-focused high schools indicates a greater preference among students for STEM careers compared to those attending regular schools, it is evident that these types of schools attract students with more interest in STEM subjects. Therefore, this dataset may not accurately depict a broader population of students.

Addressing these limitations in future research efforts is essential for advancing our understanding of the factors influencing STEM career choices. Expanding the dataset to include more participants and ensuring that all ethnic groups are adequately represented would significantly improve the study's robustness and the generalizability of its findings.

## Conclusion

In conclusion, while gender and GPA may not have been identified as a significant factor in this study, the importance of SES, ethnicity, and access to AP courses in determining STEM career choices cannot be overstated. AP course demonstrates the highest correlation with STEM career choice, although correlation does not imply causation. Addressing these disparities requires a concerted effort from all stakeholders involved in education. We can move towards a more inclusive and diverse STEM workforce by implementing supportive measures and ensuring equitable access to resources and opportunities.

I suggest that schools take proactive steps to encourage STEM careers nationwide. This could involve expanding the availability of STEM-related courses and actively promoting enrollment in AP courses. Additionally, schools should consider the impact of SES on students' STEM choices and explore alternative financial resources to ensure equal access to study materials and resources for all students. It's worth noting that the reliability of GPA as an indicator of STEM career choices was affected by the disruptions caused by the COVID-19 pandemic. In the future, conducting similar research under normal circumstances could provide deeper insights into the influence of GPA on STEM career decisions.

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