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Deconstructing the “Leaky Pipeline”: Three Studies to Describe and Explain STEM Career Trajectories with Gender Differences

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Deconstructing the “Leaky Pipeline”: Three Studies to Describe and Explain STEM Career Trajectories with Gender Differences

DISSERTATION

submitted in partial satisfaction of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

in Education

by

Yannan Gao

Dissertation Committee:
Distinguished Professor Jacquelynne S. Eccles, Chair
Professor Sandra Simpkins
Associate Professor Drew Bailey

2022

DEDICATION

I dedicate this dissertation to the boys and girls in my adolescence – the odds of getting a better education did not stand at their side.

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ABSTRACT OF THE DISSERTATION

Deconstructing the "Leaky Pipeline": Three Studies to Describe and Explain STEM Career Trajectories with Gender Differences

by

Yannan Gao

Doctor of Philosophy in Education

University of California, Irvine, 2022

Professor Jacquelynne S. Eccles, Chair

Patching the "leaky STEM pipeline" has been central to increasing the STEM labor supply as well as the gender balance of the STEM workforce. Recently, criticisms have accumulated about the limitations and the stigma conveyed by this metaphor. Yet, there lacks evidence on STEM career paths to examine to what extent and in what ways the "leaky pipeline" metaphor represents STEM career trajectories accurately. Previous studies have shown STEM entry as an alternative pathway into STEM careers and as a venue to address the gender gap in STEM degree attainment. More research is needed to further understand the profiles of people entering STEM fields at a later time point. The Situated Expectancy-Value Theory indicates that STEM career choices are linked to individual differences in the motivation about the STEM and non-STEM domains. More specifically, individuals evaluate the career choices available to them at a given point in time and choose one ranked among the highest in their hierarchy of options. The Dimensional Comparison Theory further elaborates on this inter-personal comparison, with evidence showing its implications on the formation of expectancy-value beliefs and achievement choices in different domains. To what extent understanding based on these theories about achievement-related choices at one point in time can be applied to career trajectories over time

requires further examinations. Most of the studies in this area were based on quantitative data analyzed in a confirmatory manner. Evidence is needed to demonstrate to what extent the motivational processes described in the Situated Expectancy-Value Theory occur in the spontaneous process of an individual's career decision-making.

To address these gaps in the literature, I attempted to describe and explain changes in STEM career paths in the three studies of this dissertation. In study one, I used a national, longitudinal sample to describe the existing STEM career trajectories from age 13 to 25. I plotted men's and women's career paths in the broad STEM field, as well as in the health STEM domain and the physics-related STEM domains. I included the often-overlooked distinction among STEM careers regarding the education requirement, between the blue-collar STEM jobs and the white-collar STEM jobs. My graphs and analyses visualized the much-studied STEM career trajectories and provided evidence for the limitations of the "leaky pipeline" metaphor. In study two, I used logistic regressions to examine the sociodemographic, achievement and motivational factors of the STEM entry and the STEM attrition. Results showed meaningful differences between individuals taking different trajectories. In study three, I used students' open-ended responses to understand the reasons for changes in their major plan in college introductory STEM courses. The results demonstrated that expectancy-value beliefs were a natural part of students' considerations, and that different beliefs may play roles in different types of changes in career paths. In sum, findings from the three studies supported the gender differences and more broadly, individual differences in STEM career paths and pointed to the developmental roots of these trajectories.

Keywords: STEM career trajectory, gender differences, STEM attrition, STEM persistence, STEM entry, health STEM careers, physics-related STEM careers, blue-collar STEM careers, white-collar STEM careers, cumulative disadvantage, Situated Expectancy-Value Theory, Dimensional

Comparison Theory, underrepresented racial minority, person-centered approaches, longitudinal latent class analysis

INTRODUCTION

In the U.S., the STEM (Science, Technology, Engineering and Math) career pathway is called the "leaky pipeline". The name implies a long training process for getting STEM jobs with low proportions of individuals turning into STEM workers. The attrition rates in STEM majors range from 40 to 80 percent in two-year and four-year colleges (Chen & Soldner, 2013). The high attrition rates have raised policymakers' concerns about meeting the demand for STEM labor supplies of the job market. In 2020, the U.S. Department of Education invested $578 million in STEM-related research (Department of Education, 2022). However, less is understood about the phenomenon of STEM career trajectory: what does the "pipeline" look like? How often do people leave their STEM career paths? What section of the "pipeline" sees the largest attrition? More recently, scholars have criticized the "leaky pipeline" metaphor for its failure to represent alternative, diverse STEM career trajectories (Cannady et al., 2014; Lykkegaard & Ulriksen, 2019). The discussion calls for descriptive evidence to visualize STEM career trajectories.

Gender differences in STEM persistence have been at the center of reducing STEM attrition over the past few decades. The field has seen remarkable progress in increasing women's representation in STEM, with women earning more than half of postsecondary degrees in biology and health-related STEM fields and remaining underrepresented in physics, engineering and math-related fields (Ceci et al., 2014; National Center for Education Statistics [NCES], 2017; Sax & Newhouse, 2018). Much is known about the psychological and contextual explanations for the gendered participation in STEM and the variation of gender representations across STEM domains (for a review, Kanny et al., 2014; Wang & Degol, 2013; Xie et al., 2015), underscoring the theoretical and empirical roots to consider men's and women's STEM career trajectories and motivations separately.

The Situated Expectancy-Value Theory (SEVT) developed by Eccles and colleagues (Eccles & Wigfield, 2020; Eccles et al., 1983) portrays the process through which individuals develop general and specific beliefs about themselves and their career choices that give rise to the overall gendered participation in STEM. Numerous studies have provided empirical support for the SEVT by showing the causal association between individuals' expectancy-value beliefs and their career choices (e.g., Chow et al., 2012; Guo et al., 2017; Harackiewicz et al., 2016; Simpkins et al., 2006). STEM attrition is one instance of career choices, for which the person chooses between their original career path in STEM and the alternative option in the non-STEM field. In this regard, the decisions to change career paths are similar to career choices at one time and may be understood from the perspective of the SEVT.

In this dissertation, I conducted three studies to describe and explain the STEM career trajectories with gender differences in career development and motivation in mind. I present evidence for diverse trajectories leading to STEM occupations and for the shrinkage as well as the expansion of STEM labor supply over time. The analyses were followed by examinations of men's and women's STEM career trajectories. Then I used one quantitative study and one qualitative study to understand why individuals decided to enter STEM from their non-STEM path or to leave STEM. Both studies provided insights into the decisions to change STEM career paths, with unique findings brought about by the respective analytic approach of each study.

Gendered Representations and Motivation in STEM

Researchers in sociology, psychology and education policy have conducted extensive research in the past few decades to understand gender differences in STEM career choices. In cross-disciplinary reviews of the literature, explanations have shifted from gender differences in math and science competence, which lacks empirical support, to the gender differences in motivation and in the socio-structural and contextual factors (Kanny et al., 2014; Wang & Degol, 2013; Xie et al., 2015). The literature suggests that the gender differences in STEM motivation are deeply rooted in the situated formation of motivational beliefs in a person's sociocultural context. In my dissertation, I will take the perspective of developmental psychology and focus on the motivational explanations for the phenomenon.

One way that the sociocultural context influences adolescents' career choices is through gender-role socialization. Eccles and colleagues (Eccles, 2015; Eccles et al., 1990, 1983; Simpkins et al., 2015) integrated prior work and elaborated on the socialization processes in SEVT and the parent socialization model. They discussed the process through which parents' gender-differentiated beliefs bring about children's gender-differentiated career choices. Versed in the cultural milieu, parents hold varied beliefs about what their child should do well in and what their child should value based on their child's gender (e.g., boys should be good at sports, and girls should like to read). These beliefs influence parents' gender-specific expectations for their children and their perceptions of their children's competence and interest in different domains, above and beyond their children's actual engagement and performance. These gender-typed beliefs manifest in parents' behaviors with or without the parents' intention. Parents provide gender-typed toys and activities, respond to boys' and girls' emotions differently, communicate values aligning with what they expect to see among boys and girls, and interpret boys' and girls' behaviors in a way consistent with parents' gender role beliefs. These behaviors shape children's engagement with and experience in different domains, leading children to become differentially interested in and confident about their abilities in gender-typed occupations. Qualitative studies with talented women in STEM fields showed that their experience of engaging in STEM activities in childhood and adolescence cultivated their strong interest, identity and confidence in STEM areas (DuBow et al., 2016). The gender-based socializations also appear in teacher-student interactions (Jussim et al., 1996; Upadyaya & Eccles, 2015). The socialization processes can explain why young children have gender-typed beliefs to start with and the ways through which such beliefs are reinforced over time (Bian et al., 2017; Jacobs, 1991).

As adolescents grow up, the influence of the gender-role socializations manifests in their motivational beliefs about various careers. If a career option hinders the person to fulfill their values, they will be less likely to pursue such career. The goal congruity model and the interest congruence theory document a mismatch between women's values and some male-dominant STEM fields. Building on Eagly's work on gender and social roles (Eagly & Karau, 2002; Eagly & Steffen, 1984), Diekman and colleagues (Diekman et al., 2017; Diekman & Steinberg, 2013) have posited that the social roles prescribed in society, such as traditional gender roles, encourage individuals to lean towards goals congruent with their social roles and step back from incongruent ones. STEM careers in some domains (e.g., math, physics, computer science) are perceived as incongruent with traditional gender roles of women, which prescribe that women are the caretakers and work with others (communal goals), in contrast to careers in the life and health STEM fields allowing the fulfillment of such values. Another strand of literature based on Holland's person-environment fit theory similarly highlights the match between a person's vocational interest and the type of the occupations. Different from the goal congruence theory, the interest congruence theory differentiates six types of vocational interest and occupations based on Holland's work, which are realistic, investigative, artistic, social, enterprising and conventional (Nye et al., 2017). A person is most likely to like and perform well in an occupation when the primary vocational interest of an occupation matches the person's vocational interest. Evidence has shown that the people-thing spectrum in vocational interest can explain the gender variation in non-STEM versus STEM major choices (Ertl & Hartmann, 2019). The differences in value orientation also explain the varied gender representation across STEM fields. Physics, engineering and technology fields are primarily thing-oriented and thus attract fewer women than the people-oriented biological and health fields (Su et al., 2009; Su & Rounds, 2015). Students in biological and health majors perceived their majors to be more people-oriented than thing-oriented, whereas the opposite was true for students in physics and engineering majors (Yang & Barth, 2015). Longitudinal studies have suggested that the preference of working with people and the endorsement of altruistic values predict fewer women to work in the physics and engineering versus life science STEM fields in mid-adulthood (Eccles & Wang, 2016). In a nutshell, work above reveals women's and men's different vocational interest that gives rise to the uneven gender representation in STEM and across STEM subfields.

In addition to the indirect influences of socialization when at home or in the classroom, the sociocultural environment directly shapes a person's STEM motivations, which may convey signals about the differential associations among gender identity and STEM careers. According to Turner's work on social identity theory, individuals develop a sense of identity by comparing themselves with others, and by self-referentially organizing themselves into respective groups (self-categorization, Stets & Burke, 2000). This self-classification involves comparing oneself to their own perceptions, or stereotypes, about particular social groups. Groups of individuals will be categorized as in-groups and out-groups based on the perceived degree of similarity to said persons. Self-categorization affects the extent to which individuals identify themselves as being a member of a given social group, as well as the way people in different social groups treat in-group and out-group members. Research on social roles has suggested that the numeric distributions of men and women in different occupations influence people's association of gender with respect to these occupations, more so than the distributions of leadership roles between men and women in a field (Eagly & Steffen, 1984). As a result, girls may be less likely to associate themselves with male-dominant fields, than with those of female-dominant, or gender-balanced fields. Evidence suggests that the proportion of women in STEM college classrooms is predictive of the persistence of women in STEM majors (Griffith, 2010). Furthermore, women in STEM fields with moderate percentages of women (e.g., biology, chemistry) more frequently report positive career attitudes than those in fields with low percentages (e.g., physics, engineering) (e.g., Luttenberger et al., 2019). Some aspects with which said persons compare themselves, are those of social competency and sexual attractiveness (for a review, see Cheryan et al., 2017). For instance, the perceived lack of social competency (e.g., "nerdiness") of STEM workers in some fields is negatively linked to women's identification with those fields (Starr, 2018). Self-to-prototype matching is another process through which individuals are able to attain a sense of identity, which involves the act of comparing traits of oneself with those of a prototypical member of the group. Evidence supports the notion that, at least in male-dominant STEM fields, the less that women see themselves as similar to prototypical members, the less they are interested in the careers of said field (McPherson et al., 2018).

Discriminations and biases are another way that group membership influences career choice. Random experiments have shown that people favor men over women in hiring processes for researcher or lab manager positions in the science fields (Moss-Racusin et al., 2012; Reuben et al., 2014). In fields favoring men numerically or culturally (e.g., physics, engineering, computer science), women encounter gender biases more frequently than in fields of biological and life sciences (Robnett, 2016). Gender biases also appear in form of gender microaggressions and barriers facing adolescents who intend to enter STEM fields (Grossman & Porche, 2014). Encountering these microaggressions can discourage girls from entering male-dominant fields, which in turn perpetuate the stereotypes about the gendered representation in different STEM careers. In sum, research on social identity has supported the notion that gendered career choices across STEM fields are not only a result of gendered interest in different fields but also gendered associations with social groups.

Explaining Changes in STEM Career Paths Using the SEVT

Eccles and colleagues (Eccles & Wigfield, 2020; Eccles et al., 1983) theorized the process through which individuals develop their domain-specific beliefs that affect their career choices in SEVT. They have posited that the relative expectancy and subjective task values (STVs) that the person attaches to their available career options are immediate psychological factors affecting people's career choices. These beliefs are shaped by the person's daily interactions with their socializers through the person's perception of their socializers' beliefs and behaviors. At the same time, the person interprets their accumulated experience related to a domain and attaches affective marks to the domain. The conceptualizations of these mechanisms in SEVT make it particularly informative for understanding changes in career paths. Firstly, it specifies the key factors determining career choices, which are the relative level of the expectancy and STVs of various career options. Therefore, changes in career choices can occur because of the new ranking of career options due to changes to the expectancy and STVs. The influence of "developmental deadline" (Wrosch & Heckhausen, 1996) is one such example. The “developmental deadline” in a society prescribes certain goals that a person should fulfill at a particular age. These prescriptions make certain tasks more important than at an earlier or late time and can cause a person to adjust their ranking of career options based on the extent to which each career option facilitates the fulfillment of these tasks. The “revolving door” hypothesis in sociology echoes this concept (Jacobs, 1989, cited from Ma, 2011). It states that STEM career opportunities are present on and off in women’s life, like the opening of a revolving door. This metaphor points out that the social structure regulates these developmental goals by constraining or expanding the opportunities and resources in competition or alignment with the goals (Jacobs, 1995). The traditional deadline of childbearing imposed on females is an example of the developmental deadline. Career explorations, which commonly occur in adolescence and early adulthood (Kracke, 2002), can change a person’s hierarchy of career options by adding new career options. Changes in the experience that give rise to changes in expectancy and STVs is another mechanism that career paths change. Examples of school transitions and school-to-work transitions. The change in the environment changes the person’s experience with the same domain, such as the influence of different instructional practices in college on students’ interest (Steele et al., 2020). In sum, the SEVT provides a roadmap showing specific processes that can guide the creation of research questions and hypotheses. The cyclical occurrence of the processes portrayed in the theory also takes into account the time-specific, situated nature of career choices. In this dissertation, I applied the SEVT to changes in career paths.

Overview of Studies

In this dissertation, I carried out three studies to describe and explain the gender differences in STEM career trajectories.

In study one, I described STEM career trajectories of 1026 individuals from age 13 to age 26 in the U.S. I used two person-centered approaches, the longitudinal latent class analysis and the cross-tabulation approach, to visualize numerically representative trajectories and all existing trajectories. In this approach, I further aggregated the attrition, persistence, and entry trajectories to examine to what extent men and women differed in their membership in these trajectories. I compared the number of STEM aspirants at age 13 and the number of STEM workers at age 25 and calculated the change in sizes of the STEM labor supply. I extended these analyses to subfields of STEM varying in subjects (i.e., the health and physics-related STEM careers) and in educational requirements (i.e., the "blue-collar" and the "white-collar" careers). The study was among the few to portray dynamic STEM career trajectories from early adolescence to early adulthood. The results provided substantive evidence for diverse STEM career paths and helped clarify misunderstandings about STEM persistence and about the gender differences in STEM career trajectories. My findings revealed substantial variations of STEM trajectories in the health STEM and the physics STEM careers between men and women. The distinct career paths of the "blue-collar" versus the "white-collar" STEM careers underscored the need and benefit to differentiate the varied education requirement among STEM occupations. Our findings supported a "highway" representation of STEM career trajectories, with exits from and entry into STEM fields at various points from teenage to mid-20s.

In study two, I used the SEVT and the Dimensional Comparison Theory to examine predictors of changes in STEM career paths. I focused on STEM attrition and STEM entry and conceptualized them as the result of comparisons with alternative career paths, which were persisting in the STEM field and persisting in the non-STEM field respectively. I tested to what extent prior achievement and the expectancy-value motivational beliefs in math and language domains predicted the likelihood to enter or leave the STEM field. In addition, I investigated to what extent these achievement and motivational factors accounted for the differences in attrition and entry between gender groups, underrepresented minorities and their counterparts, and among individuals from families of different socioeconomic statuses. Finding revealed distinct profiles of individuals taking different STEM career paths and underscored the influential role of subjective task values on changes in career paths. The study extended the research based on the SEVT and the Dimensional Comparison Theory to the longitudinal trajectories of career choices.

In study three, I analyzed college students' motivation to change or persist in their majors with qualitative data of students' open-ended explanations. I focused on the period of university introductory courses as an example to study how individuals make decisions at a crossroad in their career paths. Students' open-ended explanations were coded based on the expectancy-value constructs in SEVT in a deductive, phenomenological approach. Findings revealed the explanatory power of expectancy and subjective task values in persistence decisions in a naturalistic setting. Other factors, which were representative of the developmental stage of the students, highlighted the situated nature of students' choices. The qualitative data provided unique insights into what students consider in their persistence versus attrition decisions. Gender differences in students' response patterns and explanations were found. Results from the qualitative data not only provided triangulated evidence with quantitative results about career choices and motivational development, but also offered a synthetic, wholistic understanding about the ways that students navigate their career path.

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CHAPTER 1

A STEM "Highway": Evidence from A Detailed Description of STEM Career Trajectories Across Domains and Education Requirement from Age 13 to 25 with Gender Differences

In 2019, the U.S. Department of Education invested $578 million in STEM related research (U.S. Department of Education, 2020). In 2021, the National Science Foundation (NSF) spent 94 percent of its 8.5 billion dollar budget to fund research, facilities and STEM education (National Science Foundation, 2022a). The budget is projected to increase by 100 billion dollars in the coming five years (Remmel, 2021). A strong STEM workforce is the key to scientific advances, and numerous studies in the past several decades has been dedicated to patching the "leaky pipeline" of the STEM labor supply. Researchers, educators and policymakers strive to preserve the quantity of STEM labor supply that moves through various stages of education and vocational training by reducing STEM attrition and promoting STEM persistence. Yet less is known about what the STEM "pipeline" looks like.

In recent decades, researchers have contended that the "leaky pipeline" is an inaccurate and misleading representation of the development of STEM labor supply (e.g., Cannady et al., 2014; Kimmel et al., 2012). Using a national longitudinal sample of college students, Xie and Shauman (2003) presented evidence that college students not only leave STEM majors for non-STEM majors, but also enter STEM majors from non-STEM majors. Others have advocated that STEM career trajectories are numerous, individualized, and recursive (Babarović, 2021; Blikstein & Worsley, 2016; Metcalf, 2010). In this regard, a singular, linear path as the "pipeline" metaphor implies may not only stigmatize individuals taking alternative pathways to STEM careers, but also constrain and even mislead efforts to expand the STEM labor supply. In this study, I use two descriptive approaches to visualize STEM career trajectories from age 13 and 25 in a national longitudinal sample from the Panel Study of Income Dynamics (PSID).

A clear, specific, and replicable definition of "STEM" careers is the cornerstone of portraying the flow of STEM workforce. Previous studies on STEM career path have been mostly limited to course enrollment and college major (Maltese & Tai, 2011; Sadler et al., 2012; Shaw & Barbuti, 2010), which is difficult to commensurate nationwide and exclusive of non-college-attending population. Existing STEM classification systems (e.g., by NSF, the Department of Homeland Security) often lack clear information of their criteria. What is at heart of the STEM course and major enrollment is the domain-specific knowledge, which is also the defining feature of STEM careers. In this study, I use individuals' career aspirations as indicators of STEM career choices because they are not only detached from a particular educational institute but also better reflect a person's career preferences. I then use individuals' actual occupations at age 25 as the outcome indicator for STEM labor supply. I use the "knowledge" indices in the O□NET database to quantify the demand of nine types of STEM knowledge to establish our classification of STEM careers. We hope our attempt can provide an example of a STEM definition that is replicable to researchers and meaningful to participants.

Taken together, in this study, I aim to visualize the STEM "pipeline" and more broadly, STEM career trajectories from age 13 to 25. I operationalize STEM career choices with individuals' career aspiration and actual employment. I use the "knowledge" indices in the O□NET database to create the classification of STEM careers. Through these analyses, I hope to bring the much-studied phenomenon of STEM career trajectories into its concrete form.

Criticisms of the "leaky STEM pipeline" metaphor

The "leaky pipeline" metaphor once provided a useful message that investigating STEM education and training processes, the "pipeline", is necessary for a thorough understanding of STEM labor supply as the end result. It draws attention beyond the phenomenon of insufficient STEM labor supply or the gender disparity among STEM workers to the origin and mechanisms of these problems. However, more and more criticisms have accumulated in recent decades that the metaphor is a biased and oversimplified representation of STEM career trajectories.

The "pipeline" implies that STEM career trajectories are linear and one-directional. In this portrayal, individuals with STEM career interest enter the field from early on and move along various stages of educational and vocational preparations without changing their career choices. It fails to represent recursive career paths, such as leaving and then returning to STEM fields amidst educational stage, as scholars point out (Metcalf, 2010). During adolescence and early adulthood, which is an important period of STEM career development (Malanchuk et al., 2010), changes in career choices can result from adaptive updates in adolescents' career beliefs and attitudes or useful explorations in alternative careers (Gottfredson, 1981; Stephen et al., 1992). In this regard, a linear and unidirectional path may be uncommon and inaccurate. In addition, the emphasis of the metaphor on "leakage" overshadows late entrance into STEM field. Individuals differ in the development of their career interest because of the differences in their personal characteristics and social context (Messersmith et al., 2008). Some people may spend longer time before they become clear of their career goals or before they pick one career among the various options that are available and comparably desirable to them. Therefore, exclusion of the late entry into STEM fields will cause a biased representation of STEM workers by leaving out certain groups of people.

As a uniform image of the STEM career trajectories, the "leaky STEM pipeline" fails to represent the individual differences in STEM career paths. Sociological and psychological findings have underscored the individualized nature of career choices, because of the unique combination of personal characteristics and social context to each person (Eccles & Wigfield, 2020; Hirschi, 2011). In addition, if the metaphor implies that an early and persistent trajectory is optimal for pursuing STEM careers or maximizing STEM labor supply, it requires close examination of how common such trajectory occurs across individuals and different types of STEM careers. Lastly, educational scholars have criticized the metaphor for problematizing individuals who leave STEM fields (Cannady et al., 2014; Metcalf, 2010). If the goal is the expand STEM labor supply, understanding the context and reasons of attrition decisions may be more fruitful. In sum, the "leaky STEM pipeline" metaphor has become an outdated representation of STEM career paths, as our understanding about the development of career choices has advanced in the latest decades. In this study, we explore STEM career trajectories of all possibilities that exist in the full-form career path analysis and trajectories that numerically representative of heterogenous subgroups in the longitudinal latent class analysis.

Current Descriptions of STEM Career Trajectories

Though there is extensive literature on the factors and practices to promote STEM persistence, studies to describe the phenomenon of STEM persistence/attrition or STEM career trajectories in general are fewer. In a sample of 6,860 college students in a variety of postsecondary institutes, 50% boys and 53% girls reported they aspired to STEM careers in 9th grade; among them, 21% girls and 39% boys changed their career goals to non-STEM fields by the end of high school (Sadler et al., 2012). In a national longitudinal study of adolescents' career expectations, 827 out of 24,599 8th-grade students expected to work in science and engineering occupations; over a period of 6 years, 22% continued to have the career expectations in these fields (Mau, 2003). In a sample of high ability Black, Hispanic and White students, 54% plan to continue STEM course enrollment in high school or choose STEM majors in college (Andersen & Ward, 2014). The attrition rate of high school students' STEM career aspirations varies widely across studies, between 22% and 79%. These studies showed that changes in STEM career paths occur often, but the portrayal of STEM career paths has been often limited to STEM attrition and persistence in most of the studies.

The choice of college major and the major of the attained degree are predictive of the jobs that the individual takes on in the labor market. These indicators have been much studied as the key of attaining a STEM job. In a sample of 589 college freshmen in introductory Psychology class, 85% intend to choose STEM majors; over the course of 8 years, 352 students (60%) graduated with STEM degrees (Ackerman et al., 2013). In a national longitudinal study of over 19,000 students in four-year and two-year colleges, Chen and Soldner (2013) tracked students' declared major in first year of college and their degree attainment 6 years later. They found 48% to 69% students who declared a STEM major did not persist in the following years. Half of these students dropped out of college, and the other half earned their degrees in non-STEM majors. In another study, Shaw and Barbuti (2010) used a national sample of high school SAT test-takers and matched their intended choice of major in high school with their declared college major three years later. They found that 59% of students planning to major in STEM switched to non-STEM majors in college. In these studies, STEM career trajectories were studied in form of STEM persistence and attrition, and career paths were limited to two time points. Alternative career paths, such as switching out of non-STEM majors to graduate in STEM majors, were rarely investigated. The selection of college-matriculated sample excludes not only

STEM careers that do not require a college degree, the importance of which industry I will discuss in a following section, but also the STEM worker population who do not attend postsecondary education, which comprises of high proportion of individuals from disadvantaged backgrounds (Clotfelter et al., 2013).

Alternative Career Paths into STEM Fields and Gender Differences

Xie and Shauman (2003) pioneered the study on entry into the STEM fields. They used a longitudinal sample of high school graduates to track their choices of college over time. They documented students' expected major in senior year in high school, choice of major in the first semester in college, choice of major after two years in college, and the final major of degree six years after high school graduation. They carried out the reduced-form educational path analysis to represent the probability of an individual to choose a science/engineering major given their choice at an earlier time point. Between two time points of high school major plan and college degree attainment six years later, they found that persistence was the most common path taken by male science/engineering baccalaureates, whereas entry from non-science/engineering major plan was the most common path taken by female science/engineering baccalaureates. Their findings not only shed light on the STEM entry as an alternative pathway into the STEM fields but also showed that there were meaningful gender differences in the likelihood of taking this trajectory. Xie and Shauman (2003) further examined the timing of the STEM entry. Comparing a switch from non-STEM to STEM major choices, they identified such switch after high school graduation and before the first semester of college, within first two years of college and after the 2^{nd} year in college. They found that the gender gap in the switch by the first year of college was the most influential to the gender gap in STEM degree attainment. Men were two times as likely as women to switch into STEM fields by the first semester of college, whereas the probability of

STEM entry was comparable afterwards. In sum, Xie and Shauman's work shed light on the alternative paths into STEM fields, other than STEM persistence, and showed gender differences in the likelihood and patterns of STEM entry trajectories. In this study, I expand this strand of research by examining in detail how often STEM workers take entry paths into their field, the original field they aspire to, and the timing of their entry.

More work showed men and women took different trajectories into attaining STEM Bachelor's degree. Modeling Xie and Shauman's approach, Ma (2011) portrayed gendered paths between the 12^{th} grade, the 1^{st} officially declared major in college and the final degree attainment 8 years after high school graduation. She found that the STEM career trajectories of boys followed the "leaky pipeline" image with fewer and fewer boys persisting in STEM majors over time. In contrast, the percentage of girls in STEM majors remain stable over 9 years, with a small increase between high school graduation and the second year in college. Another study (Cimpian et al., 2020) using a nationally representative sample of high school students in the High School Longitudinal Study tracked high school graduates' intention to choose STEM majors and their actual choice of major after three years in college. They found that among students with high school STEM achievement in the top half of the sample, girls were more likely than boys to fulfill their intention of choosing engineering or computer science majors. In other words, among students with medium to high STEM achievement, girls were more likely than boys to persist in engineering and computer science fields. However, contradictory results were found that between sophomore years in college to 6 years after, men were more likely to persist and attain a STEM degree than women (Weeden et al., 2020). In this study, I contribute evidence to this question by examining the entry and persistence rates among women and men in STEM fields and comparing men's and women's path into STEM occupations.

The "Cumulative Disadvantage" in STEM Career Paths

The "pipeline" metaphor is linked to the "cumulative disadvantage" hypothesis about individual differences in STEM trajectories. Mainly used to explain gender differences in STEM representation, the "cumulative disadvantage" states that women are less likely to participate in STEM due to their cumulative disadvantage in STEM domains compared with men over time (Ma, 2011). The early gender role socialization leads to girls' lower likelihood to participate in STEM-related activities. As a result, girls become less confident about their abilities. This lack of confidence further drives girls to avoid participating in the STEM domain, such as enrolling in fewer STEM courses or taking part in fewer STEM extracurricular activities, which in turn undermines girls' STEM motivation. Over time, as girls miss one section in their educational and vocational preparation for STEM careers, their disadvantage will trigger this negative cycle and accumulate into considerable discrepancies in girls' and boys' STEM career choices and trajectories.

The developmental mechanism underlying the "cumulative disadvantage" hypothesis is that prior experience has a cascading effect on following choices. This effect has been supported by findings of a positive association between earlier STEM engagement and later STEM career choices. For instance, high school advanced STEM course enrollment and performance are influential predictors of students' choice of STEM majors in college or STEM interest (Sadler et al., 2014; Shaw & Barbuti, 2010; Tyson et al., 2007). Furthermore, high school course enrollment can by predicted by STEM engagement in middle school or childhood (Almeda & Baker, 2020). A conclusion seems to support the notion that STEM career choices at one time point depend on STEM participation at an earlier time point, and that the best way to promote STEM career choices is to get introduced to STEM fields early and maintain participations over time. However, the extent to which the cumulative disadvantage explains individual differences in STEM career trajectories requires further examinations for two reasons. Firstly, it remains unclear how powerful the cumulative disadvantage is for preventing a person from entering the STEM field. Theoretically, is the lack of previous experience in STEM fields a deterministic factor, a risk factor or a protective factor? Realistically, how common do people attain a STEM job without an earlier choice in the field? How much do people differ in their chance to get a STEM job based on the amount of their prior experience in STEM? Previous studies heavily focused on the contrast between STEM persistence and STEM attrition, and there lacks studies on STEM entry to examine the other part of the picture. Secondly, from the perspective of the Situated Expectancy-Value Theory of achievement choices (Eccles & Wigfield, 2020), the cumulative advantage neglects the possibility that the lack of engagement with STEM domains is due to choices, not the lack of competence. If a person is comparably high achieving and confident about their abilities in STEM and non-STEM domains, they may choose a non-STEM career because they find it valuable to them. Previous studies showed that STEM careers that fulfill women's communal or altruistic values are more likely to attract women than their counterparts (Eccles & Wang, 2016; Wegemer & Eccles, 2019). In other words, the competence-based disadvantage of entering STEM field might be of limited scale. In this study, I inspect into the implications of the cumulative disadvantage on STEM employment in several ways. I examine the prevalence of STEM entry among STEM workers. Moreover, I explore all types of trajectories that lead to STEM employment and compare the prevalence of the paths based on the number of previous choices in the field of employment. The comparison can show whether the more prior choices in a STEM field correspond to higher probability of working in the STEM field.

Specifying the Definition of STEM Careers

There lacks consensus on the definition of STEM careers and more broadly, the STEM fields. They key disagreement centers on whether social science, life science and health related fields/careers, and secondary teachers of these disciplines are STEM fields/careers or not. The NSF uses a broad definition of STEM, including social science and life and medical disciplines as STEM fields and the post-secondary teaching professions in these disciplines as STEM careers (National Science Foundation, 2022b). The Department of Homeland Security classifies postsecondary STEM education programs for immigration purposes. International students who graduate from STEM programs have extended period of stay in the U.S. (Title 8 of the Code of Federal Regulations, n.d., p. 8), increasing their likelihood of being hired on full-time, long-term positions and gaining work visas. Some social science fields, such as social psychology and econometrics, are qualified as STEM programs whereas some social science fields such as sociology are not (Department of Homeland Security, 2022). In addition, nursing and teacher education programs are not categorized as STEM programs. Another federal agency, the Department of Education, funds the SMART (National Science and Mathematics Access to Retain Talent) grant to provide need-based scholarship to undergraduates in STEM programs. Their STEM classification excludes many social science programs, such as sociology, psychology except psychobiology, but includes life sciences and several foreign languages (U.S. Department of Education, 2009). The ranges of STEM fields and careers in the different STEM classifications potentially reflect the goals and needs of each agency. Yet, they can lead to different results and conclusions about STEM labor supply and the gender differences in STEM fields (Granovskiy, 2018; Manly et al., 2018; National Science Board, 2015). For investigating STEM careers, the O□NET database, hosted by the Department of Labor, creates a list of STEM occupations based on various aspects of each occupation and experts' advice (National Center for O□NET Development, 2022). It includes life and health science occupations, social scientists, and postsecondary teachers in social science fields in STEM careers. However, there lacks information on the classification criteria of the O□NET STEM classification, making it difficult for researchers to ensure an alignment between the STEM definition and their research questions. In this study, I attempted to create a specific, replicable STEM classifications based on the demand of STEM knowledge of each occupation.

Economists and policy researchers have pointed out the variation of education requirement among STEM workers (Carnevale et al., 2011; National Science Board, 2015; Rothwell, 2013). STEM occupations that require less than a Bachelor's degree have been overlooked in previous literature, yet they comprise thirty to forty percent of STEM workforce and STEM job openings in the future (Carnevale et al., 2011; Rothwell, 2013). Moreover, the varied degree requirements have tangible implications for students' educational trajectories, making them important for understanding diverse STEM career trajectories. In this study, I differentiate STEM careers that require a Bachelor's degree or higher, named "white-collar" STEM jobs, and STEM careers that requires less than a Bachelor's degree, named "blue-collar" STEM jobs, and examine paths leading to each type of careers.

Differentiation between Health- vs Physics-related STEM Careers

The gendered pattern of career choices in STEM is perhaps the most notable between health STEM and physics-related STEM careers. In the past half century, life science related STEM fields have achieved remarkable progress in reducing gender disparities. Nowadays 52% of PhDs in life science have been earned by women (in contrast to 13% of PhDs in life science in 1970s) (Ceci & Williams, 2011). In the past ten years, a predominant number of Bachelor's and

Associate's degree in the biological sciences (61%) and health professions (84%) were conferred to women (NCES, 2017). Meanwhile, gender disparities persisted in physics-related STEM fields, such as computer sciences and engineering fields (Ceci et al., 2014; Sax & Newhouse, 2018). In engineering and computer science, 20% graduates in two-year and four-year colleges were women (NCES, 2017). In economics, women consisted of less than a third of undergraduate students (Buckles, 2019). Even within the engineering field, there was variation of student gender representation across subfields. For instance, biomedical, chemical and environmental engineering had a more balanced gender composition, with around 40% of undergraduate degree holders being women; in contrast, in computer science, electrical, mechanical, nuclear and petroleum engineering, less than 20% of bachelor degree holders were women (Chesler et al., 2010). Before entering college, high school boys and girls have shown a similar pattern in their career plans, with boys more interested in careers in engineering and girls, in health and medicine (Sadler et al., 2012). This gendered representation in health versus physics-related STEM fields can be attributed to men's and women's differences in altruistic values, people- or tool-oriented vocational interests and community or family related life goals (Dicke et al., 2019; Eccles & Wang, 2016; Sax & Newhouse, 2018; Su et al., 2009). Thus, aggregating health and physics-related STEM careers under a broad STEM category will mask meaningful gender differences in STEM career choices.

At the same time, more is to be understood about gender differences in the trajectories in these fields. The gender differences in these values might lead to gender difference in the attrition from and entry into health and physics-related STEM fields. Researchers have found that women were more likely to leave physics-related STEM fields than men in high school and college years (Ellis et al., 2016; Mau, 2003). Women who held lower intrinsic values about physics-related STEM careers were more likely to change their career path and move out of physic-related STEM fields (Frome et al., 2006). Endorsing traditional gender role beliefs about women's and men's differential family obligations and vocational interest predicted higher likelihood to work in health STEM fields than in physics-related STEM fields (Dicke et al., 2019). Therefore, these gender differences in values can lead to men's and women's varied trajectories in health and physics-related STEM careers. Moreover, some studies showed additional nuances in gendered trajectories in health and physics-related STEM fields. For instance, one longitudinal studies on high school students showed that boys and girls with STEM career interests did not differ in their likelihood to enter health STEM fields in college but differ in their likelihood to enter engineering majors (Kimmel et al., 2012). Similarly, another study showed that men were more likely than women to persist in math and engineering majors in college, but men and women did not differ in their persistence rates in health STEM majors (Weeden et al., 2020). There seemed to be less gender difference in STEM career paths in health STEM fields, but more studies are needed to test this conjecture. The evidence does support separate examinations of gender career paths in health and physics-related STEM fields. In this study, I address this question by portraying men's and women's persistence, entry and pathways leading to STEM employment in health and physics-related STEM careers.

Differentiation Between Blue-collar versus White-collar STEM Careers

According to the U.S. Bureau of Labor statistics, in 2015, 93% of STEM occupations in the U.S. were paid above the national average (Fayer, Lacey & Watson, 2017). In 2015, the average wage of all STEM occupations was $87,570, in contrast to $45,700 of non-STEM occupations (Fayer et al., 2017). This wage premium of STEM occupations has existed in past decades and can be found among jobs of all skill and knowledge levels (Carnevale et al., 2011).

Nationwide, there was a strong correlation between the geographic distribution of STEM occupations and the average wages of different states (Cover, Jones & Watson, 2011), such that states with a bigger STEM industry have higher average wages. However, considerable wage gap exists among STEM careers. For example, in 2009, the top four highest-paying occupations reached an average of $120,000 a year, but the four lowest-paying occupations earned less than a third of this amount (Cover, Jones & Watson, 2011). The size of this gap remained in 2015 (Fayer, Lacey & Watson, 2017).

This variation in wage within STEM fields parallels with the education requirement of the jobs. STEM occupations requiring less than a four-year college degree earns $53,000 annually on average, 40% lower than their highly educated counterparts (Rothwell, 2013). These "blue collar" STEM jobs, STEM jobs that require less than a Bachelor's degree, are more often excluded in the definition of STEM occupations, yet they make up of 30 to 50 percent of STEM jobs (Carnevale et al., 2011; Fayer et al., 2017; Xue & Larson, 2015). The blue-collar STEM jobs are an integral part of the STEM industries. In manufacturing and engineering industries, these jobs are at the front end of producing, installing and repairing machines and products. The workers help improve the design and reduce product defects, increasing the efficiency of the product line. In healthcare industry, these supporting STEM workers take over healthcare and hygienic routines, administer examinations, supervise and educate patients. They are key to the adherence to the treatment. In fact, estimates suggested the growth of job openings will be faster among blue-collar STEM jobs than white-collar ones in the next decade (Rothwell, 2013).

Moreover, the differed degree requirement of blue-collar STEM occupations has implications on students' educational paths. Jobs requiring an Associate's or vocational degree often draw students from two-year colleges. These students are more likely to be underrepresented ethnic minorities, come from families with lower SES, enroll at school part time and have other commitments outside of school than students in four-year universities (Clotfelter, Ladd, Muschkin & Vigdor, 2013). The mechanisms relating to students' STEM major choice may be different for two-year college students. For example, prior course enrollment in high school and perceived competence in science positively associated with students' entrance to STEM majors among four-year university students, but the association was smaller or none for community college freshmen (Wang, 2013). Likewise, community college students who intend to major in STEM at the beginning of college were less likely to attain a STEM degree 5 years later than their peers with the same academic and socioeconomic backgrounds in four-year universities, despite some of them transfer to four-year universities (Wang, 2015). These findings showed different educational and career trajectories into blue-collar STEM careers, because of the different student population and the characteristics of the occupations. In my study, I differentiate STEM careers based on their education requirement and compare the trajectories in white-collar versus blue-collar STEM jobs.

The Present Study

In this study, I aim to plot STEM career trajectories from age 13 to 25 using a national longitudinal sample. I use two descriptive approaches to portray numerically representative STEM career trajectories in longitudinal latent class analysis and to portray all existing STEM career trajectories in the full-form career path analysis. To provide a clear and replicable criteria of STEM categorization, I use the domain-specific knowledge of each occupation in the O□NET database to differentiate STEM versus non-STEM jobs, health versus physics-related STEM jobs, and blue-collar versus white-collar STEM jobs. I plot trajectories of two, three and four time points in each of the field. The results can not only show the change in the STEM labor supply between age 13 and age 25, but also reveal the dynamic movements during this time span. I aim to answer the following research questions (RQs) in this study:

RQ1: What are the trajectories for STEM career choices from age 13 to age 25,

RQ1a: in terms of 1) STEM and non-STEM careers,

RQ1b: health-STEM, physics-related STEM and non-STEM careers, and

RQ1c: blue-collar/white-collar STEM and non-STEM careers?

RQ2: How does STEM labor supply change over time?

RQ2a: Does STEM labor supply grow or reduce over time?

RQ2b: How does STEM labor supply compare with non-STEM labor supply?

RQ2c: How does STEM labor supply compare between men and women?

RQ3: what are the trajectories of STEM attrition in STEM and non-STEM fields?

RQ3a: What is the attrition rate of STEM and non-STEM aspirations respectively?

RQ3b: Which field do individuals leaving STEM field move into by age 25?

RQ3c: Which attrition trajectory is the most common?

RQ3d: Do results of questions above differ by gender?

RQ4: What are the trajectories of STEM entrance for STEM and non-STEM employment?

RQ4a: What is the entrance rate among STEM workers?

RQ4b: Which field do STEM workers who enter STEM field come from?

RQ4c: Which entry trajectory is the most common?

RQ4d: Do results of questions above differ by gender?

RQ5: Do men and women differ in their trajectories to obtain STEM employment?

Hypotheses

Based on prior research on STEM attrition and STEM entry (Chen & Soldner, 2013; Xie & Shauman, 2003), I hypothesize to find trajectories of STEM persistence, STEM attrition, STEM entrance, and non-STEM paths between age 13 and 25. Based on the literature on the gender differences in motivation and career choices in the health STEM field and the physics-related STEM fields (Eccles & Wang, 2016; Su et al., 2009), I hypothesize to find more women than men choose health STEM careers at age 13 and age 25 and more men than women choose physics-related STEM careers at age 13 and age 25.

Regarding changes in the size of the STEM labor supply, as previous studies showed higher STEM attrition rates and lower STEM entry rate among women than among men (Chen & Soldner, 2013; Xie & Shauman, 2003), I hypothesize to find a greater shrinkage in STEM labor supply among women than among men in STEM careers in general. Because of findings that women were less likely to choose physics-related STEM careers than health STEM careers (Ma & Liu, 2017; Toh & Watt, 2022), I hypothesize to find a greater shrinkage of the women labor supply than the men labor supply in the physics-related STEM careers, and a greater shrinkage of men labor supply than the women labor supply in the health STEM careers.

As previous studies showed a higher attrition rate among STEM careers than non-STEM careers (Chen & Soldner, 2013), I hypothesize to replicate this result and find a higher attrition rate in the STEM field than in the non-STEM field. Considering a better fit between health STEM careers (than physics-related STEM careers) and women's altruistic value (Diekman et al., 2017; Eccles & Wang, 2016), I hypothesize to find a lower attrition rate among women than among men in the health STEM careers and a higher attrition rate among men than among women in the physics-related STEM careers.

Regarding STEM entry, I hypothesize to find a lower STEM entry rate among women than among men based on previous findings by Xie and Shauman (2003); in addition, I hypothesize to find the most entry into STEM between age 18 and 21, because of Xie and Shauman's (2003) finding of the largest group of entrants between high school graduation and first year in college.

Regarding the trajectories leading to STEM employment, based on the studies by Ma (2011), I hypothesize to find that women were more likely than men to take a path of late entry followed by persistence in STEM careers. Based on the findings of (Ma & Liu, 2017), I hypothesize to find that persistence route was more common among women than among men in health STEM fields and the reverse in physics-related STEM careers.

Methods

Participants

Participants are 1026 adolescents in the original cohort of the Child Development Supplement (CDS) of the Panel Study of Income Dynamics (PSID) launched in 1997 (54% girls; 47% White, 42% Black, 7% Latino, 1% Asian, 3% other; average age in 2002 = 13.08 years old [SD = 1.94]). They were recruited as the children of families in the PSID main study, which are nationally representative of US families, and interviewed separately by the project team. The original CDS sample consist of 3563 children from birth to age 12 in 1997 and have been followed every 5 years until age 18. In 2005, the Transition to Adulthood Supplement (TAS) was launched to follow any participants reaching age 18. The participants were followed every 2 years until they start their own households and enter the main PSID sample. This study uses all available waves by the time of data coding in 2019: CDS 1997', CDS 2002', TAS 2005', CDS 2007', TAS 2007', TAS 2009', TAS 2011', TAS 2013', main PSID 2013', TAS 2015' and main PSID 2015'. Figure 1 showed waves of CDS and TAS data used in this study.

In CDS, questions on career aspiration were first asked in 2002. Children needed to be at least 8 years old to be eligible for CDS child interviews and at least 12 years old to be eligible for questions on career aspirations. Participants were included in the current study if 1) they named at least one desired occupation in CDS 2002' interview, and 2) they reported their occupation(s) in 2013' or 2015'. Detailed sample exclusion information can be found in Table Appendix A.

Procedure

PSID project researchers interviewed participants at home face to face or on phone based on protocols and scripts. Responses were recorded, cleaned and documented by the PSID project team and made available on PSID online data center. Authors of this paper recoded and analyzed the data.

Measures

Career aspirations

Adolescents were asked "What are the three kinds of jobs you would like to have when you are done with school?" Respondents were free to name any jobs they like. Up to three jobs were recorded for each adolescent, in the order of being mentioned. When the respondent listed more than one aspiration, they were asked to identify the one that they desired the most. One response, the 1st mentioned or the most desired, was used for one participant. For respondents of age 18 and older, the question was worded as "What job would you most like to have when you are 30?" Responses were recorded in 3-digit 2000 Census occupation code in PSID dataset. Responses in CDS 2002', TAS 2005', CDS 2007', TAS 2007', TAS 2009' and TAS 2011' were used.

Occupation in adulthood

Participants were asked about their current or most recent job in the past two years, including self-employed jobs (e.g., any work for money since Jan. 1, 2011, in 2013 interview). If the participant worked in multiple jobs, they were asked to identify one as their main job. Responses were recorded in the 2000 Census occupation code, in the same way as career aspirations.

Responses in 2013 and 2015 TAS interviews and PSID main interviews were used. If the participant started their own households by the time of the interview, they will be interviewed in the PSID main study; otherwise, in TAS study. The questions were worded in the same way in all interviews.

Census-O□NET translation

Because the original PSID career aspirations and occupations were coded as three-digit 2000 Census occupation codes, the codes were first translated into the eight-digit O□NET occupation codes by the 1st author. No crosswalk exists between 2000 Census codes and 2019 O□NET codes. The coding used the occupation description in O□NET database to identify the best matching occupation and referenced a crosswalk between 2000 Census codes and 2018 SOC system, which is a set of six-digit occupation codes that the 2019 O□NET codes are based on. One to six O□NET occupations were matched for one census occupation, listed in the order of the best to least match.

STEM classification

The classification criteria were created using the “Knowledge” information on O□NET. The “Knowledge” dimension in O□NET database indicates the demand for a given type of knowledge in a specific occupation. We chose this dimension instead of “work activities” or “skills” because the knowledge category focuses content knowledge and skill set that are domain specific, such as “chemistry”, “transportation”, “sales and marketing”, “law and government”, etc. There are a total of 33 knowledge domains available to describe each occupation. For each knowledge domain, an “importance” score is given to represent how important it is for an employee to possess the STEM knowledge for conducting the job in a typical situation. The score is an integer ranging from 0 to 100, which was created from the ratings of a national sample of current incumbents and supervisors of each occupation. The scores are standardized to represent the relative importance of the knowledge domain for a given job compared with all other jobs. An occupation may have “not applicable” on the scale for a knowledge domain that is not relevant.

The importance scores of nine knowledge domains were used to create our STEM classification criteria: 1) Biology, 2) Chemistry, 3) Computers and Electronics, 4) Economics and Accounting, 5) Engineering and Technology, 6) Mathematics, 7) Mechanical, 8) Medicine and Dentistry, and 9) Physics. This list was created by asking two raters to mark whether each of the 33 O□NET knowledge domains is STEM or not based on common sense. The nine knowledge domains above were consistently marked as STEM by two raters and thus were used. The inter-rater reliability is 85%. The two raters were counter-balanced on gender and whether or not their racial/ethnic group is underrepresented in STEM fields.

STEM occupations were classified based on two criteria: the absolute importance and the relative importance of STEM knowledge. The *absolute importance* means that for one occupation to be listed as STEM, it needs to be scored 60 or higher on importance in at least one STEM knowledge domain. For example, the occupation “accountants and auditors” fulfills this criterion because it is scored 73 on “mathematics”. This criterion reflects how important the STEM knowledge is for fulfilling tasks of the occupation. The *relative importance* means that for one occupation to be listed as STEM, at least one of its STEM knowledge domains is ranked in the top half among its knowledge domains with a score greater or equal to 50. In other words, when knowledge domains with a score lower than 50 are excluded, there needs to be at least one STEM knowledge domain ranked among the top half of the rest of the knowledge domains. For example, for “accountants and auditors”, 8 of the 33 knowledge domains are scored higher than 50; among these 8 domains, in the four highest ranked domains, two were STEM domains (i.e., “economics and accounting” and “math”). Therefore, the occupation fulfills the relative importance criterion. The relative importance criterion reflects how important STEM knowledge is, compared with other knowledge domains that are important for a job. This criterion is useful for ruling out occupations that generally require significant amount of knowledge but may not particularly specialize in STEM domains. For instance, “chief executives” is one example. It is scored 60 on “math” knowledge, but people usually would not consider it STEM job, like a job of pharmacist. An occupation needs to fulfill both the absolute importance criterion and the relative importance criterion to be classified as STEM occupations.

Among STEM occupations, the distinction between physics vs health STEM is made based on the highest ranked STEM knowledge domain. Physics-related STEM occupations are STEM jobs whose highest ranked STEM knowledge domain is one of the following types: 1) Computers and Electronics, 2) Economics and Accounting, 3) Engineering and Technology, 4) Mathematics, 5) Mechanical, or 6) Physics. A STEM occupation is classified as health STEM if its highest ranked STEM knowledge is 1) Biology or 2) Medicine and Dentistry. This distinction among these STEM knowledge domains is created by asking the two raters to group the 9 STEM knowledge domains into either physics or health STEM. The raters agreed on all domains, except for Chemistry (inter-rater reliability is 89%). For STEM occupations of which the highest ranked STEM knowledge domain is Chemistry, the second highest ranked STEM knowledge is used.

A group of occupations were manually classified because of a lack of information on their knowledge domains in O□NET. Most occupations were aggregated items, such as "Miscellaneous Plant and System Operators", "Engineers, all other". They are usually listed at the end of a family of occupations to capture rare or new jobs that are not covered by specific occupations in the family. They were manually flagged by referencing the other occupations in the same family. For example, "Miscellaneous Plant and System Operators" were coded as physics STEM because other "Plant and System Operators" jobs in the family were classified as physics STEM. Four military occupations also lacked information on the knowledge dimension, so they were manually coded as non-STEM or physics STEM. One occupation, "Musicians, singers and other workers", was originally categorized as physics-related STEM based on the criteria and was manually recoded as non-STEM. A full list of occupations present in the sample with STEM classification labels were provided in Appendix B.

"Blue-collar" and "white-collar" classification

The classification differentiates whether or not an occupation requires a Bachelor's degree in the U.S. based on the O□NET Job Zone category. The Job Zone category indicates how much education and training is usually required for one occupation, on a scale from 1 "some of these occupations may require a high school diploma or GED certificate" to 5 "Most of these occupations require graduate school". Blue-collar STEM jobs are STEM occupations that do not require a Bachelor's degree (Job Zone 1, 2, 3), and white-collar STEM jobs are STEM occupations that require at least a Bachelor's degree (Job Zone 4 and 5).

Analyses

Two approaches were used to describe the longitudinal patterns of career aspirations, with each of them extracting patterns with different rationale. The longitudinal latent class analysis (LLCA) uses algorithm to model the most statistically probable pattern in existing trajectories. The generated results show the most common, representative pattern in the sample. Taking into account of subgroup differences, it generates a summary of a few most common patterns in several heterogeneous subgroups, in a similar manner as growth mixture modeling does. LLCA is common method to describe heterogeneous longitudinal patterns, so the results can be familiar to interpret with existing literature. The second approach uses cross-tabulations to identify all existing trajectories and then select and aggregate trajectories that are of interest. There are two prominent advantages of this approach. First, it provides targeted extraction of patterns based on *a priori* research questions and hypotheses. The search for patterns is guided by theory and literature, so it can provide direct evidence for hypothesis testing. Moreover, this approach allows for the flexibility to select and compare trajectories that are developmentally meaningful, such as trajectories sharing the same starting point but different endpoints later on, which are STEM persistence and non-persistence in the topic of this dissertation. Moreover, after trajectories of interest are selected, further computation for the total, ratio, differences of trajectories can be calculated with the exact frequencies of each trajectory readily available. Therefore, there is great flexibility for investigating the trajectories in greater depth based on research questions. This feature is particularly useful for studying STEM trajectories, given the extensive literature for formulating research questions and hypotheses for certain types of trajectories and the need to understand them further. Second, this approach overcomes the assumption of LLCA to identify the numerically dominant patterns, so it allows for discovering trajectories that are not expected based on probability (Feinstein & Peck, 2008). For example, the trajectories of attaining a STEM occupation without an earlier STEM aspiration is rarely studied, but it is meaningful for understanding diverse STEM career paths and expanding STEM labor supply. These types of unexpected paths might be of smaller sizes and thus not extracted in LLCA.

Cross-tabulation

In cross-tabulations, we counted the frequency of the total group and subgroups for each existing trajectory. The cross-tabulation, despite a simple technique, is well suited for accurately identifying every existing trajectory of how career choices evolve over time. It shows all possible paths without reducing them to a representative, average trajectory, thus displaying individual differences to the full extent. The Chi-square Test of Independence were used to test any associations between gender and career paths when needed. Adjusted standardized residuals with Bonferroni corrections for multiple tests were used as post-hoc tests to examine the over- or under-representation of a given subgroup when the Chi-square test shows statistically significant associations. Summary tables of frequencies about the timing, direction and trajectories of attrition and entry were created by aggregating selective subgroups in the cross-tabulation results.

We plotted three sets of trajectory trees using cross-tabulation. The first set is two-wave trees between adolescents' career aspiration at age 13 using data in CDS 2002' and their actual occupations at age 25 using data in TAS 2013', TAS 2015', main PSID 2013' or main PSID 2015. Responses in TAS or main PSID 2015' were used to replace missing values in TAS or main PSID 2013' for reducing missing values. This set of trees consists of three trees on the same sample of 1026 adolescents using different grouping categories of occupations: the first tree focused on whether adolescents chose STEM careers versus non-STEM ones; the second tree focused on whether adolescents chose non-STEM careers, physics-related STEM careers or health STEM careers; and the third tree focused on whether adolescents chose blue-collar non-STEM careers, blue-collar STEM careers, white-collar non-STEM careers or white-collar STEM careers. Each tree is created from a two-way cross-tabulation of frequency between career aspiration at age 13 and actual occupation age 25.

The second set is three-wave: career aspiration at age 13 (CDS 2002'), career aspiration at age 19 (CDS 2007', TAS 2007' or TAS 2009'), and actual occupation at age 25 (TAS/main PSID 2013', TAS/main PSID 2015'). Data in TAS 2009' were used to fill any missing values in CDS 2007' or TAS 2007'. Consistent with the first set of trees, this set consists of three trees based on the same grouping category.

The third set is four-wave: career aspiration at age 13 in 2002, career aspiration at age 18 in 2005/2007 (TAS 2005', CDS 2007' or TAS 2007'), career aspiration at age 21 in 2009/2011 (TAS 2009' or TAS 2011'), and actual occupation at age 25 in 2013/2015. Similarly, to create an aggregated variable, data from a later year (e.g., 2007) were used to fill in missing values from an earlier year (e.g., 2005).

After individual paths were plotted, the gender composition of each trajectory was calculated. We aggregated individual trajectories into categories based on our predetermined research questions. Specifically, we aggregated trajectories with an aspiration in a STEM field but ending with an occupation in a different field as "attrition" trajectories, and trajectories ending with an occupation in a STEM field following an aspiration in different field as "entry" trajectories. Trajectories starting with an aspiration in a STEM field and ending with an occupation in the exact same STEM field were treated as "persistence" trajectories. In a nutshell, when we aggregated trajectories for studying STEM attrition, we used the person's career aspiration at age 13 as the reference and compared following career choices against it (i.e., continuing in the same field or not); when we aggregated trajectories for studying STEM entry, we used employment at age 25 as the reference and compared previous career choices against it (i.e., originating from the same field or not). When we studied career paths leading to STEM employment, we included all trajectories with an endpoint of STEM employment, with previous choices in or not in the field of employment.

Chi-square Test of Independence and Fisher's Exact Test were used to examine the association between gender and types of trajectory groups, when we tested the gender differences in attrition trajectories, entry trajectories and paths leading to STEM employment. Standardized adjusted residuals were calculated at $\alpha = .05$ level to identify statistically significant over- or underrepresentation of a gender in a given type of trajectory.

LLCA. We ran LLCA to model trajectories of adolescents' STEM career choices over three and four time points. We chose longitudinal latent class analysis (LLCA) instead of other longitudinal mixture modeling techniques because 1) our data is strictly multinominal by nature, and 2) the changes to be modelled do not increase or decrease along a continuous scale but are patterns of states across time (Feldman et al., 2009). In this case, LLCA is the only suitable technique meeting these premises. Instead of modeling individual intercepts and slopes, LLCA estimates class-specific patterns of outcome variables over time by modeling the probability of meeting category thresholds.

We tested a total of six models corresponding to the three-wave and four-wave cross-tabulation trees: three-wave trajectory with binary STEM grouping, three-wave trajectory with three-level STEM grouping (i.e., non-STEM, health STEM and physics-related STEM), three-wave trajectory with four-level STEM grouping (i.e., blue-collar non-STEM, blue-collar STEM, white-collar non-STEM and white-collar STEM) and the same set of models with four-wave data.

Each model was tested with 2 to 7 class solutions in Mplus 7.0. with 2000 initial stage starts and 500 final stage optimizations to avoid local maxima. Gender differences in class membership in the three-wave and four-wave class solutions were tested with Two-way Chi-square Test of Independence with adjusted standardized residuals calculated to indicate the over- and under-representation of a gender in a given cell.

Results

Sample descriptive information was presented in Table 1.1.

STEM Career Choices at Age 13 and 25

Frequencies of career choices at each time point were shown in Table 1.2. More adolescents aspired to non-STEM occupations than STEM ones, at age 13, 18, 21 and 25. Health STEM were more common than physics-related STEM in aspirations between age 12 and 21, whereas physics-related STEM were more common than health STEM in employment at age 25. Blue-collar non-STEM aspirations and white-collar STEM aspirations were two most common aspirations at age 13. Between age 18 and 21, white-collar non-STEM aspirations were the most common, followed by blue-collar non-STEM aspirations. Among employment at age 25, blue-collar non-STEM and blue-collar STEM occupations were most common.

Gender differences

The gender compositions of career choices at age 13 and at age 25 were presented in Table 1.3. At age 13, disproportionally more girls aspired to non-STEM and health STEM occupations than expected by chance, and disproportionally more boys aspired to physics-related STEM occupations. Across the educational ladder, boys were overrepresented in blue-collar non-

STEM and blue-collar STEM aspirations, and girls are overrepresented in white-collar non-STEM aspirations. No gender was over- or under-represented in the white-collar STEM aspirations, with a gender position close to that of the sample. Nearly all these gender-related patterns discrepancies maintained in occupation attainment at age 25, except that blue-collar non-STEM occupations are no longer gendered.

Results of LLCA

Model selection

Models were selected based on the quality of convergence, relative fit and residuals guided by Feldman, Masyn and Conger's paper on longitudinal growth modeling with categorical indicators (Feldman et al., 2009). Based on convergence, two models, three-wave trajectory with binary (STEM vs non-STEM) indicators and four-wave trajectories with binary indicators, did not generate reliable estimates in 3 to 7 class solutions, potentially due to model under-identification. Therefore, no solution was picked for these two models.

The likelihood ratio test of comparing the difference in Chi-square index between two models could not be used, because solutions with various classes were not nested models within one another. BIC (Bayesian Information Criteria) and adjusted BIC were chosen over AIC because these two indices were more reliable for models with various sample sizes, number of indicators and class sizes (Nylund et al., 2007; Tein et al., 2013). The lower BIC and adjusted BIC indicates a better fit of a solution (Nylund et al., 2007). Though not a model selection criterion, extremely low entropy indicates a poor fit of a solution; thus, entropy was referenced to exclude poor solutions (Feldman et al., 2009). Lo-Mendell-Rubin (LMR) test and the bootstrapped LMR test were used to compare the improvement of a solution with K+1 classes relative to a solution with K classes (Feldman et al., 2009; Nylund et al., 2007). The *p* values of the tests were listed in the column of K+1 classes. A *p* value lower than .05 indicates that a solution with K+1 classes is a better fit than a solution with K classes. These model fit indices were listed in Appendix C. Furthermore, the standard Pearson residuals, the standardized residuals from univariate margins and bivariate margins were inspected. Most of these residuals in all models were lower than 2, indicating a good fit of the class solutions.

Based on the model fit criteria above, a three-class solution for three-wave trajectories with 3-level and 4-level indicators were selected respectively. A four-class solution for four-wave trajectories with 3-level and 4-level indicators were selected respectively. The plots for these solutions of the three-wave trajectory and four-wave trajectory were shown in Figure 2 and Figure 3, in form of class probabilities.

Three-wave trajectories

Across non-STEM, health STEM and physics STEM fields, three distinct trajectories were discovered (Figure 1.2A). One small class (N = 116, 12% of sample) featured a probability of nearly 70 percent to choose health STEM at age 13, with an even higher probability of choosing the health STEM field at age 19 but a considerable decrease in the probability to nearly 40 percent to work in health STEM jobs at age 25. Between age 19 and age 25, the probability of working in non-STEM occupations increased from less than 10 percent to approximately 50 percent. A second class was a large group (N = 555, 57% of sample) featuring a high probability (about 70 percent) of aspiring to non-STEM careers at age 13 and age 19, followed by an even higher probability (over 80 percent) of working in non-STEM jobs at age 25. At the same time, the probability of choosing health STEM careers decreased from around 20 percent to less than 5 percent. The last class (N = 307, 31% of sample) consisted of roughly a third of the sample, featuring comparable probabilities (around 40 percent) of choosing physics STEM careers and non-STEM careers at age 13. The probability of choosing physics-related STEM careers increased to around 60 percent from age 13 to age 19, followed by a decrease to less than 30 percent by age 25. At the same time, the probability of choosing non-STEM careers increased to over 60 percent by age 25. Gender was associated with class membership, χ^2 (2, N = 978) = 147.94, $p < .001$. Women were overrepresented in class 1 and 2 and men were overrepresented in class 3 (Table 1.4).

Three groups were found with distinct movement across the educational ladder in STEM and non-STEM fields (Figure 1.2B). One class comprised a fourth of the sample (N = 243, 25% of sample). This group featured around 50 percent of the probability to choose white-collar STEM careers at age 13, followed by a higher probability (over 60 percent) of doing so at age 19 and a drop in the probability (to less than 30 percent) of working in white-collar STEM jobs at age 25. At the same time, the probabilities of choosing blue-collar non-STEM jobs and blue-collar STEM jobs increased between age 19 and age 25. A second group comprised 29 percent of the sample (N = 279), characterizing nearly 50 percent of probability to choose white-collar non-STEM aspirations at age 13. The probability increased to nearly 80 percent by age 19 and dropped to around 30 percent by age 25. Similar to the first group, the field that grew in its size was the blue-collar non-STEM field. A third group was the largest (N = 456), consisting nearly half of the sample (46% of sample). It featured the largest probability of choosing blue-collar STEM among the three groups, ranging from around 40 to 70 percent. The probability of choosing blue-collar STEM careers was also high, which increased from around 15 to over 30 percent between age 13 and age 19 and dropped to around 25 percent by age 25. Gender was associated with class membership, χ^2 (2, N = 978) = 136.43, $p < .001$, such that women were overrepresented in class 2 and men were overrepresented in class 3 (Table 1.4).

Four-wave trajectories

Four classes emerged for trajectories spanning four time points. Across non-STEM, health STEM and physics STEM fields (Figure 1.3A), there was one group (N = 209, 26% of sample) featuring medium to high probabilities of choosing physics STEM over time. The probability increased from around 40 to over 60 percent between age 13 and 21 and decreased to 40 percent by age 25. At the same time, the probability of choosing non-STEM careers decreased and then increased over time, showing an opposite trend. A second group is the smallest across all four groups (N = 72), comprising only 9 percent of the sample. This group featured substantial probabilities of choosing health STEM careers over time. The probability started with over 80 percent at age 13 and peaked at over 90 percent by age 18. The probability decreased considerably by age 25, ending at a level less than 50 percent. The decrease in the probably of pursuing health STEM careers paralleled an increase in the probability of pursuing non-STEM careers. A third group was the largest, comprising half of the sample (N = 418, 51% of sample). It featured stable and high probabilities (over 60 to 90 percent) of choosing non-STEM careers over time. The probability increased steadily between age 13 and age 21 and dropped slightly by age 25, to over 80 percent. Between age 13 and age 21, the increase in the probability of choosing non-STEM careers paralleled a decrease in the probability of pursuing health STEM careers; between age 21 and age 25, the lower probability of pursuing non-STEM careers paralleled a higher probability of pursuing physics-related STEM careers. A fourth group was also small (N = 115, 14% of sample) and featured late entry into and attrition from health STEM careers. There was a probability (nearly 80 percent) of choosing non-STEM careers at age 13. By age 18, the probability of choosing health STEM careers increased more than two times; it continued to increase and reached over 90 percent by age 21, after which it dropped considerably to less than 20 percent by age 25. The change paralleled a decrease and then increase in the probability of pursuing non-STEM careers. Chi-square Test showed a statistically significant association between gender and class membership, χ^2 (3, N = 814) = 139.63, $p < .001$, with more men than expected by chance present in class 1, and more women than expected by chance present in class 2, 3 and 4 (Table 1.4).

Across the educational ladder of STEM and non-STEM careers, four distinct trajectories were found (Figure 1.3B). One was the largest (N = 315, 39% of sample) with sizable and stable probabilities (between 50 and 60 percent) of choosing blue-collar non-STEM careers between age 13 and 21; the probability further increased to nearly 80 percent by age 25. The increase in the probability of blue-collar non-STEM careers was accompanied by decreases in the probabilities of choosing white-collar non-STEM and white-collar STEM careers between age 21 and age 25. A second group (N = 146, 18% of sample) featured substantial probabilities of choosing white-collar STEM careers over time. The probability started at around 50 percent at age 13, increased steadily between age 21 and age 21 to nearly 80 percent. Between age 21 and age 25, the probability of choosing white-collar STEM careers dropped considerably, to nearly 40 percent by age 25. The change paralleled decreases in the probabilities to choose blue-collar non-STEM careers between age 13 and age 21, followed by an increase in the probability between age 21 and age 25. The probability of choosing white-collar non-STEM careers also decreased considerably between age 21 and age 25. A third group (N = 155, 19% of sample) featured sizable and increasing probabilities (around 30 to 70 percent) of choosing blue-collar STEM careers between age 13 and age 21, which was followed by a remarkable drop of the probability to less than 40 percent by age 25. The change was accompanied by a decrease and then increase in the probabilities of pursuing blue-collar non-STEM careers between age 13 and age 25. The probabilities of pursuing white-collar non-STEM and white-collar STEM careers decreased considerably over time. A fourth group (N = 198, 24% of sample) featured high probabilities of choosing white-collar non-STEM careers, with an increase from 40 to 90 percent between age 13 and age 21 and a decrease to around 40 percent by age 25. The change paralleled a decrease and then increase in the probability of pursuing blue-collar non-STEM careers. Gender was associated with class membership, with men overrepresented in class 1 and women overrepresented in class 4 (Table 1.4).

Results of Cross Tabulation

Career trajectories were shown in Sankey diagram in Figures 1.4 to 1.6. Sankey diagram is a common visualization method to display processes and directions of flow, with each node representing one time point and each branch representing one subgroup in this study. The height of branches represents the relative size of subgroups.

Changes of STEM Labor Supply

Changes of STEM labor supply was examined via a “change ratio” of individuals in a STEM field over time. The ratio was calculated by dividing the number of STEM workers at age 25 by the number of STEM aspirants at age 13, showing the relative size of STEM workers to aspirants. A change ratio greater than 100% indicated an expansion of the STEM labor supply in a field, and a change ratio lower than 100% indicated a shrinkage. For example, in the broad STEM field, there were 414 aspirants at age 13 and 255 workers at age 25. Dividing 255 by 414 and converting the number into percentage was 61.6%, meaning the size of STEM workers by age 25 was 61.6% of the size of STEM aspirants at age 13. In other words, the labor supply shrank to 61.6% of its original size over time. The change ratios of various types of STEM careers were displayed in Table 1.5. Within STEM, the change ratio of physics-related STEM careers was 101.6%, whereas the change ratio of health STEM careers was 27.7%. That is, the labor supply of physics-related STEM careers approximately remained its original size with a tiny increase, and the labor supply of health STEM careers shrank remarkably, to less than a third of its original size. In comparison, the change ratio of non-STEM labor supply was 126.0%, indicating a moderate increase in its size.

Across the educational ladder, the blue-collar STEM “pipeline” expanded to 115.7% of its original size whereas the white-collar STEM “pipeline” shrank to 33.9% of its original size. In comparison, the change ratio for blue-collar non-STEM labor supply was 182.6%, and the change ratio for white-collar non-STEM labor supply was 52.8%.

Gender Differences. To compare by gender groups, a change ratio was calculated for men labor supply and women labor supply respectively. For example, 203 girls aspired to STEM careers at age 13 and 111 women worked in STEM jobs at age 25. The change ratio of women STEM labor supply is 54.7% (111 divided by 203, Table 1.6). Among men, 111 boys aspired to STEM careers at age 13 and 211 men worked in STEM jobs at age 25; thus, the change ratio of men STEM labor supply was 68.2%. A comparison suggested that the labor supply across all STEM careers shrank more among women than among men. The counts of aspirants and workers and change ratios were listed in Table 1.6 by gender.

Within STEM, the health STEM labor supply shrank at comparable rates for both men (25.5%) and women (28.4%); the number of health STEM workers by age 25 was less than a third of the number of aspirants at age 13 for both men and women. The woman labor supply in the physics-related STEM field expanded to 185.3% of its original size, whereas the men labor supply in the same field shrank to 83.3%. In the blue-collar STEM field, the labor supply expanded among both men and women, slightly larger among men than among women (men:

123.1%, women 106.5%). In the white-collar STEM field, the change ratios were close between genders, with a shrinkage to around a third of its original size (women: 31.9%, men: 36.1%).

Attrition

Attrition rates. Between age 13 and 25, 69.3% STEM aspirants changed their career path and switched into non-STEM careers (Table 1.5). Within STEM subfields, 71.1% physics-related STEM aspirants worked in a different field, and 85.3% health STEM aspirants switched out of their field. In comparison, 20.9% non-STEM aspirants left their field. Across the educational ladder, 70.0% aspirants in the blue-collar STEM field and 84.3% aspirants in the white-collar STEM field worked in a field different from their initial choice. In comparison, 30.4% blue-collar non-STEM aspirants and 77.5% white-collar non-STEM aspirants did so.

Gender Differences. Across STEM careers in various subfields, women switched out of the careers at a higher rate than men did (women: 73.9%, men: 64.9%, Table 1.6). Within the subfields, men left health STEM careers at a higher rate than women did (men: 96.4%, women: 81.7%), and women left physic-related STEM careers at a higher rate than men did (women: 85%, men: 68%). Across the educational ladder, men and women switched out of blue-collar STEM careers at comparable rates (men: 67.9%, women: 72.6%), with a slightly higher rate among women. In white-collar STEM field, 87.2% of women and 81.2% of men switched out of the field, with a slightly higher rate among women.

Destinations of Attrition. Eighty-five percent of people leaving the health STEM field worked in non-STEM jobs, and the rest worked in physics-related STEM jobs (Table 1.7). Ninety-three percent of people leaving the physics-related STEM field worked in non-STEM jobs, and the rest worked in health-related STEM jobs. Eighty-five percent of people leaving the blue-collar STEM field worked in blue-collar non-STEM jobs, another 9% worked in white-collar non-STEM jobs, and 6% worked in white-collar STEM jobs. Sixty-eight percent of people leaving the white-collar STEM field worked in blue-collar STEM jobs, another 16% worked in blue-collar STEM jobs, and 17% worked in white-collar non-STEM jobs.

Gender Differences. Among health STEM aspirants, 89% women and 74% men switched into non-STEM jobs, and the rest 11% women and 26% men worked in physics-related STEM jobs (Table 1.7). Among physics-related STEM aspirants, 93% women and 92% men worked in non-STEM jobs, and the rest 7% women and 8% men worked in health STEM jobs. Among blue-collar STEM aspirants, 82% women and 87% men worked in non-STEM jobs, another 13% women and 6% men worked in white-collar non-STEM jobs, and the rest 4% women and 8% men worked in white-collar STEM jobs. Among white-collar STEM aspirants, 67% women and 68% men worked in blue-collar non-STEM jobs, another 13% women and 19% men worked in blue-collar STEM jobs, and the rest 20% women and 14% men worked in white-collar non-STEM jobs.

Paths of Attrition. Among people leaving all types of STEM careers, 42% of them exited between age 13 and 18, another 17% exited between age 18 and 21, 32% exited between age 21 and 25, and the rest 9% exited by age 18, returned by age 21 and finally exited by age 25 (Table 1.8). Among people leaving health STEM careers, 56% exited between age 13 and 18, another 12% exited between age 18 and 21, 23% exited between age 21 and 25, and the rest 9% took the recursive path. Among people leaving physics-related STEM careers, 50% exited between age 13 and 18, another 21% exited between age 18 and 21, 19% exited between age 21 and 25, and the rest 10% took the recursive path.

Among people leaving blue-collar STEM careers, 60% exited between age 13 and 18, another 10% exited between age 18 and 21, 21% exited between age 21 and 25, and the rest 9%

took the recursive path. Among people leaving white-collar STEM careers, 59% exited between age 13 and 18, another 18% exited between age 18 and 21, 14% exited between age 21 and 25, and the rest 9% took the recursive path.

Gender Differences. Two-way Chi-square Tests of Association between gender and attrition trajectories showed no statistically significant associations between gender and trajectory group membership in any field (Table 1.9). Standardized adjusted residuals indicated no over- or under-representation of women or men in any STEM attrition trajectories ($\alpha = .05$).

Entry

Entry rates. Fifty-two percent of workers at age 25 across STEM careers did not aspire to STEM careers at age 13 (Table 1.5). Within STEM subfields, 46.8% health STEM workers aspired to careers in a different field at age 13, and 71.5% physics-related STEM workers aspired to careers in non-STEM or health-related STEM field at age 13. In comparison, 37.2% non-STEM workers entered their field after age 13. Across the educational ladder, 74.1% workers in the blue-collar STEM jobs and 53.8% workers in the white-collar STEM field switched into their field after age 13. In comparison, 61.9% blue-collar non-STEM aspirants and 57.4% white-collar non-STEM aspirants did so.

Gender differences. Across STEM careers in various subfields, the entry rates among men and women were comparable (women: 52.3%, men: 48.6%, Table 3.6). Within the subfields, men entered the health STEM careers at a higher rate than women did (men: 85.7%, women:

35.4%), and women entered physic-related STEM careers at a higher rate than men did (women: 92.1%, men: 61.5%). Across the educational ladder, men and women entered blue-collar STEM careers at nearly the same rates (men: 74.2%, women: 74.0%). In white-collar STEM field, 60.0% of women and 47.9% of men entered into the field, with a slightly higher rate among women.

Origins of Entry. Sixty-six percent of people entering the health STEM careers chose non-STEM careers at age 13, and the rest 34% chose physics-related STEM careers (Table 1.10). Seventy-nine percent of people entering the physics-related STEM field chose non-STEM careers as teenagers, and the rest 21% aspired to health-related STEM careers. Forty-one percent blue-collar STEM workers chose blue-collar non-STEM careers as teenagers, another 29% chose white-collar non-STEM careers, and 30% chose in white-collar STEM careers. Forty-six percent of white-collar STEM workers had aspirations in the blue-collar STEM field at age 13, another 12%, in the blue-collar STEM field, and 42%, in the white-collar non-STEM field.

Gender Differences. Among women health STEM entrants, 88% chose non-STEM careers and 12% chose physics-related STEM careers at age 13 (Table 1.10). Among men health STEM entrants, 33% chose non-STEM careers and 67% chose physics-related STEM careers at age 13. In the physics-related STEM field, 74% women entrants and 83% men entrants aspired to non-STEM careers in teenage years. The rest 26% women entrants and 18% men entrants aspired to health STEM careers at age 13.

In the blue-collar STEM field, 33% women entrants and 46% men entrants chose blue-collar non-STEM careers at age 13, 35% women entrants and 25% men entrants, white-collar non-STEM careers and the rest 33% women entrants and 28% men entrants, white-collar STEM careers. In the white-collar STEM field, 44% women entrants and 48% men entrants aspired to blue-collar non-STEM careers at age 13, 7% women entrants and 17% men entrants, blue-collar STEM careers, 48% women entrants and 35% men entrants, white-collar STEM careers.

Paths of Entry. Among people entering all types of STEM careers, 35% of them entered between age 21 and 25, another 28% entered between age 18 and 21, 28% entered between age 13 and 18, and the rest 9% entered by age 18, exited by age 21 and then returned by age 25 (Table 1.11). Among people entering health STEM occupations, 24% entered between age 21 and 25, another 32% entered between age 18 and 21, 40% entered between age 13 and 18, and the rest 4% took the recursive path. Among people entering physics-related STEM occupations, 51% entered between age 21 and 25, another 26% entered between age 18 and 21, 17% entered between age 13 and 18, and the rest 6% took the recursive path.

Among people entering blue-collar STEM occupations, 52% entered between age 21 and 25, another 20% entered between age 18 and 21, 17% entered between age 13 and 18, and the rest 10% took the recursive path. Among people entering white-collar STEM occupations, 40% entered between age 21 and 25, another 24% entered between age 18 and 21, 33% entered between age 13 and 18, and the rest 2% took the recursive path.

Gender Differences. Two-way Chi-square Tests of Independence and Fisher's Exact Tests showed statistically significant associations between gender and entry trajectories in the health STEM field, the white-collar non-STEM field, and the white-collar STEM field (Table 1.12). Among entrants of health STEM occupations, standardized adjusted residuals indicated that fewer women than expected entered the field between age 21 and 25, and that more women than expected entered the field between age 18 and 21. Among entrants of white-collar STEM occupations, fewer women than expected entered the field between age 13 and 18.

Trajectories of STEM workers

Among workers across all STEM careers, 18% did not have prior aspirations in the STEM field, 25% had one prior aspiration, 29% had two aspirations, and 28% had three aspirations (that is, the individual chose the same field as their final occupation at age 13 and persisted at the following time points; Table 1.13). Among health STEM workers, 10% entered the field without any prior aspiration, 18% had one prior aspiration, 30% had two prior aspirations, and 42% chose the field and persisted since age 13. Among physics-related STEM workers, 36% did not have prior aspirations, 29% had one prior aspiration, 22% had two prior aspirations, and 13% had three prior aspirations.

Among blue-collar STEM workers, 39% entered the field without any prior aspiration, 27% had one prior aspiration, 21% had two prior aspirations, and 13% chose the field at age 13 and persisted afterwards. Among white-collar STEM workers, 21% entered the field without any prior aspiration, 24% had one prior aspiration, 36% had two prior aspirations, and 19% chose the field and persisted since age 13.

Gender Differences. Two-way Chi-square Tests of Independence Tests showed statistically significant associations between gender and paths leading to STEM occupations in the health STEM field, the physics-related STEM field, the blue-collar non-STEM field, the white-collar non-STEM field, and the white-collar STEM field (Table 1.14). Standardized adjusted residuals indicated imbalanced gender compositions of some paths in several subfields. Among health STEM workers, fewer women than expected by chance entered the field without prior aspirations, and that more women than expected chose health STEM careers at age 13 and persisted throughout the following three time points. Among physic-related STEM workers, more women than expected worked in the field without any prior aspirations. Among white-collar STEM workers, fewer women than expected worked in the field after choosing it twice.

Discussion

In this study, we portrayed trajectories of STEM career choices across domains and the educational ladder from age 13 and 25. We used two descriptive approaches, the longitudinal latent class analysis and the full-form career path analysis and provided visualizations of STEM career trajectories. Our graphs showed diverse, more often recursive than linear, STEM career trajectories with dynamic movements within STEM subfields and across the STEM and the non-STEM fields. In the full-form career path analysis, we examined evidence for the various aspects of the "leaky STEM pipeline" notion. Firstly, we investigated the changes in the quantity of labor supply in STEM fields, in comparison with the non-STEM field. We discovered that the labor supply shrank in the health STEM field and the white-collar STEM field, maintained its size in the physic-related STEM field, and expanded in the blue-collar STEM field. Moreover, we are the first to report an expansion of women labor supply in the physics-related STEM careers. Secondly, we examined the attrition across STEM fields, in terms of the attrition rate, the destination of attrition and the path of attrition. We found that the attrition rates in STEM fields was higher than those across non-STEM fields and those in blue-collar non-STEM field, but not higher than the attrition rate in the white-collar non-STEM field. Between genders, the attrition rates were comparable, without sizable discrepancies. The majority of people leaving a STEM field landed in non-STEM jobs, and around half or more of attrition occurred between age 13 and age 18. Thirdly, we examined the entry into STEM fields, which was defined as working in a STEM field without an aspiration in the same field at age 13. We inspected the rate, destination and paths of entry into various STEM careers. The entry rates varied considerably across different STEM and non-STEM careers; it was higher in the physics-related STEM field than the health STEM field. Moreover, the entry rate was remarkably higher among men than among women in the health STEM field, and considerably higher among women than among men in the physic-related STEM field. Most entry into a STEM career originated from the non-STEM field, instead of a different STEM field. However, most women entering health STEM jobs originated from the non-STEM field, whereas most entering men in the health STEM field originated from the physics-related STEM field. Most entry into various STEM jobs occurred between age 21 and 25, except that most entry into the health STEM jobs occurred between age 13 and 18. Women were more likely than chance to enter health STEM jobs between age 18 and 21, and less likely than chance to do so between age 21 and 25. Lastly, we examined all existing paths that led STEM workers to where they were at age 25, in test of the "cumulative disadvantage" hypothesis about STEM career trajectories. Our results did not support the hypothesis, because it showed that the most commonly taken paths into STEM employment were not those with frequent prior choices in the same field. The only exception was the health STEM careers, such that the most commonly taken path was the early entry and persisting path, followed by paths with fewer prior choices. We discovered the gender differences that women were more likely than chance to take the "early entry and persist" path into health STEM and blue-collar STEM careers, the path without any prior aspirations into physics-related STEM careers.

In general, our discoveries did not support the "leaky STEM pipeline" metaphor in more aspects than it did. The STEM labor supply does not necessary shrink due to "leaks" – it depended on how much entry there were relative to the attrition. The sizable entry into STEM fields objects to the image of a closed, one-directional career path into STEM employment. The numerous, diverse trajectories showed that a "pipeline" representation is neither accurate nor representative. By visualizing STEM career trajectories, we put the "leaky pipeline" image in perspective. We propose a "STEM highway" metaphor as an alternative representation. We also presented evidence supporting gender similarities or gender discrepancies favoring women's entry and persistence in STEM careers. Because of the richness of our finding, we discuss our results in more details in each of the following sections based on our research questions.

Labor Supply Expanded or Shrank Across Subfields, Comparably Between Gender, but Women Physics STEM Labor Supply Expanded

We discovered that the STEM labor supply did not always shrink among all STEM careers as the "leaky pipeline" implied. A shrinkage was found for health STEM and white-collar STEM labor careers, a maintenance of size was found for physics-related STEM careers, and an expansion was found for blue-collar STEM. This finding shows that the "pipeline" is not "leaky" in all types of STEM careers, and it might even expand in some fields.

The health STEM field and the white-collar STEM field were two STEM fields featuring considerably shrinkage in the labor supply over time. The number of people working in these fields were less than or around a third of the number of people aspiring to these careers in their adolescence. Some characteristics of careers in these two fields might be relevant. Firstly, both fields attracted large number of adolescents at the beginning. The health STEM careers, such as doctors and nurses, are familiar to adolescents from their daily experience of visiting doctors. The content, context and impact of these jobs are concrete to adolescents from early on. In contrast, physics-related STEM careers might be specifically known to teenagers who have family members working the field or watch particular TV programs or other media coverage. The possible differences in adolescents' knowledge and exposure of careers in the health versus the physics-related STEM fields might underlie the varied popularity of these two types of jobs among adolescents. Regarding the differences between white-collar and blue-collar STEM careers, our previous work showed that white-collar career aspirations were more common than blue-collar ones (Gao & Eccles, 2020). Adolescents might have learned explicitly or implicitly about which jobs are highly valued and respected in our society. In addition, when asked to envision a scientist, children tend to imagine someone who works in labs (for a review, Ferguson

& Lezotte, 2020), which are more likely to be white-collar STEM jobs. In a nutshell, these mechanisms might lead to the particularly high prevalence of health STEM and white-collar STEM aspirations among adolescents. Secondly, recent evidence suggests that the small number of works compared to aspirants in the health STEM and white-collar STEM fields might result from a labor surplus in these fields. One analysis showed that in 2009, there was a surplus of STEM workers who hold an Associate's to a Ph.D. degree (Charette, 2013). In addition, the biomedical field was one STEM area that saw a surplus of Ph.D. degree holders (Xue & Larson, 2015). Nationwide, the growth of white-collar STEM jobs was smaller than that of white-collar STEM jobs (Rothwell, 2013). Taken together, the evidence points to an overflow of workers in the health and white-collar STEM area, thus manifesting in the small number of workers relative to aspirants. Thirdly, the high educational requirement of white-collar STEM careers and some healthcare professions might make it particularly challenging to fulfill aspirations in these fields. A comparable group of careers, the white-collar non-STEM ones, also saw a shrinkage in its labor supply, pointing to the common factor of high educational demand of white-collar jobs.

More gender similarities than differences were found in the changes of STEM and non-STEM labor supplies. The change ratios were close between men and women in health STEM, and white-collar STEM fields. In blue-collar STEM field, the changes in labor supply were in the same direction among men and women, both expanding. Physics-related STEM field was the only field with divergent patterns between gender, with the labor supply expanding among women and shrinking among men. Taken together, these findings showed that the STEM labor supply was not more likely to shrink among women than among men. In the man-dominant physic-related STEM field, the women labor supply even expanded, and the man labor supply shrank. To our knowledge, our study is the first to report such findings. The pattern might result from the decade-long efforts to promote women's participation in the STEM field. Bachelor's degree attainment is a useful reference for interpretation, for its proximity to the job attainment at age 25 in our study, as well as for its predictive power on STEM career attainment (Wright et al., 2017). In the past few decades, increasing portions of Bachelor's degree in the physical science and engineering have been awarded to women, and the percentage of women Bachelor's holders in economics field has been at an historically high level (Ceci et al., 2014). In addition, our findings underscore gender similarities, more than discrepancies, in STEM career trajectories, adding supportive evidence for the gender similarity hypothesis proposed by the leading scholar in gender studies, Janet Hyde (Hyde, 2005).

The women labor supply for physics-related STEM careers expanded to nearly two times of its original size. This finding does not contradict with another result in this study that women were underrepresented in physics-related STEM jobs at age 25. The small number of women choosing physics-related STEM careers as initial aspirations and as the field to enter was the main factor of this underrepresentation. The literature has documented reasons such as the lack of appeal of physic-related STEM careers to women's altruism values and people-oriented vocational interest, the influence of socializers' gender biases and stereotypes, and an unsupportive atmosphere in professional settings (Fouad et al., 2011; Frome et al., 2006). More efforts are yet needed to achieve a more balanced gender composition in physics-related STEM careers. In this study, we found a sizable group of women entering these careers. Understanding the conducive and supportive factors and practices in their experience can possibly provide directions for future research and policies.

Attritions in STEM were Frequent, Complete, Early and Downward

We provided a more comprehensive understanding about STEM attrition, regarding not only the attrition rate across various STEM fields, but also the destination and paths of the attrition flow. As hypothesized, the attrition rate was higher in STEM fields than in non-STEM fields. Moreover, more than seventy percent of people leaving STEM switched into non-STEM jobs, instead of a different STEM field, leaving the STEM field entirely; about half of this group changed their career paths early, between age 13 and 18. These findings carry four implications for efforts to reduce STEM attrition. Firstly, there is plenty of room to lower the STEM attrition rate. The attrition rate in various STEM fields was around seventy percent or higher; in contrast, it ranged around twenty to thirty percent in non-STEM fields, except the white-collar non-STEM field. From this study, it remained unclear what caused the contrasting attrition rates in the STEM and non-STEM fields. One factor might be the educational demand of some STEM occupations. Another domain with high educational requirement, the white-collar non-STEM field, saw a similarly high attrition as STEM fields did. However, the high attrition rate in the blue-collar STEM field suggested factors other than the educational demand might be related to the high attrition. Further understanding about the general and specific factors of attrition across STEM careers can facilitate and guide future efforts to lower the STEM attrition rate.

Secondly, the fact that most STEM attrition flowed into non-STEM field instead of another STEM field suggested one approach to reduce STEM attrition can be leading the attrition to flow into a different STEM field. Some of the preparation a person had for white-collar STEM careers, for example, might be transferrable to blue-collar STEM careers, giving the person an advantage for pursuing a career in the other STEM field. Currently, considerably more attrition from the white-collar STEM field flowed into the blue-collar non-STEM field and the white-collar non-STEM field than the blue-collar STEM field. The reason for this complete withdrawal from the STEM fields was unclear from this study, yet our detailed tracking of the attrition flow suggested one promising approach to reduce STEM attrition.

Thirdly, the fact that about half of people who left STEM exited the field by age 18 indicates the focus on reducing STEM attrition by increasing high school STEM participation might be of limited effects. Although the participation and career plans in later years of high school and during college have been much studied as influential antecedents of STEM career choices in following years (Sadler et al., 2014; Shaw & Barbuti, 2010), in my study, individuals who left STEM after age 18 only comprised of thirty to fifty percent of all STEM attrition in various STEM fields. Early attrition between age 13 and age 18 took up a larger share of the attrition. Therefore, shifting the focus to the younger age range might reach a broader attrition population.

Lastly, over eighty percent of attrition from the white-collar STEM field flowed into blue-collar occupations. For researchers and policy makers to reduce STEM attrition, this finding might indicate a sobering message: adolescents who aspired to the white-collar STEM careers might be unlikely to obtain not only a typical, white-collar STEM job, but any white-collar jobs at all. In other words, the issue of STEM attrition might interweave with the barrier to attain four-year college education. This issue is particularly worth addressing considering that white-collar STEM career aspirants comprised two thirds of all STEM aspirants. Prior research on the education-based “aspiration-attainment gap” pointed to sociodemographic disadvantages (Croll, 2008), and more research is needed to understand the causes and antecedents of this downward STEM attrition.

More Gender Similarities than Discrepancies in Attrition Rates, Destination and Paths

In this study, we found that the STEM attrition rate was higher among women than among men only in physics-related STEM careers. In the health STEM field, the attrition rate was higher among men than among women. In the blue-collar STEM field and the white-collar STEM field, the attrition rates were comparable between men and women.

There was a lack of gender differences in attrition rates in the education-differentiated STEM subfields and the presence of gender differences in attrition rates in content-differentiated STEM subfields. Girls' high academic performance and achievement in secondary and postsecondary education (for a review, Buchmann et al., 2008) may be an important factor for the gender similarity of attrition rates in white-collar fields. Blue-collar STEM also saw high attrition rates among both men and women. It appeared that a high educational or knowledge demand of the jobs is related to the high attrition rates, independent of the gender of aspirants. Thus, supporting students to overcome these challenges and increase their educational attainment may help reduce STEM attrition. In addition, we found that men were more likely to leave health STEM careers than women. The contrast with women's higher attrition rate in physics-related STEM fields matched previous findings on men's value congruity in physics-related STEM careers and women's in health STEM careers (Diekman et al., 2017; Eccles & Wang, 2016; Su et al., 2009). It seems that people are just more likely to leave the field that cannot fulfill their values, and this might be true for both men and women. Therefore, in order to keep both men and women in a STEM field, career advisors in schools and media coverage can link a STEM field to a wide range of career options that include those appealing to men's vocational interests and those appealing to women's vocational interest. The contrasting gender differences in health and physics-related STEM field also matched with the gender compositions in these careers. Women left the physics-related STEM fields more often than men, a field that was men-dominant, and men left the health STEM careers more often than women, a field that was women-dominant. Further studies are needed to unpack to what extent the difference in attrition rates was due to the mere numerical representation of gender in these fields. The loss of talents for this reason should be a focus of the efforts to reduce STEM attrition.

There was a lack of gender differences in the destination and paths of people leaving STEM careers, and this held true across various types of STEM fields. This finding again supports the gender similarity in STEM attrition and suggests that other mechanisms might be a bigger force driving the gendered representation in STEM careers. This result may be the fruit of the long-time investment in reducing gender imbalance in the STEM field. Meanwhile, other mechanisms, such as STEM entry based on our findings in this study, may be a more effective focus for future research and policy efforts.

Entry into STEM Were Consequential and Varied Across Fields

The entry rates of the STEM fields ranged from 47 to 74 percent, meaning that around half or more workers in various STEM jobs did not aspire to work in the field at age 13. The considerable portion of STEM entrants suggest the flexibility of entering STEM fields without an early aspiration. The entry rates were higher in the physics-related STEM field and the blue-collar STEM field, which were two fields with a comparable or expanding labor supply over time. My findings suggest that securing and boosting the amount of STEM entrants can be influential for the STEM labor supply.

Intricate Contrasts Between Health Versus Physics-related STEM Fields

The entry rate was lower in the health STEM field than the physics-related STEM careers, indicating that persisters comprised of a larger portion of the workforce in the health

STEM field than in the physics-related STEM field. Moreover, the entry rate was lower among women workers than among men workers in the health STEM field, whereas the entry rate was lower among men than among women in the physics-related STEM field. In other words, the entry rate was lower in a gender group that was overrepresented in a field. Why was this the case? The flip side of the pattern is that the proportion of persisters was higher in the gender group that was overrepresented in a field. Aspiring to the field at an early age and attaining occupations in the same field was more common among women than among men in the health STEM jobs and among men than among women in the physics-related STEM jobs. This varied gender contrast in different fields may reflect the gender-differentiated formation of an adolescent's perception of their possible career choices and their long-term goals, as conceptualized in the left and middle section of the Situated Expectancy-Value Theory (Eccles & Wigfield, 2020). In this study, men and women envisioned different possible future careers in early adolescence, which aligned with gender stereotypes about male-dominant, physics-related STEM careers (Makarova et al., 2019). They possibly used this envision to set their long-term career goals and directed their career paths in adolescence and early adulthood. Cultural and family influences might have contributed to their early aspirations in their field, and family, school and social influences might have facilitated the fulfillment of their aspirations (Hadjar & Aeschlimann, 2015; Jussim et al., 1996; Simpkins et al., 2015). In contrast, the men entrants in health STEM fields and the women entrants in physics-related STEM fields, who pursued counter-stereotypical careers, might have lacked the conducive contextual influence to develop aspirations to and commit to their field of employment from early on. Theoretically, these individuals took the "off-diagonal" career paths (Feinstein & Peck, 2008), which were "against the odds" given the external influences. For researchers and policymakers striving to improve the gender parity in STEM workforce, understanding how these individuals beat the odds may provide useful lessons.

Most of entrants in health and physics-related STEM jobs originated from non-STEM fields, except for the men entrants in health STEM jobs. Eight out of the twelve men entrants transitioned from physics-related STEM aspirations, whereas fifteen out of seventeen women entrants transitioned from non-STEM aspirations. This gender differences might reflect more of the gender composition of the physics-related STEM aspirants and non-STEM aspirants. There were disproportionally more women among non-STEM aspirants and more men among physics-related STEM aspirants. Considering the limited group sizes, more research is needed to replicate this finding and explore the explanations for the phenomenon.

Forty percent of health STEM entrants switched into the field between age 13 and 18, and 24 percent between age 21 and 25. In comparison, the early entry made up only 17 percent of physic-related STEM entrants and the late entry comprised of 51 percent of total entry. Firstly, it suggests that it was quite common for physics-related STEM entrants to get into their field at a rather late stage of the educational and vocational training system. It was approximately three to seven years after high school graduation, one to five years after two-year college graduation and up to three years after four-year college graduation for some individuals that half of the physics-related STEM entrants switched into their field. For researchers and policymakers to expand physics-related STEM labor supply, the finding indicates that the quantity of entry might potentially be malleable in a wide time span. Secondly, the relatively larger portion of early entry than late entry among health STEM workers might result from the unique characteristics of the field. Health care professions are familiar to adolescents on a daily basis. Adolescents may be clear about whether or not they are interested in pursuing the profession at an earlier age, compared with other professions. In addition, the financial and educational demand of medical schools may drive earlier entry and commitment to the field for ample preparation. If so, efforts to boost health STEM entry may benefit from interventions at an earlier age range than in the physics-related STEM field. Understanding about the reasons for the late of late entry in health STEM field may also provide useful insights.

Gender was not associated with entry trajectories into physics-related STEM careers but was associated with entry trajectories in the health STEM careers. The late entry path (i.e., entering between age 21 and 25) consisted of fewer women than expected, whereas the mid-entry path (i.e., entering between age 18 and 21) consisted of more women than expected. The pattern might indicate the role of postsecondary education in career development, but much more research is needed to replicate the finding and explore its causes. The lack of gender differences in physics-related STEM careers indicates the wide time frame of entry into the fields apply to both men and women. This implication is particularly promising considering our finding that entry was critical for the expansion of women workforce in physics-related STEM careers. Efforts to improve women's representation in the physics STEM labor supply may harness interventions at various age range or educational stages.

Consistent Education-based Contrasts Between Blue-collar and White-collar STEM Fields

We found consistent education-based discrepancies between blue-collar and white-collar STEM careers. Firstly, the entry rate was higher among blue-collar STEM workers than white-collar STEM workers, indicating greater barriers to enter white-collar STEM fields without an early aspiration. This field differences held true for both men and women. In addition, there were approximately even shares of blue-collar STEM entrants from the blue-collar non-STEM, the white-collar non-STEM or the white-collar STEM fields, but a disproportionally larger share of white-collar entrants originated from white-collar non-STEM field. The education demand of white-collar careers might facilitate the movement across the two white-collar fields. Relatedly, a disproportionally larger share of white-collar non-STEM entrants originated from the white-collar STEM field. Lastly, there was field differences in the trajectories entering each of the field. In blue-collar STEM, 17 percent of entrants switched into the field between age 13 and 18, and 52 percent entrants between age 21 and 25. In contrast, in the white-collar STEM, 33 percent of entrants switched into the field between age 13 and 18, and 40 percent between age 21 and 25. The early entry took up a larger share of blue-collar STEM entrants than of white-collar STEM entrants. The educational and financial demand of white-collar careers may require adolescents to plan and prepare for at an early age. Evidence shows that adolescents who had plans to attend college were more likely to actually enroll in college than their peers of similar academic performance and family socioeconomic status (Eccles et al., 2004). Gender was not associated with the types of entry trajectories in blue-collar or white-collar STEM fields.

It was worth noting that there seemed to be disproportionally more white-collar STEM entrants originating from the blue-collar non-STEM field than from the blue-collar STEM field. In the sample, there were approximately two times as many blue-collar non-STEM aspirants as blue-collar STEM aspirants, but nearly four times as many as entrants from the blue-collar non-STEM field as from the blue-collar STEM field. Although the overall entry into white-collar STEM careers was small, but a sizable portion of entrants overcome not only the education requirement but also the transition into a different field. There was a similarly large portion of white-collar non-STEM entrants from the blue-collar non-STEM field, but not the blue-collar STEM field, pointing to factors specific to entrants from the blue-collar non-STEM field. More research is needed to understand what this group is like and what facilitated their entries into the challenging white-collar careers.

Limited Evidence for "Cumulative Disadvantage" in Paths Leading to STEM Careers

We found the paths leading to STEM careers were diverse and eclectic. STEM workers entered their field of employment after zero, one, two or three prior choices in the same field, with no type of trajectories covering a predominant portion of the group.

The stereotypical "pipeline" path, with an early entry into the field followed by uninterrupted persistence, was not the most common trajectory among STEM workers in the physics-related STEM careers, blue-collar or white-collar STEM careers. This finding shows that the "pipeline" metaphor was not an accurate or representative image of STEM career trajectories. It represented less than 20 percent of workers in physics-, blue-collar and white-collar STEM jobs. Considering the diverse and prevalence of other types of paths leading to STEM employment, it remains a question of how useful and beneficial to focus on promoting a "pipeline" trajectory. Moreover, our findings showed that trajectories with more prior choices in the field of employment were not always more frequent. For instance, the most frequent path leading to physics-related STEM and blue-collar STEM jobs was working in the field without any prior aspirations. These results did not support the "cumulative disadvantage" hypothesis about STEM career trajectories, such that the continuation between prior and later career choices was not observed in these fields.

The health STEM field was an exception to the findings above. Among health STEM workers, the trajectory of an early entry followed by uninterrupted persistence was the most common path. It was taken by around 40 percent of workers in the field. Moreover, a gradient pattern was found such that the second common trajectory was one with frequent prior choices, and third common trajectory was one with infrequent prior choices, and the least common trajectory was the one with no prior choices. This finding adds to our results about STEM entry which point to uniqueness of health STEM careers. It seemed that the career path leading to health STEM careers was less open to entry compared with persistence, less open to late entry than early entry, and less open to infrequent previous choices in the field than to frequent, persistent previous choices. The health STEM career trajectories matched characteristics of the stereotypical "pipeline" trajectory. However, it was also evident that the labor supply shrank the most among health STEM careers across various types of STEM careers. The more closed, "pipeline"-like system might be pertinent to the drastic shrinkage, due to the limited amount of entry from other fields. More research is needed to understand what caused the unique career trajectories of the health STEM careers and what can be done to remove the barriers for people to enter the field.

Intricate Gender Differences in Persistence

We found that more women than expected by chance in the health STEM and blue-collar STEM careers took the uninterrupted "pipeline" path to their STEM careers. In other words, women were more likely than expected to follow the stereotypical "pipeline" in these two fields. In particular, the health STEM "pipeline" trajectory entirely consisted of women. This finding may indicate that in STEM fields that match women's vocational interest and provides supportive environment, women were very likely to show early interest and carry on their choice into employment in the field by early adulthood. The lack of such match and support seemed to correlate with a late entry. In physics-related STEM careers, more women than expected entered the field without any prior aspirations, and in health STEM careers, more men than expected by chance entered the field without any prior aspirations. It may take explorations and resilience to pursue a STEM career that is atypical for a person's gender group, and our finding showed that this may hold true for both women and men.

It remains a question of why women were overrepresented in the "pipeline" trajectory to blue-collar STEM careers, especially considering that girls tend to have higher career aspirations than boys in adolescence (Howard et al., 2011). The other field that women are overrepresented in the "pipeline" trajectory is the health STEM field. Therefore, one direction is to investigate which blue-collar STEM jobs women aspired to and to how many of these jobs were health STEM jobs.

Limitations and Future Directions

In this study, we differentiated STEM careers between the content (health vs physics-related STEM) and between the education requirement (e.g., blue-collar vs white-collar STEM). These two dimensions can intersect with each other in reality, but we were unable to investigate it due to the limit of our sample size. The intersection would create smaller subgroups, leading to less reliable conclusions.

We believe that STEM teachers in elementary and secondary schools are STEM workers, because these jobs rely on STEM content knowledge. Unfortunately, teaching occupations in elementary and middle school stages were aggregated under one job title, without differentiations of the teachers' subject, in the Census occupation and the O□NET database, so we were unable to identify STEM teachers among them. This constraint is one tradeoff of using secondary data. Researchers who collect their own data in the future can make such distinction so that STEM teachers can be included as STEM careers. More broadly, we call for an update in the Census occupation and the O□NET database to identify the subject of elementary and middle school teachers, as did for postsecondary school teachers.

Future studies could use differentiations within the non-STEM field to investigate the trajectories of humanities, law, business, social science, arts, and sports careers. Restricted by our sample size, we did not intersect health/physics STEM with blue/white-collar to avoid small subgroups that may not warrant reliable conclusions. National longitudinal studies, such as High School and Beyond, Add Health and Early Childhood Longitudinal Studies could be valuable data sources by including questions on participants' career choices over time.

Conclusion

In this study, we portrayed STEM career trajectories from age 13 to age 25 across domains and education requirement. We showed frequent exits as well as entry into STEM careers and demonstrated considerable field- and gender-variation in the changes of the labor supply across various types of STEM careers. We believe a broad "STEM" category would mask these meaningful discrepancies for understanding gendered pattern in STEM career paths. Our examinations of gender differences in the career paths clarified previous notion and showed gender similarities in STEM attrition in various STEM careers. Moreover, we pointed to great variations in STEM entry as the understudied aspect of the gender differences in STEM career paths. We showed evidence in support of higher persistence of women in the health STEM field, and higher late entry of women into the physics-related STEM careers. These findings point to a shift toward understanding and encouraging men's and women's distinct career trajectories into the STEM workforce. Lastly, we propose a "STEM highway" metaphor for a complete and up-to-date representation of STEM career trajectories.

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Table 1.1
Descriptive Information of Sample

	N	Women	Percentage of women in sample	Age (Mean [SD])				
				2002'	2005'/07'	2007'/09'	2009'/11'	2013'/15'
2-wave sample	1026	552	54%	13.08 (1.94)	---	---	---	25.15 (1.95)
3-wave sample	978	530	54%	13.07 (1.94)	---	19.4 (2.07)	---	25.14 (1.95)
4-wave sample	814	450	55%	13.12 (1.94)	18.23 (1.39)	---	21.18 (1.92)	25.19 (1.93)

Table 1.2
Frequency of Career Choices by Year and Sample

	Two-wave sample		Three-wave sample			Four-wave sample			
Occupation	Age 13	Age 25	Age 13	Age 19	Age 25	Age 13	Age 18	Age 21	Age 25
Non-STEM	612 (60%)	771 (75%)	579 (59%)	556 (57%)	735 (75%)	484 (59%)	474 (58%)	452 (75%)	602 (74%)
STEM	414 (40%)	255 (25%)	399 (41%)	422 (43%)	243 (25%)	330 (41%)	340 (42%)	362 (25%)	212 (26%)
Total	1026 (100%)	1026 (100%)	978 (100%)	978 (100%)	978 (100%)	814 (100%)	814 (100%)	814 (100%)	814 (100%)
Non-STEM	612 (60%)	771 (75%)	579 (59%)	556 (57%)	735 (75%)	484 (59%)	474 (58%)	452 (75%)	602 (74%)
Health STEM	224 (22%)	62 (6%)	217 (22%)	199 (20%)	61 (6%)	185 (23%)	167 (21%)	187 (6%)	57 (7%)
Physics STEM	190 (18%)	193 (19%)	182 (19%)	223 (23%)	182 (19%)	145 (18%)	173 (21%)	175 (19%)	155 (19%)
Total	1026 (100%)	1026 (100%)	978 (100%)	978 (100%)	978 (100%)	814 (100%)	814 (100%)	814 (100%)	814 (100%)
Blue-collar non-STEM	345 (33%)	630 (61%)	330 (34%)	237 (24%)	597 (61%)	272 (33%)	202 (25%)	187 (61%)	483 (59%)
Blue-collar STEM	140 (14%)	162 (16%)	134 (14%)	197 (20%)	152 (16%)	111 (14%)	162 (20%)	190 (16%)	131 (16%)
White-collar non-STEM	267 (26%)	141 (14%)	249 (25%)	319 (33%)	138 (14%)	212 (26%)	272 (33%)	265 (14%)	119 (15%)
White-collar STEM	274 (27%)	93 (9%)	265 (27%)	225 (23%)	91 (9%)	219 (27%)	178 (22%)	172 (9%)	81 (10%)
Total	1026 (100%)	1026 (100%)	978 (100%)	978 (100%)	978 (100%)	814 (100%)	814 (100%)	814 (100%)	814 (100%)

Table 1.3
Gender Composition of Aspirations at Age 13 and Employment at Age 25.

Field	Aspiration at age 13	% Women	Employment at age 25	% Women
Non-STEM	612	57%$^{+}$	771	57%$^{+}$
STEM	414	49%$^{-}$	255	44%$^{-}$
Non-STEM	612	57%$^{+}$	771	57%$^{+}$
Health STEM	224	75%$^{+}$	62	77%$^{+}$
Physics STEM	190	18%$^{-}$	193	33%$^{-}$
Blue-collar non-STEM	345	45%$^{-}$	630	55%
Blue-collar STEM	140	44%$^{-}$	162	41%$^{-}$
White-collar non-STEM	267	72%$^{+}$	141	68%$^{+}$
White-collar STEM	274	51%	93	48%
Total	1026	54%	1026	54%

Note. $^{+}/^{-}$ indicates over-/under-representation of women with standardized adjusted residual greater than 1.96 or less than -1.96.

Table 1.4
Gender Composition of Each Class in Longitudinal Latent Class Solutions.

	3-wave non-/health/physics STEM trajectory		3-wave blue-/white-collar STEM/non-STEM trajectory		4-wave non-/health/physics STEM trajectory		4-wave blue-/white-collar STEM/non-STEM trajectory	
	N	% women	N	% women	N	% women	N	% women
Class 1	116	76.7+	243	52.7	209	23.9-	315	48.9-
Class 2	555	65+	279	68.8+	72	77.8+	146	51.4
Class 3	307	26.1-	456	46.1-	418	59.1+	155	54.2
Class 4	---	---	---	---	115	84.3+	198	69.2+
Total	978	54.2	978	54.2	814	55.3	814	55.3

Note. +/- indicates over-/under-representation of women with standardized adjusted residual greater than 1.96 or less than -1.96.

Table 1.5

Frequency of Aspiration and Employment in Each Field and the Change in "Pipeline" Sizes.

Field	Aspirants at age 13				Workers at age 25				
	Total	Attrition	Persistence	Attrition rate	Total	Entry	Persistence	Entrance rate	Change ratio
Non-STEM	612	128	484	20.9%	771	287	484	37.2%	126.0%
STEM	414	287	127	69.3%	255	128	127	50.2%	61.6%
Non-STEM	612	128	484	20.9%	771	287	484	37.2%	126.0%
Health STEM	224	191	33	85.3%	62	29	33	46.8%	27.7%
Physics STEM	190	135	55	71.1%	193	138	55	71.5%	101.6%
Blue-collar non-STEM	345	105	240	30.4%	630	390	240	61.9%	182.6%
Blue-collar STEM	140	98	42	70.0%	162	120	42	74.1%	115.7%
White-collar non-STEM	267	207	60	77.5%	141	81	60	57.4%	52.8%
White-collar STEM	274	231	43	84.3%	93	50	43	53.8%	33.9%

Note. W = women, M = men. Attrition rate equals attrition size divided by total number of aspirants. Entry rate equals entry size divided by total number of workers. Change ratio equals the total number of workers divided by the total number of aspirants.

Table 1.6

Frequency of Aspiration and Employment in Each Field by Gender

	Aspirants at age 13								Workers at age 25									
	Total		Attrition		Persistence		Attrition rate		Total		Entry		Persistence		Entry rate		Change ratio	
Field	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M
Non-STEM	349	263	58	70	291	193	16.6%	26.6%	441	330	150	137	291	193	34.0%	41.5%	126.4%	125.5%
STEM	203	211	150	137	53	74	73.9%	64.9%	111	144	58	70	53	74	52.3%	48.6%	54.7%	68.2%
Non-STEM	349	263	58	70	291	193	16.6%	26.6%	441	330	150	137	291	193	34.0%	41.5%	126.4%	125.5%
Health STEM	169	55	138	53	31	2	81.7%	96.4%	48	14	17	12	31	2	35.4%	85.7%	28.4%	25.5%
Physics STEM	34	156	29	106	5	50	85.3%	67.9%	63	130	58	80	5	50	92.1%	61.5%	185.3%	83.3%
Blue-collar non-STEM	156	189	47	58	109	131	30.1%	30.7%	345	285	236	154	109	131	68.4%	54.0%	221.2%	150.8%
Blue-collar STEM	62	78	45	53	17	25	72.6%	67.9%	66	96	49	71	17	25	74.2%	74.0%	106.5%	123.1%
White-collar non-STEM	193	74	146	61	47	13	75.6%	82.4%	96	45	49	32	47	13	51.0%	71.1%	49.7%	60.8%
White-collar STEM	141	133	123	108	18	25	87.2%	81.2%	45	48	27	23	18	25	60.0%	47.9%	31.9%	36.1%

Note. W = women, M = men. Attrition rate equals attrition size divided by total number of aspirants. Entry rate equals entry size divided by total number of workers. Change ratio equals the total number of workers divided by the total number of aspirants.

Table 1.7

Frequency of Attrition Based on Destination

	Aspiration at age 13																	
	non-STEM						Health STEM						Physics STEM					
Employment at age 25	Everyone		Women		Men		Everyone		Women		Men		Everyone		Women		Men	
Non-STEM	---	---	---	---	---	---	162	85%	123	89%	39	74%	125	93%	27	93%	98	92%
Health STEM	19	15%	15	26%	4	6%	---	---	---	---	---	---	10	7%	2	7%	8	8%
Physics STEM	109	85%	43	74%	66	94%	29	15%	15	11%	14	26%	---	---	---	---	---	---
Total attrition	128	100%	58	100%	70	100%	191	100%	138	100%	53	100%	135	100%	29	100%	106	100%

	Aspiration at age 13																							
Empt. at age 25	Blue-collar non-STEM						Blue-collar STEM						White-collar non-STEM						White-collar STEM					
	Everyone		Women		Men		Everyone		Women		Men		Everyone		Women		Men		Everyone		Women		Men	
BCNS	---	---	---	---	---	---	83	85%	37	82%	46	87%	151	73%	116	79%	35	57%	156	68%	83	67%	73	68%
BCS	49	47%	16	34%	33	57%	---	---	---	---	---	---	35	17%	17	12%	18	30%	36	16%	16	13%	20	19%
WCNS	33	31%	19	40%	14	24%	9	9%	6	13%	3	6%	---	---	---	---	---	---	39	17%	24	20%	15	14%
WCS	23	22%	12	26%	11	19%	6	6%	2	4%	4	8%	21	10%	13	9%	8	13%	---	---	---	---	---	---
Total attri.	105	100%	47	100%	58	100%	98	100%	45	100%	53	100%	207	100%	146	100%	61	100%	231	100%	123	100%	108	100%

Note. Empt = employment, BCNS = blue-collar non-STEM, BCS = Blue-collar STEM, WCNS = white-collar non-STEM, WCS = white-collar STEM, Attri. = attrition.

Table 1.8
Frequency of Attrition Trajectories

Attrition trajectory	Aspiration at age 13							
	Non-STEM	STEM	Health STEM	Physics STEM	Blue-collar non-STEM	Blue-collar STEM	White-collar non-STEM	White-collar STEM
Exit by age 18: y-n-n-n	30 (29%)	93 (42%)	86 (56%)	49 (50%)	54 (62%)	47 (60%)	73 (45%)	106 (59%)
Exit by age 21: y-y-n-n	29 (28%)	37 (17%)	18 (12%)	21 (21%)	17 (19%)	8 (10%)	27 (17%)	32 (18%)
Exit by age 25: y-y-y-n	37 (35%)	72 (32%)	35 (23%)	19 (19%)	10 (11%)	16 (21%)	45 (28%)	26 (14%)
Recursive: y-n-y-n	9 (8%)	21 (9%)	14 (9%)	10 (10%)	7 (8%)	7 (9%)	17 (10%)	16 (9%)
Total attrition	105 (100%)	223 (100%)	153 (100%)	99 (100%)	88 (100%)	78 (100%)	162 (100%)	180 (100%)

Note. Each letter in career path represents one time point (Age 13 – age 18 – age 21 – age 25). Y = choice in the field of each column, n = choice in other fields. No path is found to be over- or under-represented for any field with standardized adjusted residual greater than 1.96 or less than -1.96.

Table 1.9
Gender Differences in Attrition Trajectories

Attrition trajectories	Aspiration at age 13 (frequency in cell, percentage of women in parentheses)							
	Non-STEM	STEM	Health STEM	Physics STEM	Blue-collar non-STEM	Blue-collar STEM	White-collar non-STEM	White-collar STEM
Exit by age 18: y-n-n-n	30 (47%)	93 (56%)	86 (69%)	49 (24%)	54 (54%$^{+}$)	47 (40%)	73 (63%)	106 (56%)
Exit by age 21: y-y-n-n	29 (55%)	37 (49%)	18 (78%)	21 (24%)	17 (35%)	8 (63%)	27 (70%)	32 (50%)
Exit by age 25: y-y-y-n	37 (32%)	72 (54%)	35 (77%)	19 (11%)	10 (10%$^{-}$)	16 (63%)	45 (80%)	26 (54%)
Recursive: y-n-y-n	9 (44%)	21 (57%)	14 (86%)	10 (20%)	7 (43%)	7 (57%)	17 (76%)	16 (50%)
Total attrition	105 (44%)	223 (54%)	153 (73%)	99 (21%)	88 (44%)	78 (49%)	162 (70%)	180 (54%)
Test statistics	Chi-square Test of Association Between Gender and Trajectory Group Membership in Each Field							
χ_2	3.57	0.64	2.51	1.71	7.27	3.32	4.20	0.43
df	3							
n	105	223	153	99	88	78	162	180
p value	.31	.89	.47	.64	.06	.35	.24	.94

Note. Each letter in career path represents one time point (age 13 – age 18 – age 21 – age 25). Y = choice in the field of each column, n = choice in other fields. +/- indicates over-/under-representation of women with standardized adjusted residual greater than 1.96 or less than -1.96.

Table 1.10
Frequency of Entry Based on Origin

	Employment at age 25																	
	non-STEM						Health STEM						Physics STEM					
Aspiration at age 13	Everyone		Women		Men		Everyone		Women		Men		Everyone		Women		Men	
Non-STEM	---	---	---	---	---	---	19	66%	15	88%	4	33%	109	79%	43	74%	66	83%
Health STEM	162	56%	123	82%	39	28%	---	---	---	---	---	---	29	21%	15	26%	14	18%
Physics STEM	125	44%	27	18%	98	72%	10	34%	2	12%	8	67%	---	---	---	---	---	---
Total attrition	287	100%	150	100%	137	100%	29	100%	17	100%	12	100%	138	100%	58	100%	80	100%

	Employment at age 25																							
	Blue-collar non-STEM						Blue-collar STEM						White-collar non-STEM						White-collar STEM					
Asp. at age 13	Everyone		Women		Men		Everyone		Women		Men		Everyone		Women		Men		Everyone		Women		Men	
BCNS	---	---	---	---	---	---	49	41%	16	33%	33	46%	33	41%	19	39%	14	44%	23	46%	12	44%	11	48%
BCS	83	21%	37	16%	46	30%	---	---	---	---	---	---	9	11%	6	12%	3	9%	6	12%	2	7%	4	17%
WCNS	151	39%	116	49%	35	23%	35	29%	17	35%	18	25%	---	---	---	---	---	---	21	42%	13	48%	8	35%
WCS	156	40%	83	35%	73	47%	36	30%	16	33%	20	28%	39	48%	24	49%	15	47%	---	---	---	---	---	---
Total attri.	390	100%	236	100%	154	100%	120	100%	49	100%	71	100%	81	100%	49	100%	32	100%	50	100%	27	100%	23	100%

Note. Asp = aspiration, BCNS = blue-collar non-STEM, BCS = Blue-collar STEM, WCNS = white-collar non-STEM, WCS = white-collar STEM.

Table 1.11
Frequencies of Entry Trajectories

Entry trajectory	Occupations at age 25							
	Non-STEM	STEM	Health STEM	Physics STEM	Blue-collar non-STEM	Blue-collar STEM	White-collar non-STEM	White-collar STEM
Enter after age 21: n-n-n-y	72 (32%)	37 (35%)	6 (24%)	56 (51%)	181 (61%)	51 (52%)	18 (26%)	17 (40%)
Enter after age 18: n-n-y-y	37 (17%)	29 (28%)	8 (32%)	28 (26%)	46 (15%)	20 (20%)	10 (14%)	10 (24%)
Enter after age 13: n-y-y-y	93 (42%)	30 (28%)	10 (40%)	18 (17%)	38 (13%)	17 (17%)	34 (49%)	14 (33%)
Recursive: n-y-n-y	21 (9%)	9 (9%)	1 (4%)	7 (6%)	34 (11%)	10 (10%)	7 (10%)	1 (2%)
Total attrition	223 (100%)	105 (100%)	25 (100%)	109 (100%)	299 (100%)	98 (100%)	69 (100%)	42 (100%)

Note. Each letter in career path represents one time point (Age 13 – age 18 – age 21 – age 25). Y = choice in the field of each column, n = choice in other fields.

Table 1.12
Gender Composition of Entry Trajectories

Entry trajectory	Occupations at age 25 (frequency in cell, percentage of women in parentheses)							
	Non-STEM	STEM	Health STEM	Physics STEM	Blue-collar non-STEM	Blue-collar STEM	White-collar non-STEM	White-collar STEM
Enter after age 21: n-n-n-y	72 (54%)	37 (32%)	6 (17%$^-$)	56 (45%)	181 (65%)	51 (31%)	18 (56%)	17 (59%)
Enter after age 18: n-n-y-y	37 (49%)	29 (55%)	8 (100%$^+$)	28 (36%)	46 (59%)	20 (40%)	10 (60%)	10 (70%)
Enter after age 13: n-y-y-y	93 (56%)	30 (47%)	10 (60%)	18 (33%)	38 (47%$^-$)	17 (59%)	34 (76%$^+$)	14 (29%$^-$)
Recursive: n-y-n-y	21 (57%)	9 (44%)	1 (0%)	7 (29%)	34 (68%)	10 (40%)	7 (14%$^-$)	1 (100%)
Total entry	223 (54%)	105 (44%)	25 (60%)	109 (39%)	299 (62%)	98 (39%)	69 (62%)	42 (52%)
Test statistics	Chi-square Test of Association Between Gender and Trajectory Group Membership in Each Field							
χ_2	0.64	3.57	--	1.42	4.65	4.07	--	--
df	3	3	--	3	3	3	--	--
n	223	105	--	109	299	98	--	--
p value	.89	.31	.004▲	.70	.20	.25	.02▲	.11▲

Note. Each letter in career path represents one time point (age 13 – age 18 – age 21 – age 25). Y = choice in the field of each column, n = choice in other fields. +/- indicates over-/under-representation of women with standardized adjusted residual no less than 1.96 or no greater than -1.96. ▲ Fisher's exact test (two-tailed) was used, instead of Chi-square test of independence, because of small cell sizes.

Table 1.13
Frequency of Trajectories Leading to STEM Employment at Age 25

		Employment at age 25							
Number of prior aspirations	Trajectory	Non-STEM	STEM	Health STEM	Physics STEM	Blue-collar non-STEM	Blue-collar STEM	White-collar non-STEM	White-collar STEM
0	n-n-n-y	72 (12%)	37 (18%)	6 (10%)	56 (36%)	181 (37%)	51 (39%)	18 (15%)	17 (21%)
1	y-n-n-y	71 (12%)	15 (7%)	1 (2%)	10 (6%)	85 (18%)	6 (5%)	6 (5%)	9 (11%)
	n-y-n-y	21 (4%)	9 (4%)	1 (2%)	7 (5%)	34 (7%)	10 (8%)	7 (6%)	1 (1%)
	n-n-y-y	37 (6%)	29 (14%)	8 (14%)	28 (18%)	46 (9%)	20 (15%)	10 (8%)	10 (12%)
	Subtotal	129 (22%)	53 (25%)	10 (18%)	45 (29%)	165 (35%)	36 (27%)	23 (19%)	20 (24%)
2	y-y-n-y	60 (10%)	13 (6%)	3 (5%)	8 (5%)	34 (7%)	3 (2%)	2 (2%)	6 (7%)
	y-n-y-y	48 (8%)	19 (9%)	4 (7%)	8 (5%)	27 (6%)	7 (6%)	6 (5%)	9 (11%)
	n-y-y-y	93 (15%)	30 (14%)	10 (18%)	18 (12%)	38 (8%)	17 (13%)	34 (29%)	14 (17%)
	Subtotal	201 (33%)	62 (29%)	17 (30%)	34 (22%)	99 (20%)	27 (21%)	42 (36%)	29 (36%)
3	y-y-y-y	200 (33%)	60 (28%)	24 (42%)	20 (13%)	38 (8%)	17 (13%)	36 (30%)	15 (19%)
	Total	602 (100%)	212 (100%)	57 (100%)	155 (100%)	483 (100%)	131 (100%)	119 (100%)	81 (100%)

Note. Each letter in career path represents one time point (age 13 – age 18 – age 21 – age 25). Y = aspiration in the field of each column, n = aspiration in other fields.

Table 1.14
Gender Differences in the Trajectories Leading to Employment at Age 25

	Employment at Age 25 (Total frequency in cell, percentage of women in parentheses)							
Number of prior aspirations	Non-STEM	STEM	Health STEM	Physics STEM	Blue-collar non-STEM	Blue-collar STEM	White-collar non-STEM	White-collar STEM
0	72 (54%)	37 (32%)	6 (17%$^{-}$)	56 (45%$^{+}$)	181 (65%$^{+}$)	51 (31%)	18 (56%)	17 (59%)
1	129 (54%)	53 (45%)	10 (90%)	45 (27%)	165 (57%)	36 (39%)	23 (43%$^{-}$)	20 (50%)
2	201 (60%)	62 (39%)	17 (65%)	34 (21%)	99 (46%$^{-}$)	27 (48%)	42 (79%)	29 (31%$^{-}$)
3	200 (64%)	60 (55%$^{+}$)	24 (100%$^{+}$)	20 (20%)	38 (45%)	17 (65%$^{+}$)	36 (83%$^{+}$)	15 (67%)
Total	602 (59%)	212 (44%)	57 (79%)	155 (31%)	483 (57%)	131 (41%)	119 (70%)	81 (48%)
Test statistics	Chi-square Test of Association Between Gender and Trajectory Group Membership in Each Field							
χ_2	3.99	5.70	23.21	8.13	11.09	6.53	13.94	6.27
df	3							
n	602	212	57	155	483	131	119	81
p value	.26	.13	< .001	.04	.01	.09	.003	.10

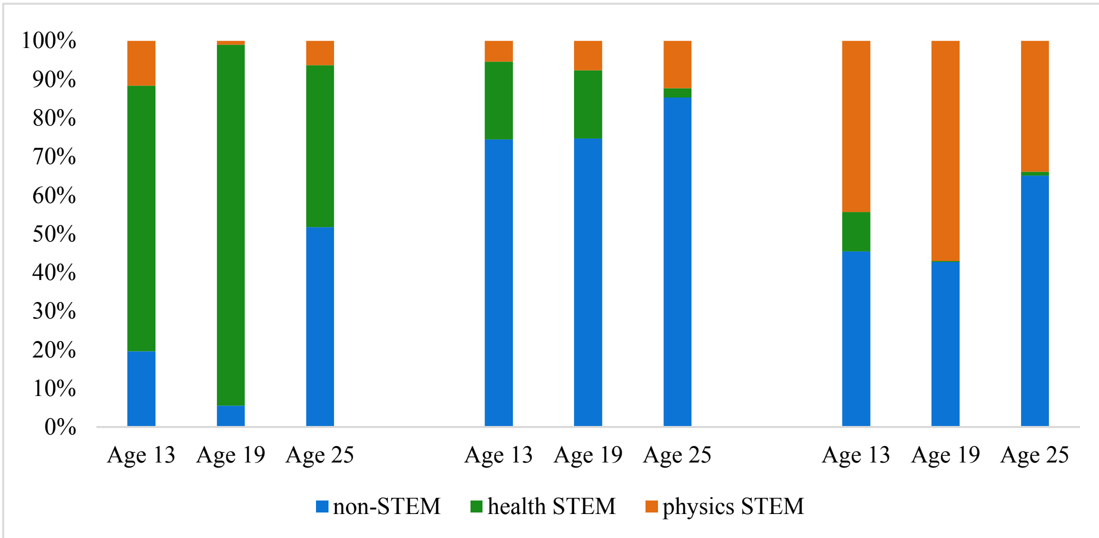
Note. Each letter in career path represents one time point (Age 13 – Age 18 – Age 21 – Age 25). Y = choice in the field of each column, n = choice in other fields. +/- indicates over-/under-representation of women with standardized adjusted residual greater than 1.96 or less than -1.96.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30

Sample data
Original CDS
Original TAS
Main study

Figure 1.1. Age of participants in related waves of CDS and TAS.

(A)



(B)

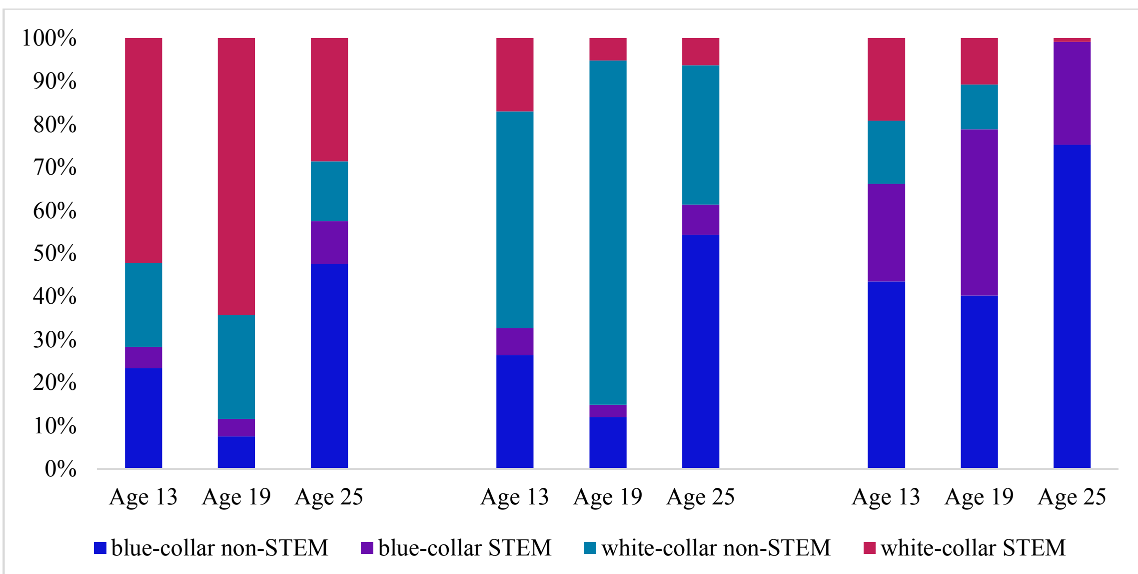
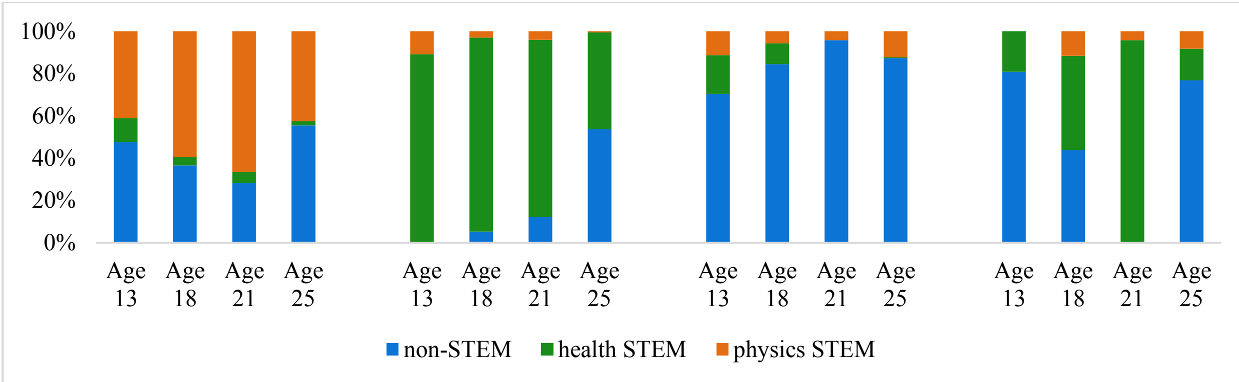


Figure 1.2. LLCA Three-class Solutions Shown in Category Probabilities for Three-wave Trajectories.

Graph (A) shows the class solution when aspirations were grouped by non-STEM, health STEM, or physics STEM. The group size of each class from left to right is 116 (12% of sample), 555 (57%) and 307 (31%). Graph (B) shows the class solution when aspirations were grouped by blue-/white-collar non-STEM/STEM. The group size of each class from left to right is 243 (25% of sample), 279 (29%) and 456 (46%).

(A)



(B)

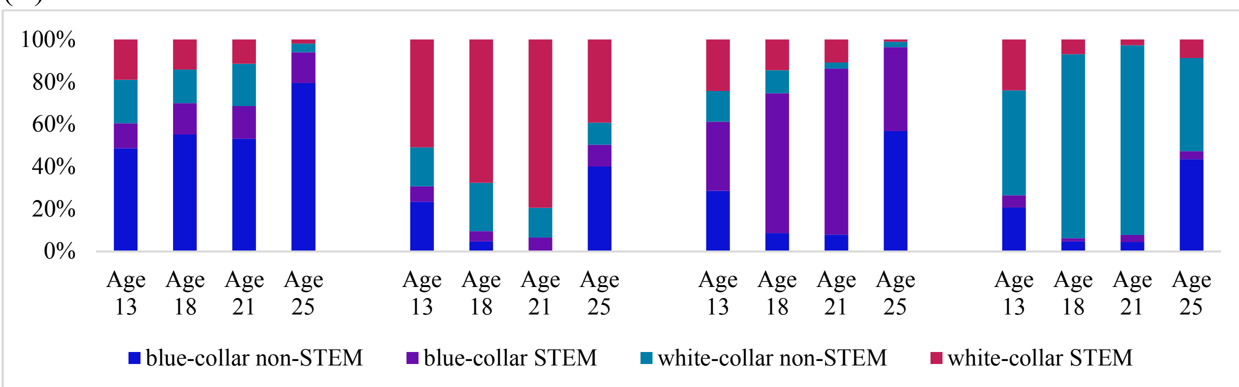
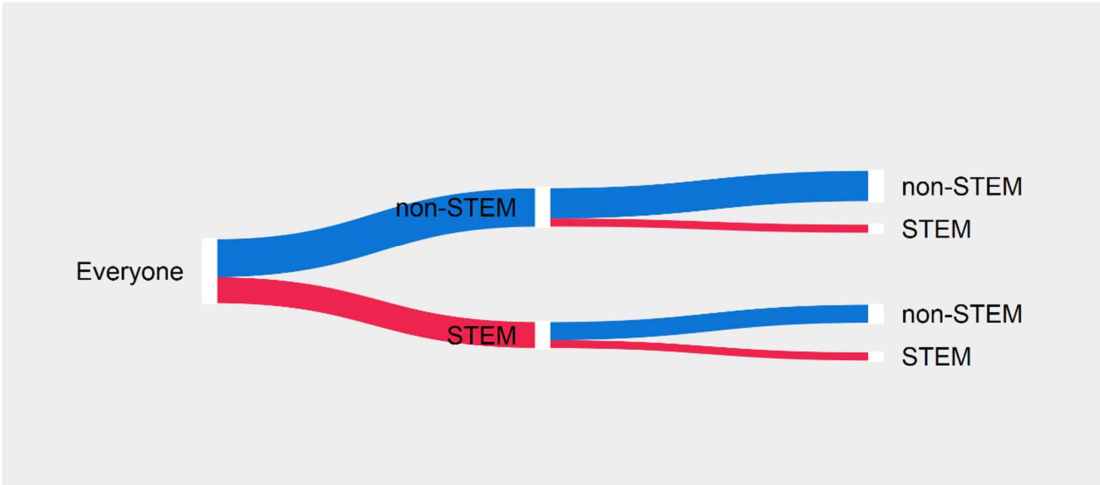


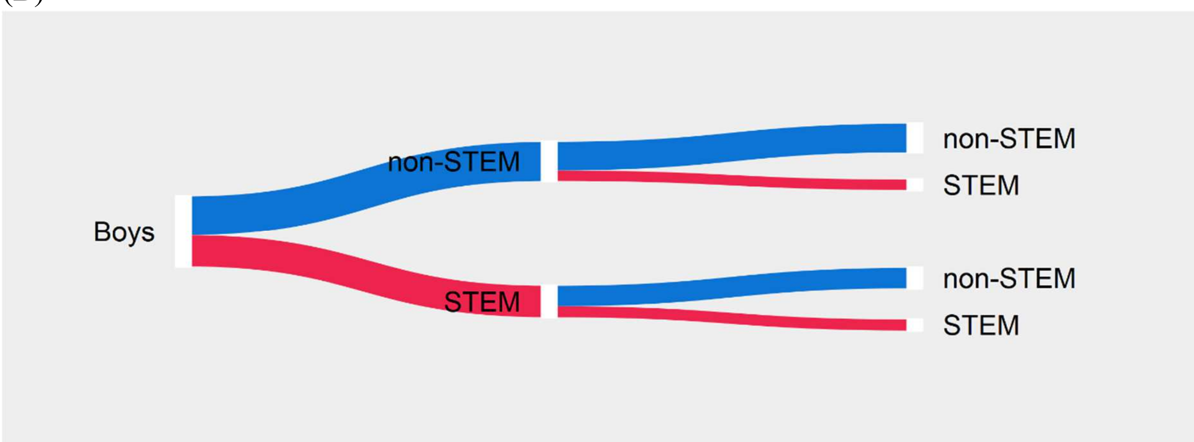
Figure 1.3. LLCA Four-class Solutions Shown in Category Probabilities for Four-wave Trajectories.

Graph (A) shows the class solution when aspirations were grouped by non-STEM, health STEM, or physics STEM. The group size of each class from left to right is 209 (26% of sample), 72 (9%), 418 (51%) and 115 (14%). Graph (B) shows the class solution when aspirations were grouped by blue-/white-collar non-STEM/STEM. The group size of each class from left to right is 315 (39% of sample), 146 (18%), 155 (19%) and 198 (24%).

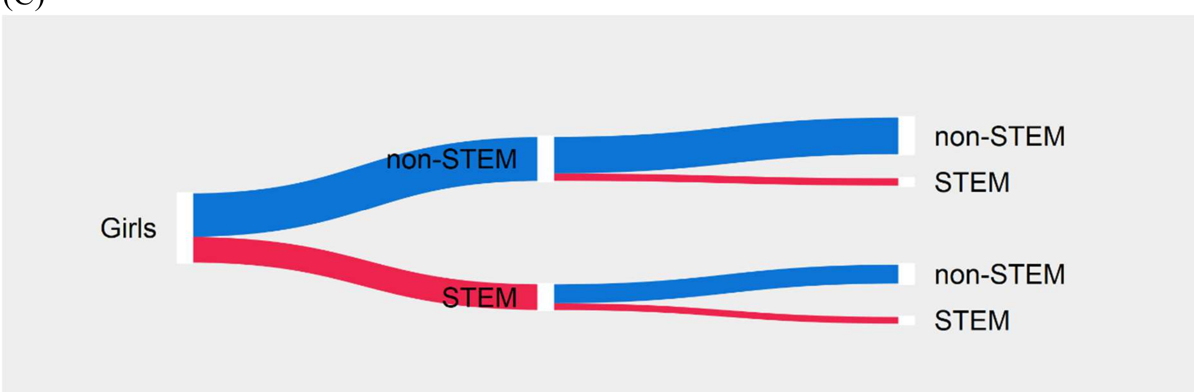
(A)


non-STEM
non-STEM
STEM
Everyone
non-STEM
STEM
STEM

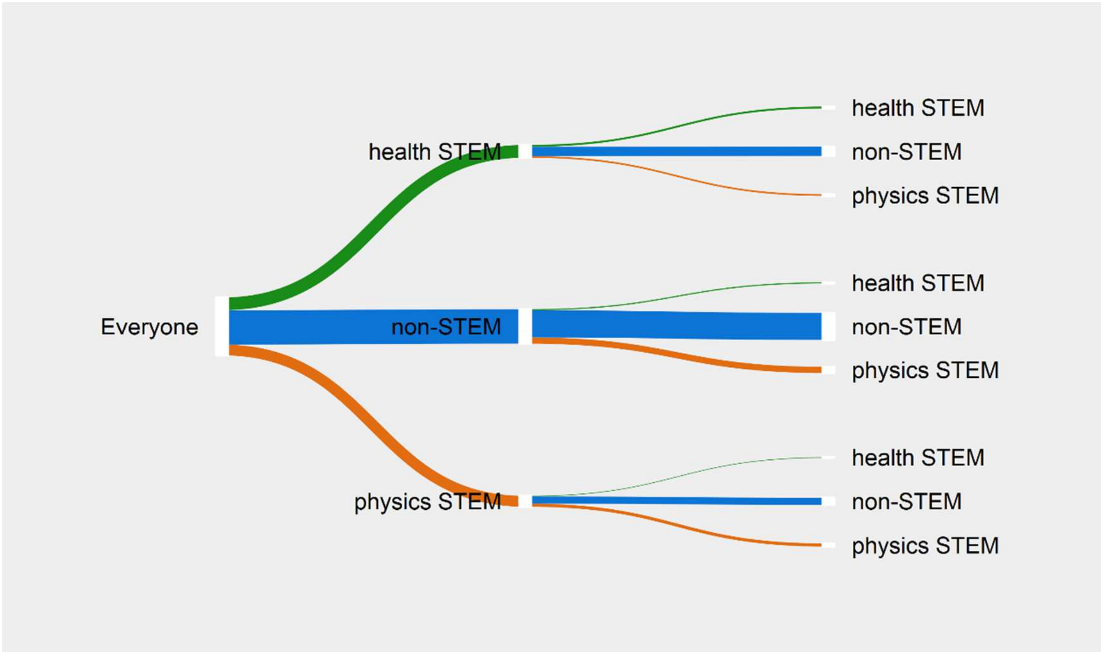
(B)


non-STEM
non-STEM
STEM
Boys
non-STEM
STEM
STEM

(C)

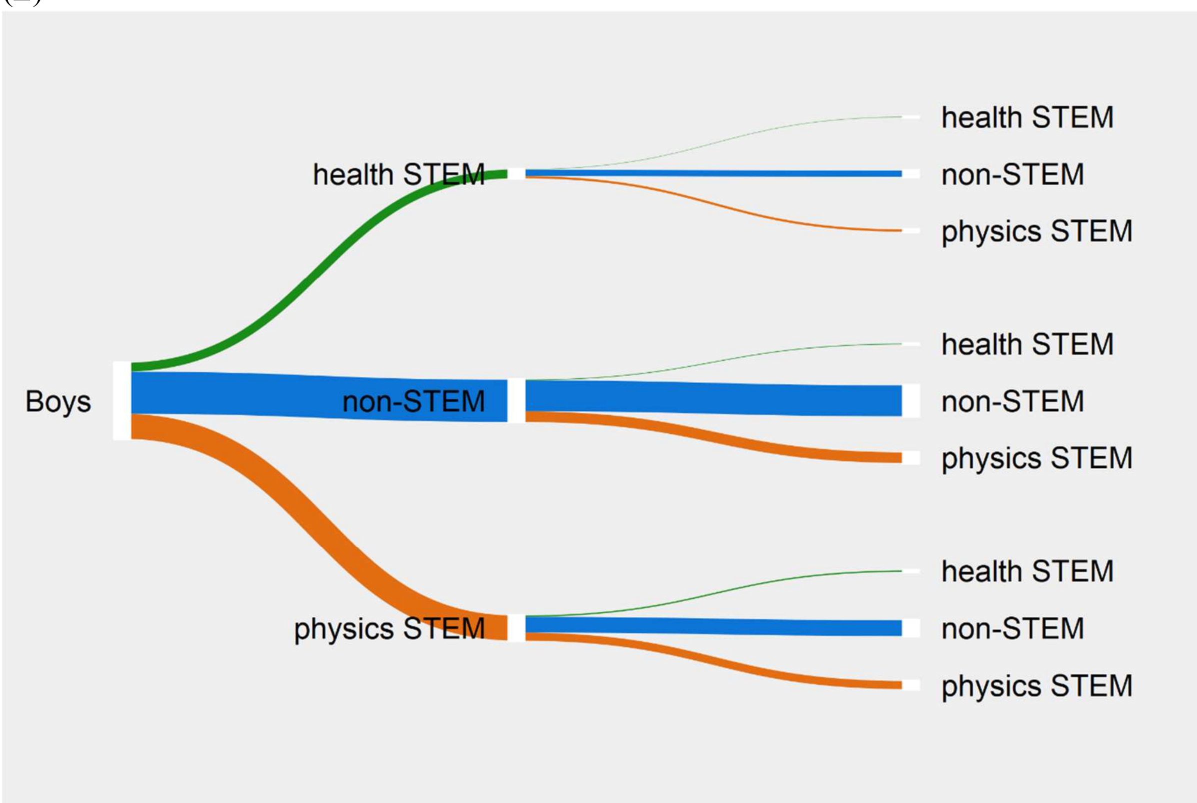

non-STEM
non-STEM
STEM
Girls
non-STEM
STEM
STEM

(D)



health STEM
non-STEM
physics STEM
health STEM
non-STEM
physics STEM
health STEM
non-STEM
physics STEM
health STEM
Everyone
non-STEM
physics STEM

(E)



health STEM
non-STEM
physics STEM
health STEM
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physics STEM
health STEM
non-STEM
physics STEM
health STEM
Boys
non-STEM
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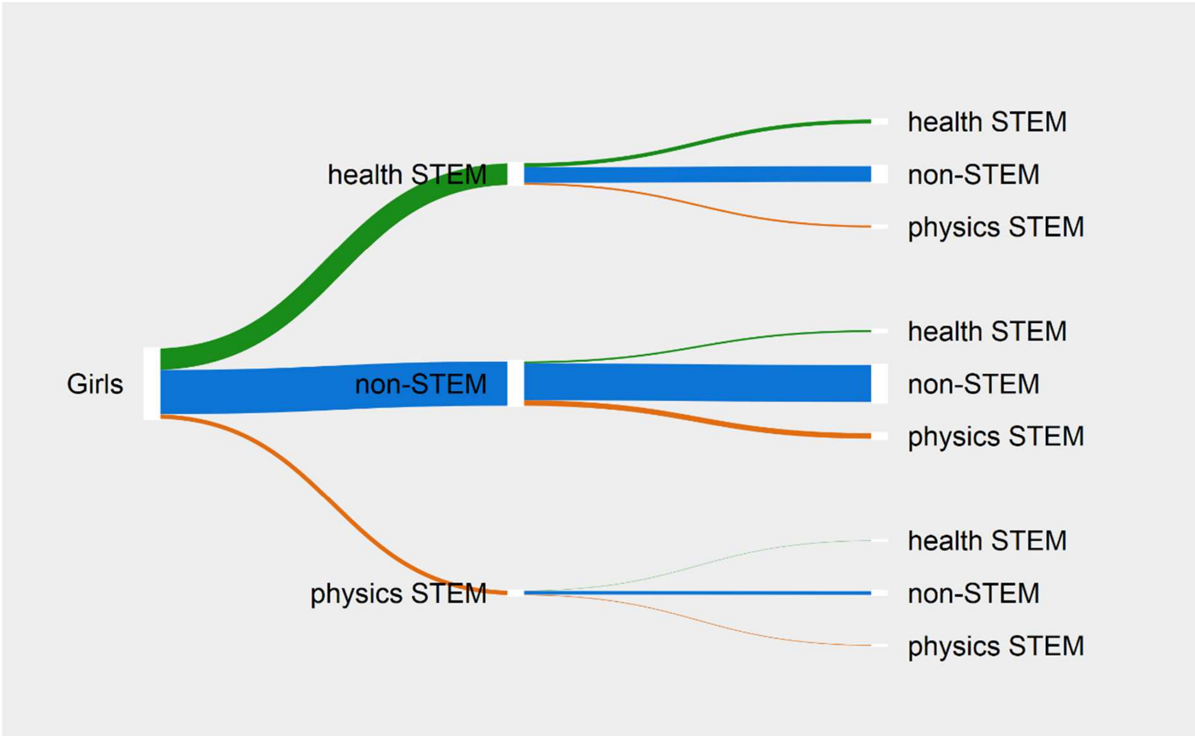
(F)


Girls
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non-STEM
physics STEM
health STEM
non-STEM
physics STEM
health STEM
non-STEM
physics STEM
health STEM
non-STEM
physics STEM
(G)

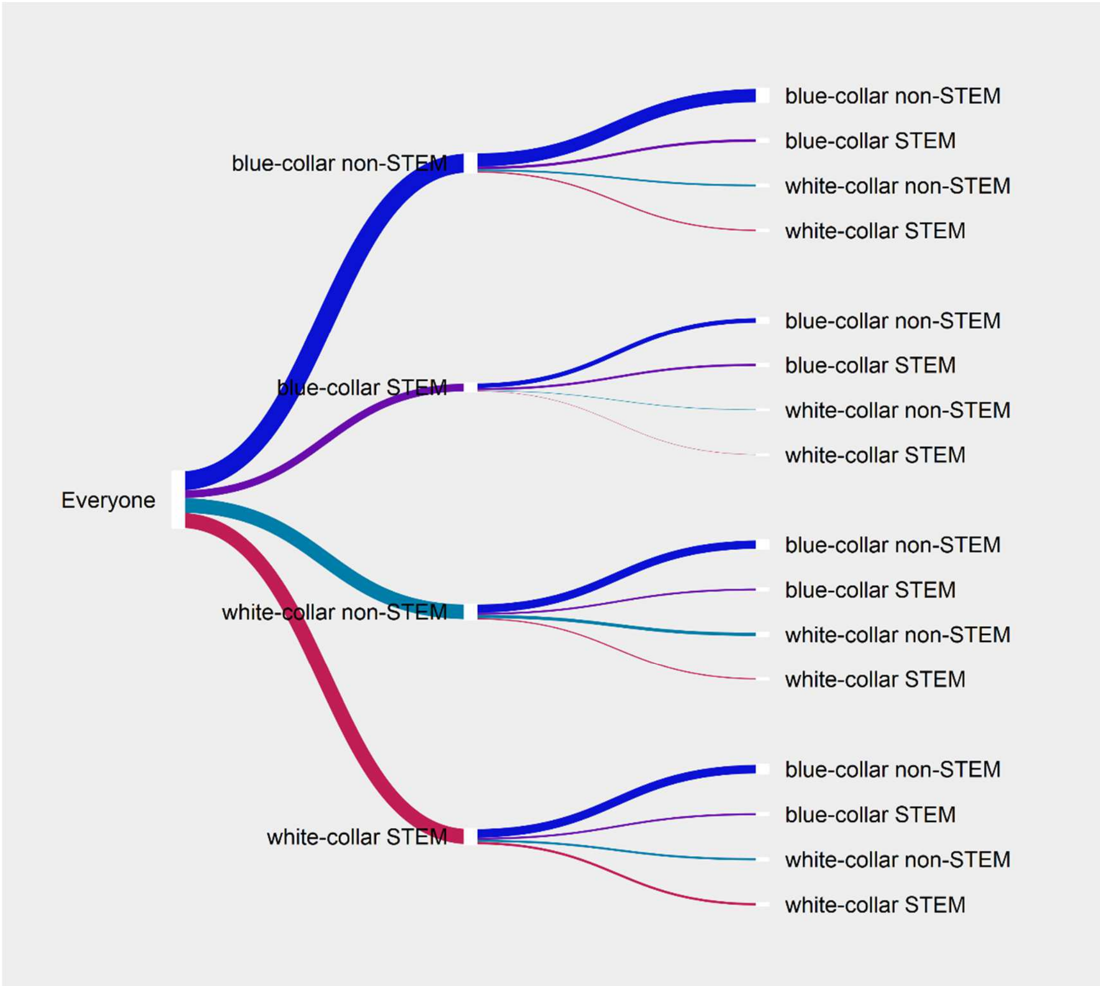
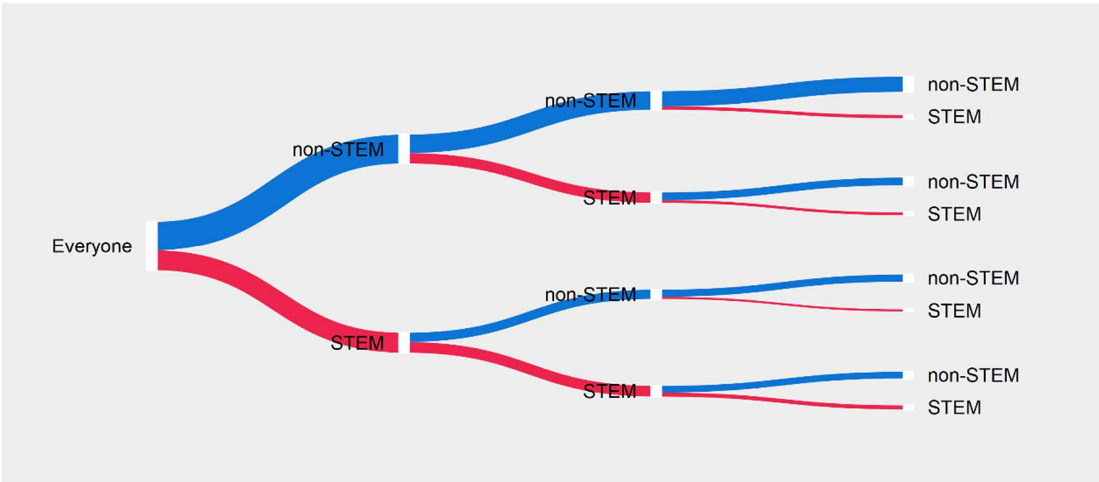


Figure 1.4. Career paths between career aspirations at age 13 and employment at age 25.

Trajectories (N = 1026) of aspirations were grouped by (A) STEM vs Non-STEM among (B) boys and (C) girls, by (D) non-STEM, health STEM or physics STEM among (E) boys and (F) girls and by (G) blue-collar non-STEM, blue-collar STEM, white-collar non-STEM or white-collar STEM. Participants with missing data were excluded. Each column represents one time point, and the height of branch indicates the size of subgroups.

(A)


Everyone
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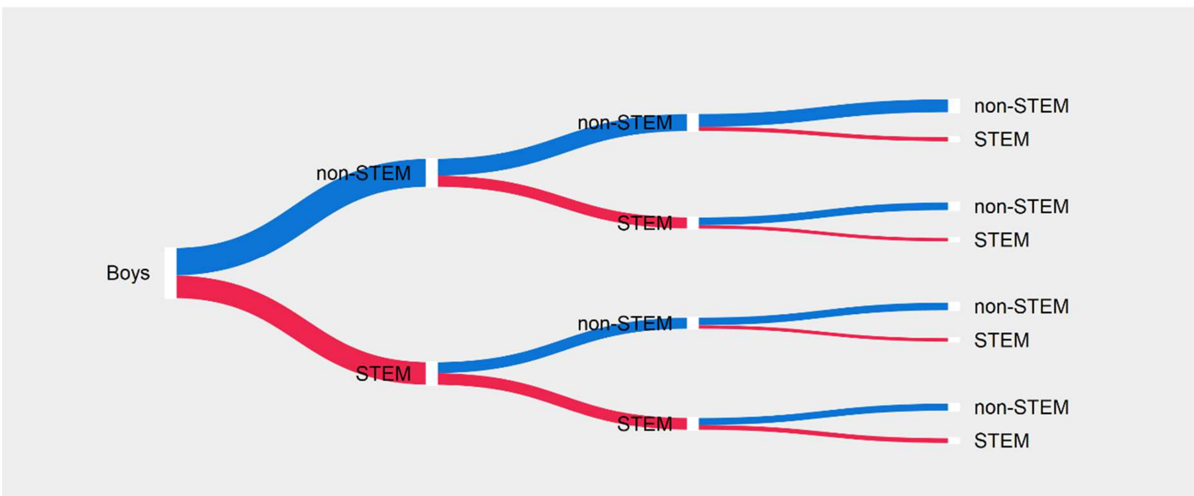
non-STEM
STEM

(B)


Boys
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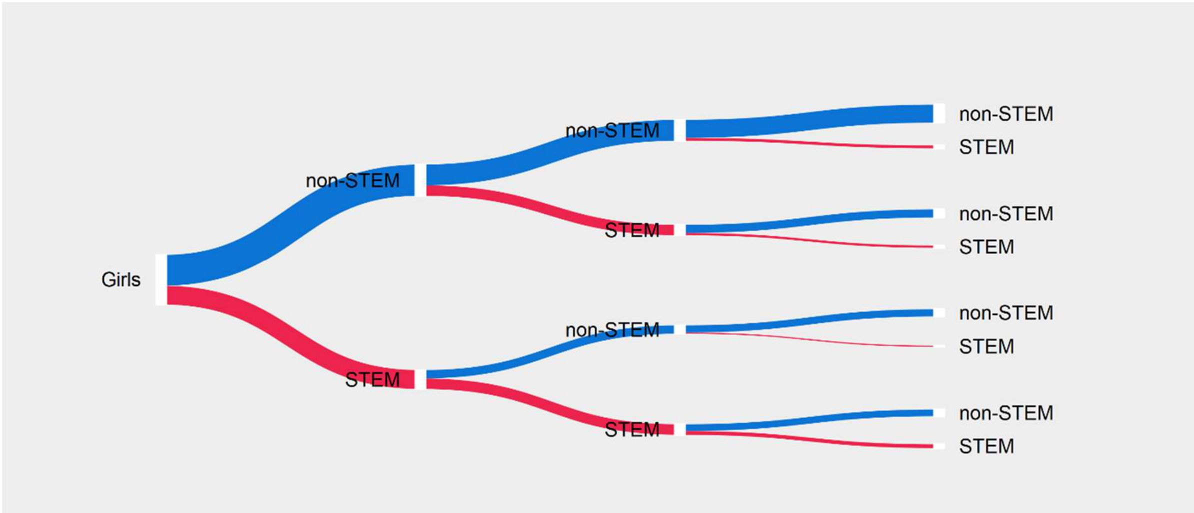
(C)


Girls
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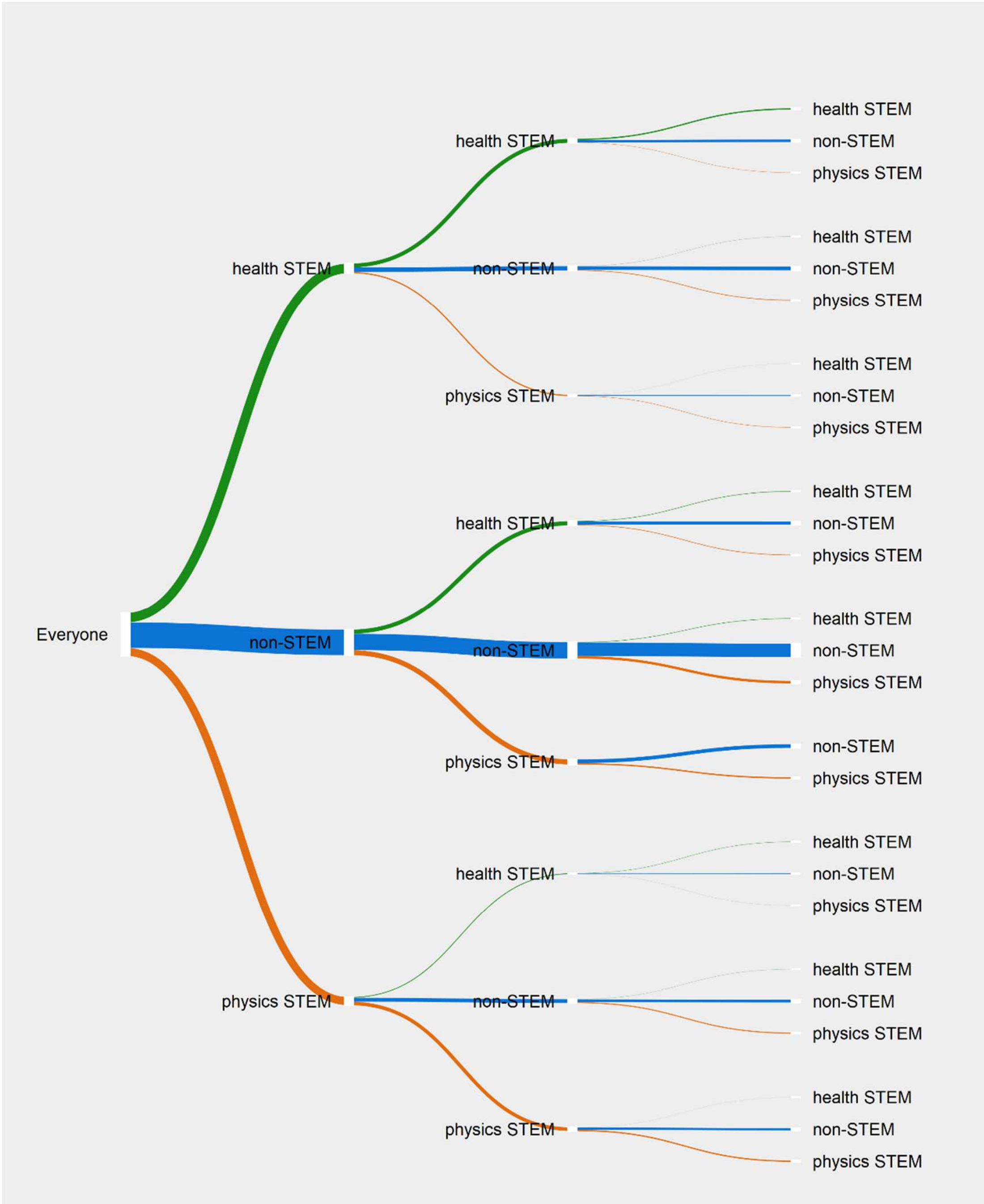
STEM
(D)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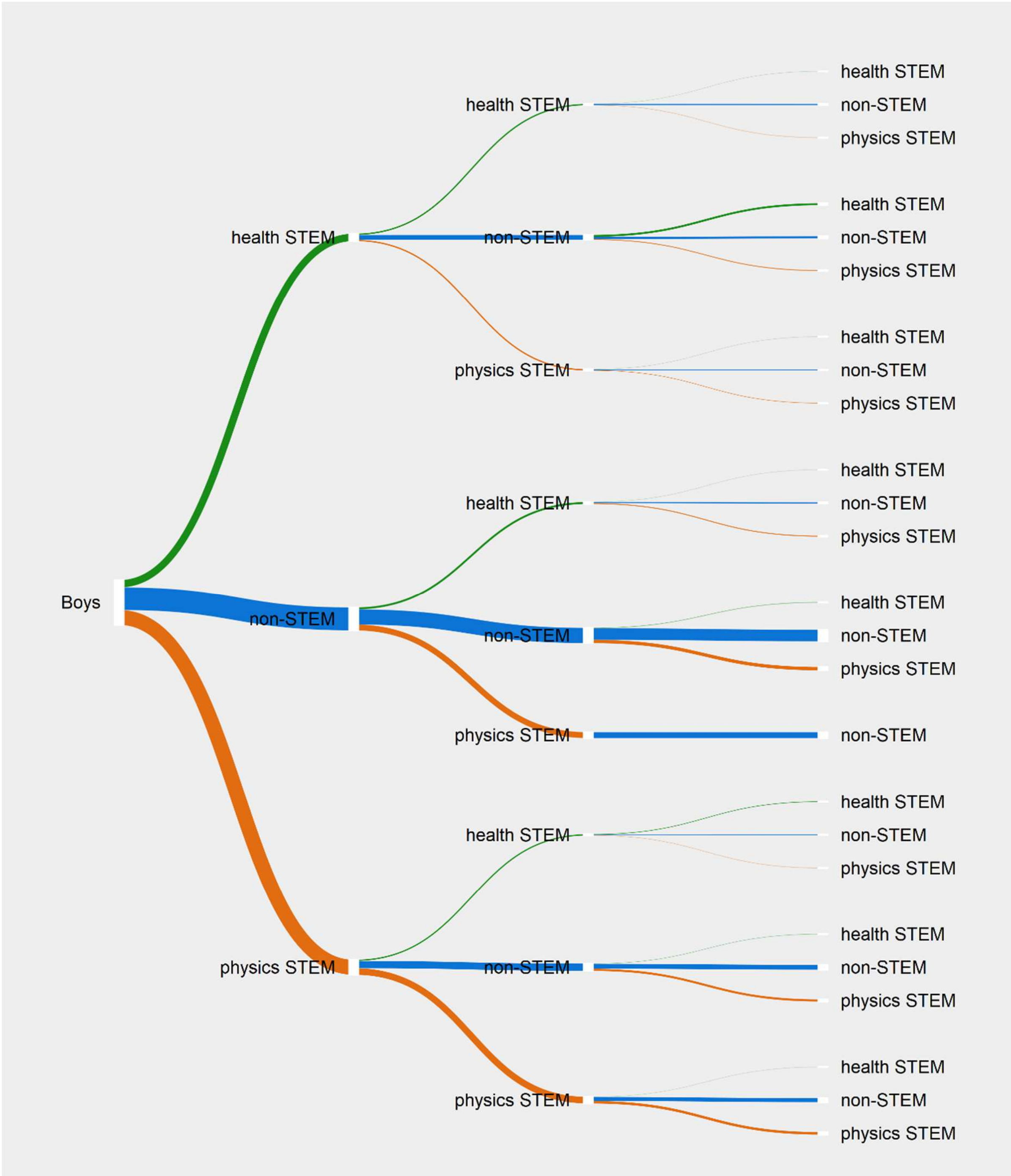
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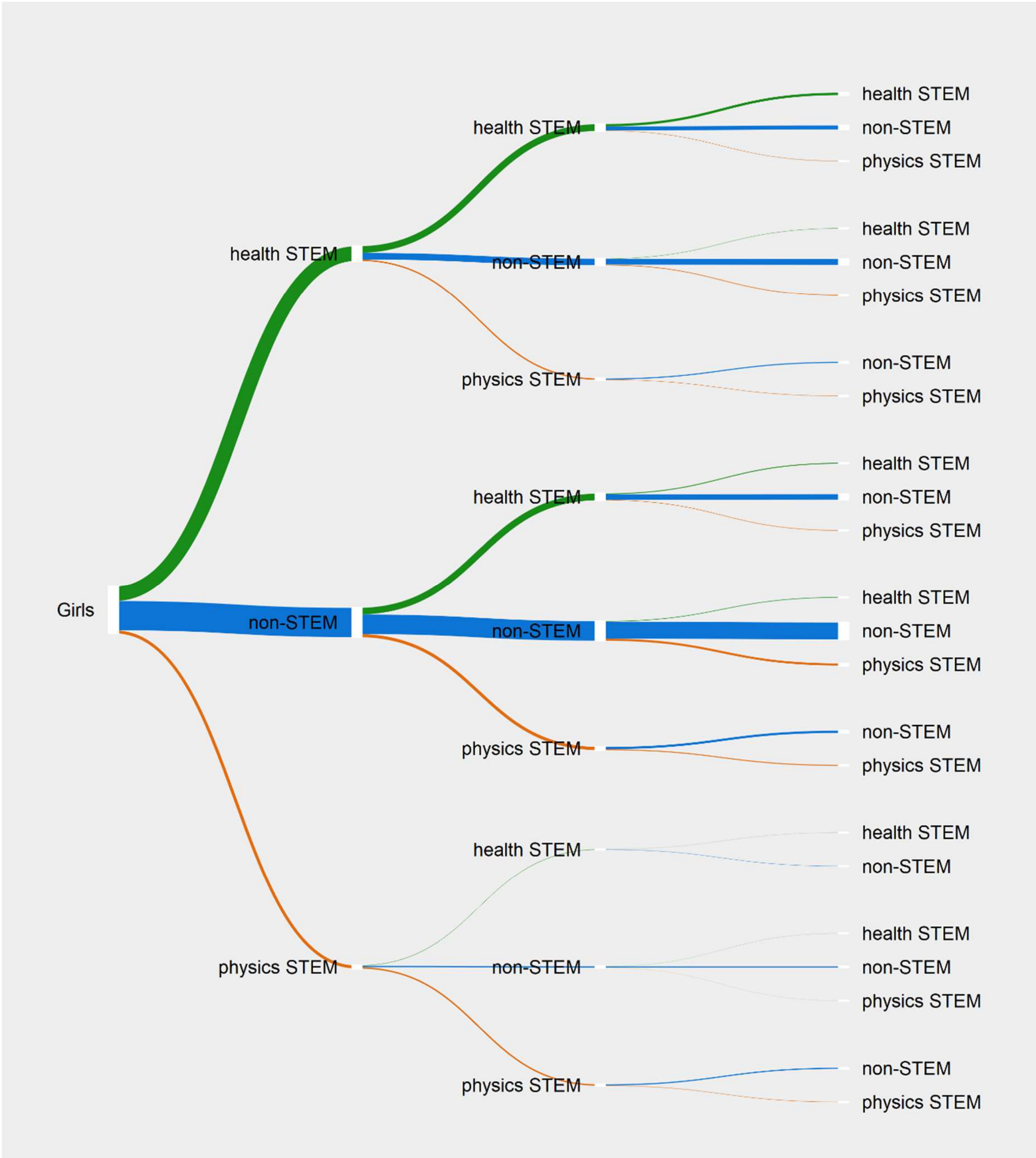

Girls
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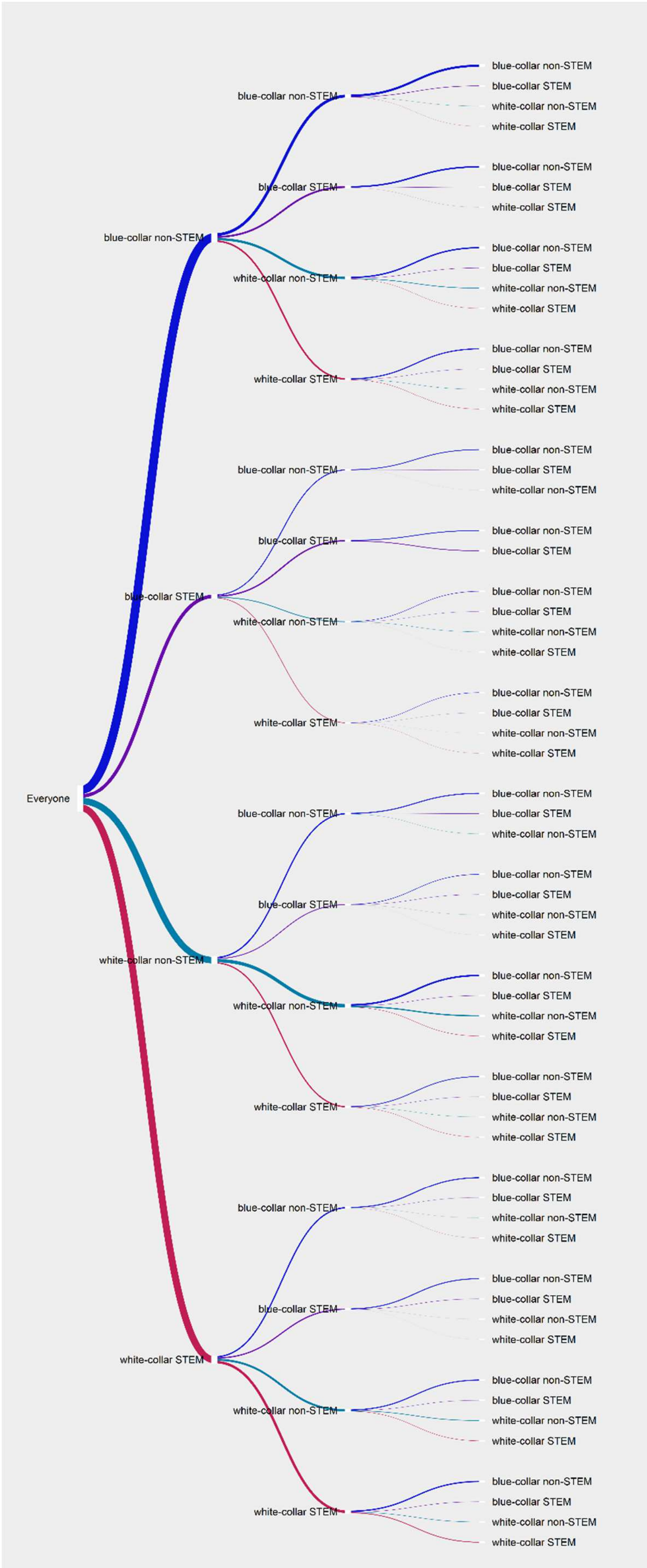
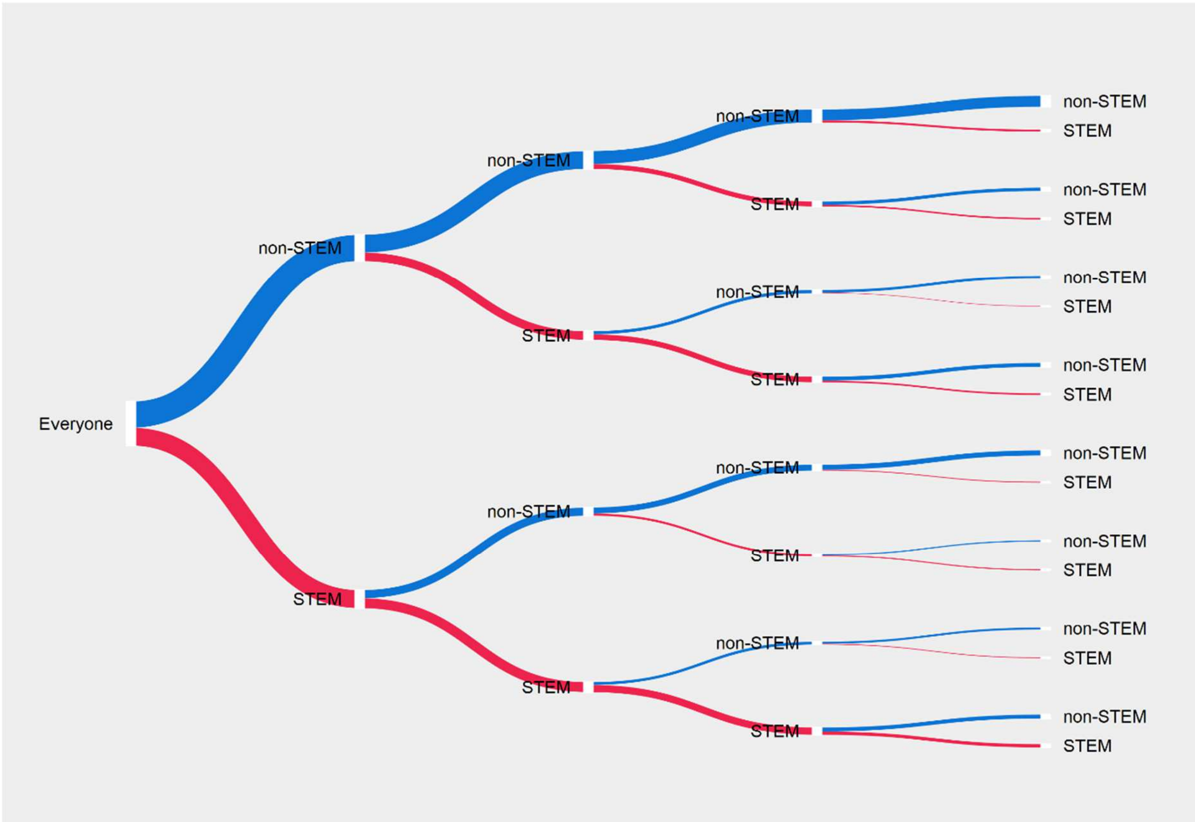

Everyone
blue-collar non-STEM
blue-collar STEM
white-collar non-STEM
white-collar STEM
blue-collar non-STEM
blue-collar STEM
white-collar non-STEM
white-collar STEM

Figure 1.5. Career paths between career aspirations at age 13 and age 19 and employment at age 25.

Trajectories (N = 978) of aspirations were grouped by (A) STEM vs Non-STEM among (B) boys and (C) girls, by (D) non-STEM, health STEM or physics STEM among (E) boys and (F) girls, and by (G) blue-collar non-STEM, blue-collar STEM, white-collar non-STEM or white-collar STEM. Participants with missing data were excluded. Each column represents one time point, and the height of branch indicates the size of subgroups.

(A)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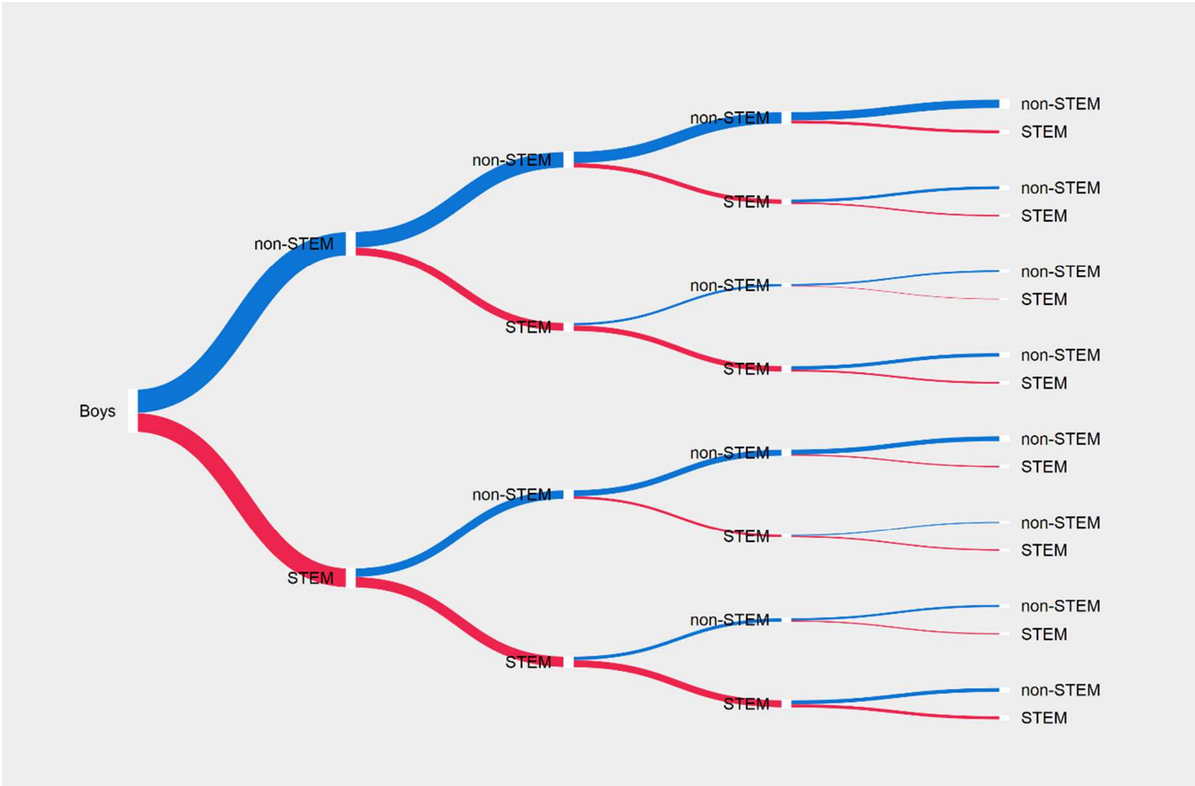
(B)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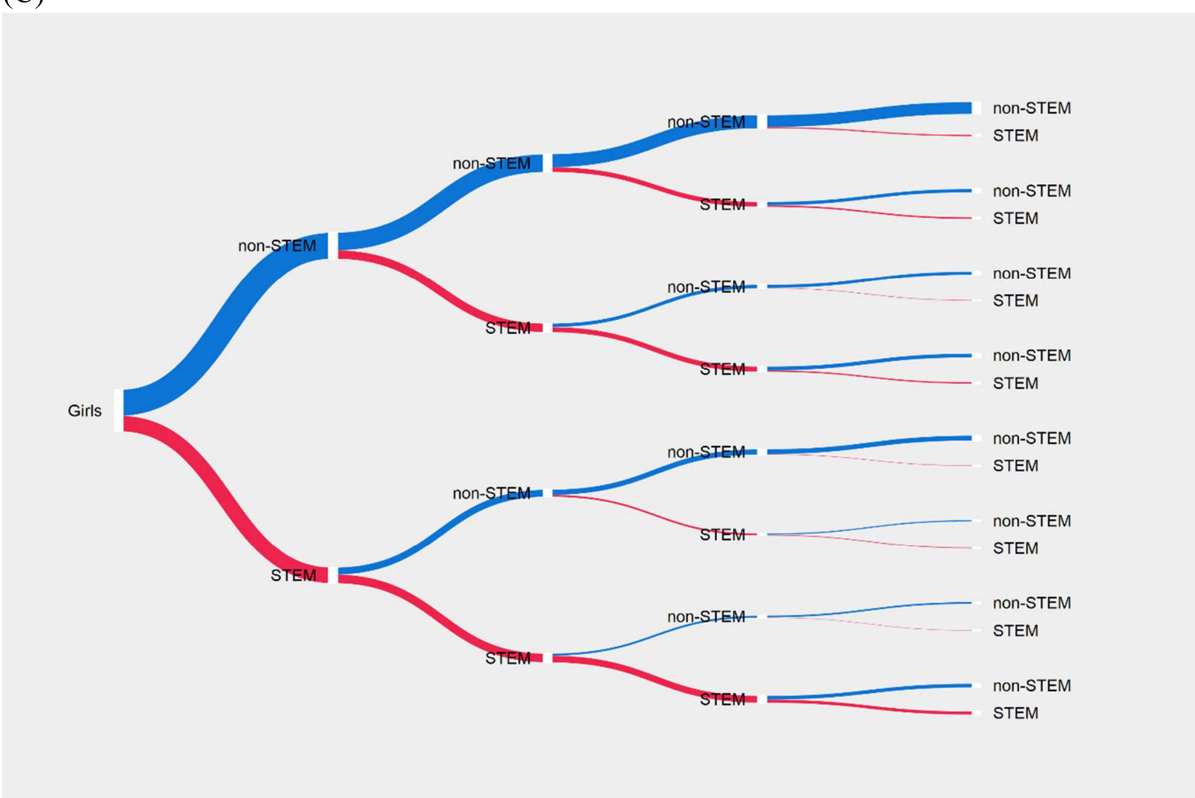
(C)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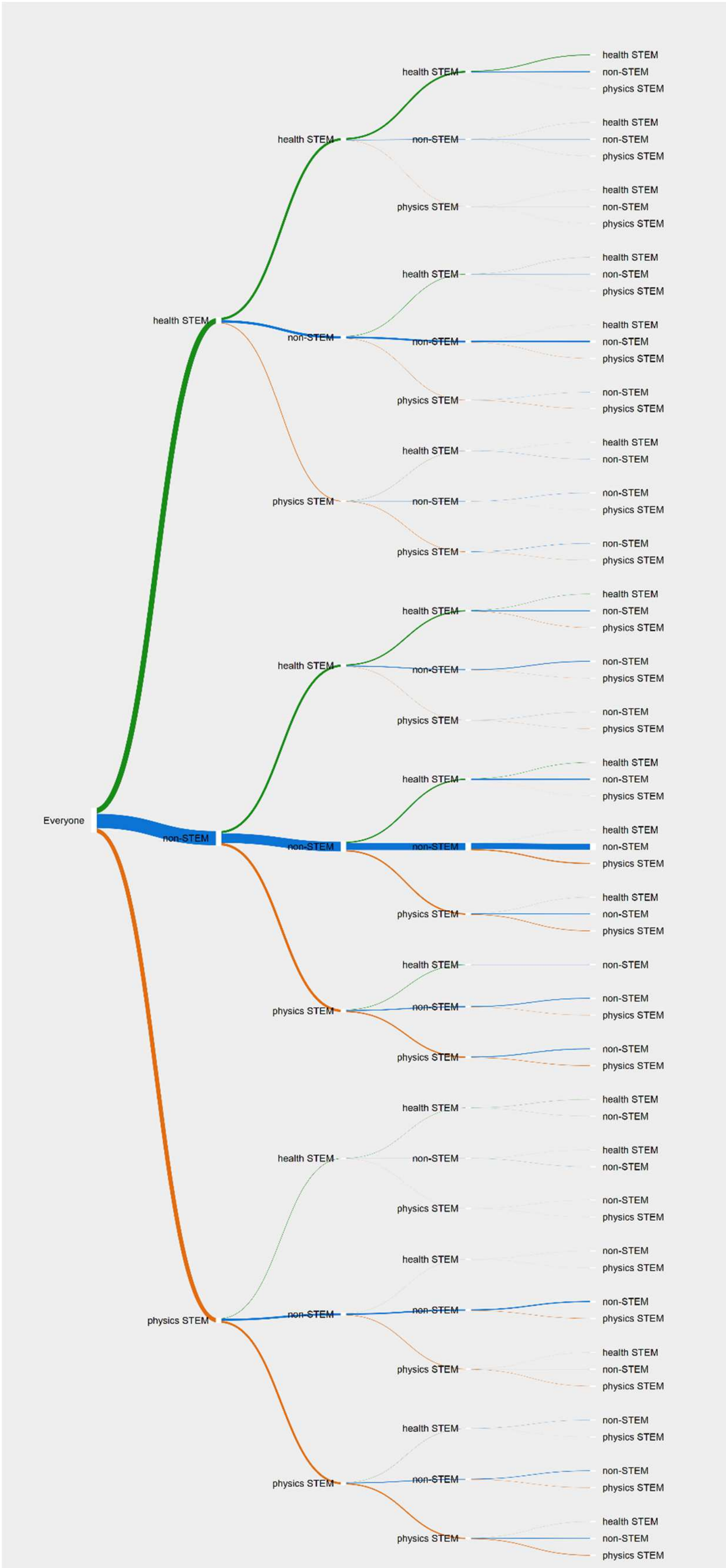
Everyone
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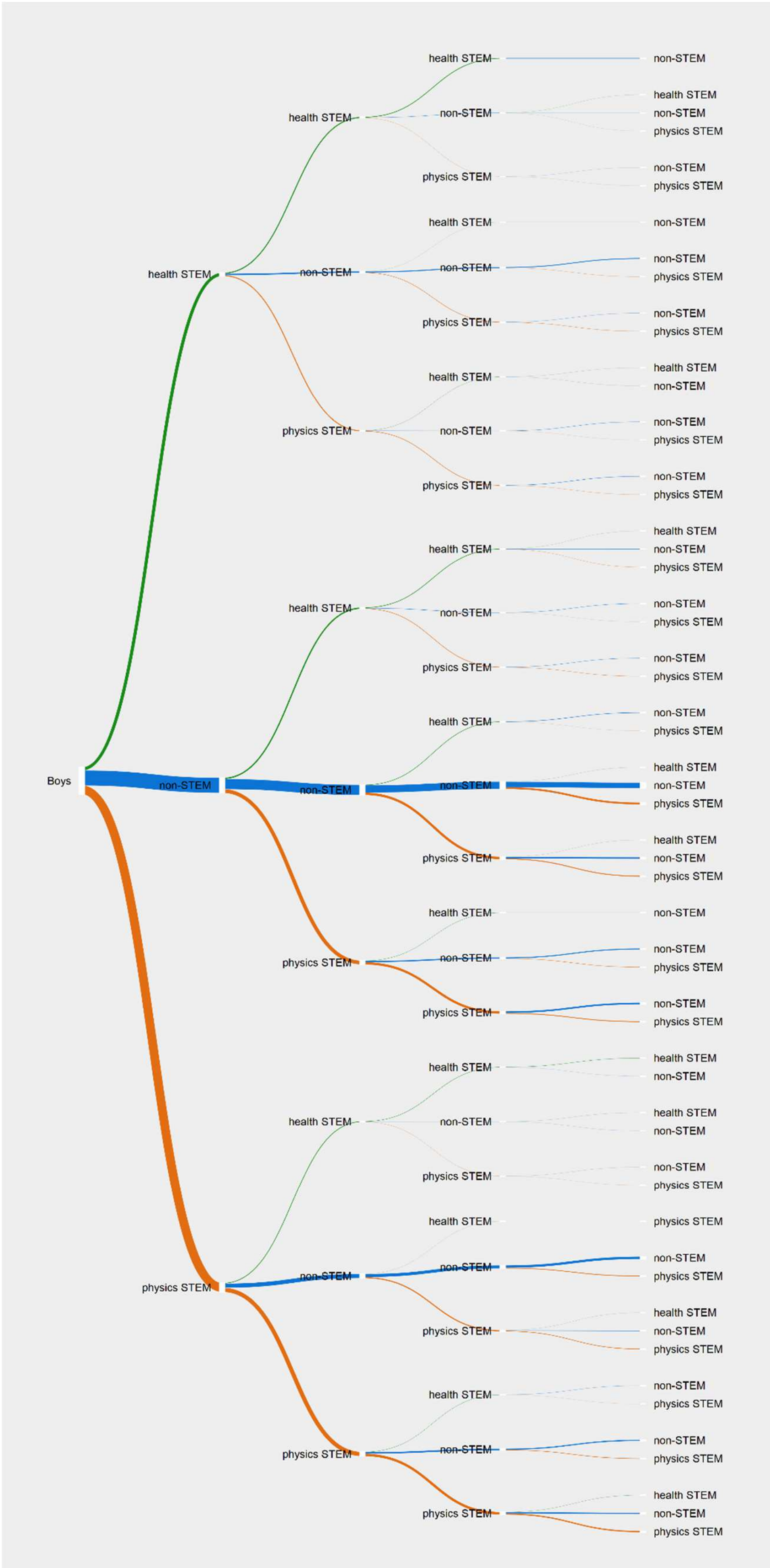
non-STEM
physics STEM

(E)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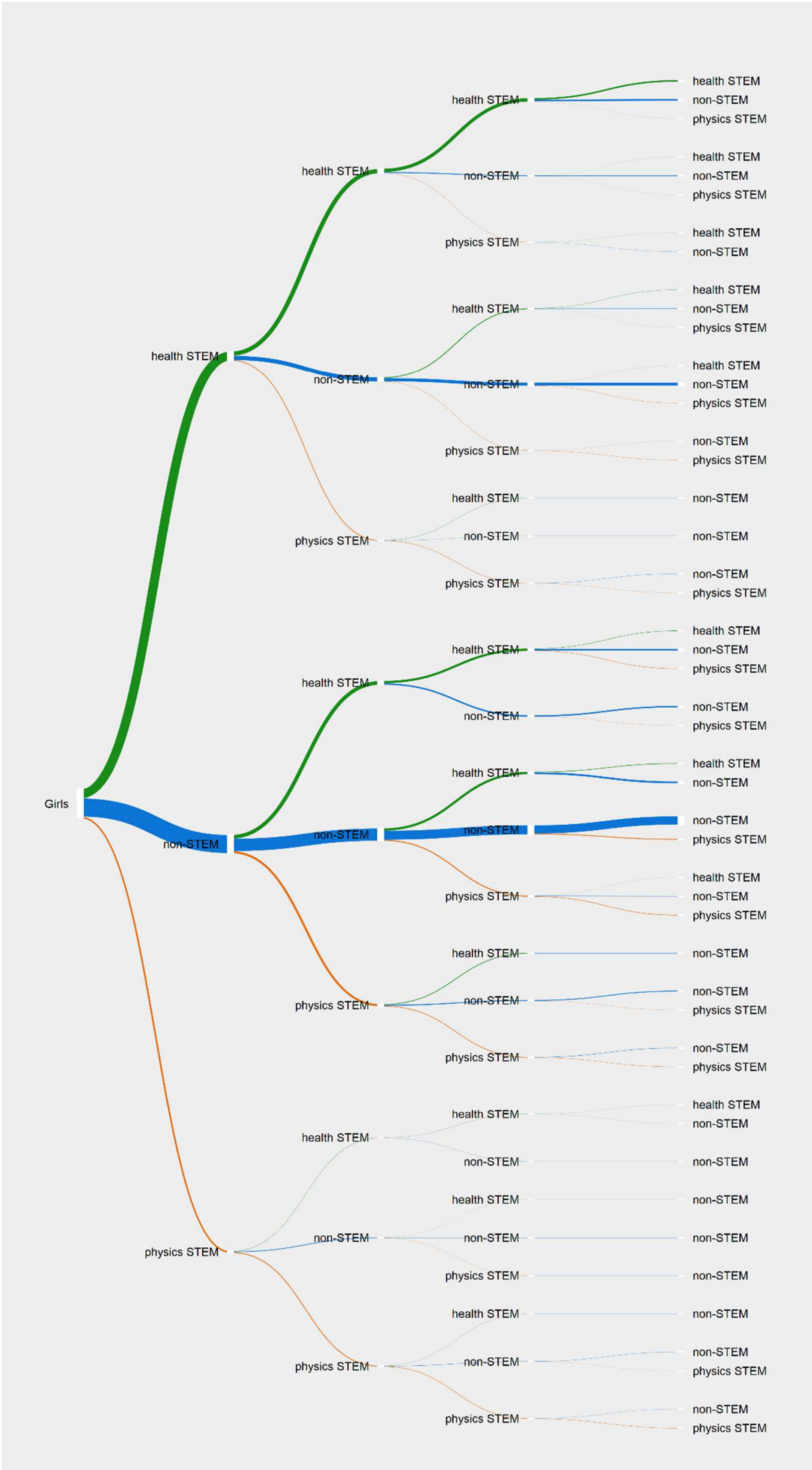

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(G)

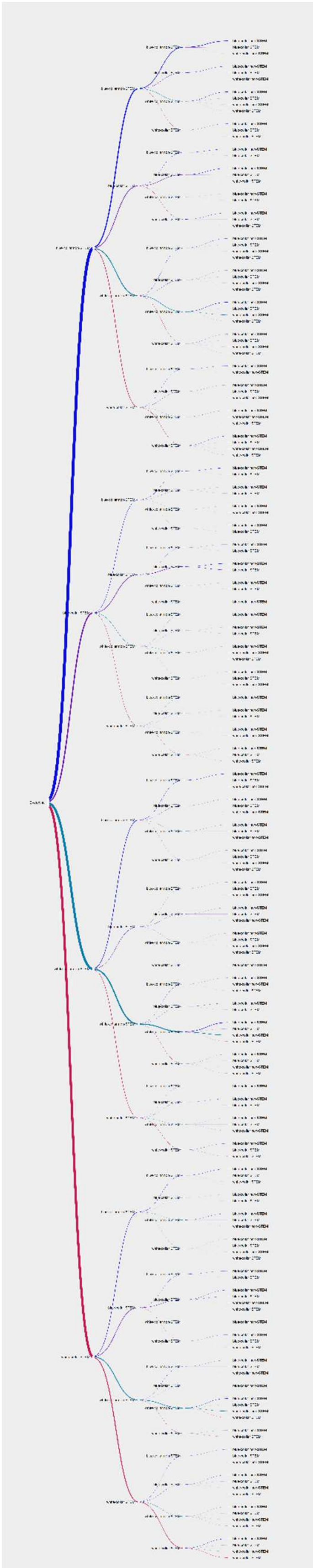

Figure 1.6. Trajectories of adolescent aspiration at age 13, age 18, age 21, and employment at age 25.

Trajectories (N = 814) of aspirations were grouped by (A) Non-STEM vs STEM among (B) boys and (C) girls, by (D) non-STEM, health STEM or physics STEM among (E) boys and (F) girls, and by (G) blue-collar non-STEM, blue-collar STEM, white-collar non-STEM or white-collar STEM. Participants with missing data were excluded. Each column represents one time point, and the height of branch shows the size of subgroups

CHAPTER 2

The Sociodemographic, Achievement and Motivational Predictors of STEM Attrition and Entry from the Perspective of the Situated Expectancy-Value Theory and the Dimensional Comparison Theory

Reducing STEM attrition has been at the center of efforts to increase the number of STEM college graduates and expand STEM labor supply. The attrition rate in STEM majors ranges from 40 to 80 percent in two-year and four-year colleges (Chen & Soldner, 2013), highlighting abundant room to improve STEM retention. Why do individuals change their career path? The Situated Expectancy-Value Theory (SEVT, Eccles & Wigfield, 2020) states that motivational beliefs are a major influence on individuals 'achievement choices, such as choice of major and occupations. Individuals are more likely to choose a career if they can see themselves succeeding in it and think it is highly valuable to them (Eccles & Wigfield, 2020; Eccles et al., 1983). At the same time, the Dimensional Comparison Theory (DCT, Möller & Marsh, 2013) focuses on the way that individuals compare their performance in and attitudes about various domains to form their hierarchy of expectancies and subjective task values (STVs). Prior studies found that higher performance in the language domain predicts lower expectancy in the math domain (Wolff et al., 2019). Taken together, these theoretical frameworks point to the key process of the within-person comparison between different options for career decision-making. STEM persistence results from the decision of whether to stay in the STEM field or to switch to a non-STEM field, so it involves the comparison between the two fields. However, there lacks evidence on the extent to which the cross-domain comparisons influence long-term career outcomes, such as changes in career paths. In this study, I will address this gap in the literature by examining this question.

Findings on STEM career trajectories also suggest that individuals also switch from non-STEM fields into the STEM field (Ma, 2011; Xie & Shauman, 2003; also see results in Chapter 2). Increasing the entrance into STEM occupations is an untapped solution to expanding the STEM labor supply. Understanding students ’motivation for this choice is an important step to encourage more entrants. Similar to the persistence decision, the entry into STEM field is another example of changes in career path that involve the intra-personal comparison of motivational beliefs for forming the choice. Therefore, I will investigate the motivational factors both STEM entry and attrition choices as two examples of the same topic of STEM career changes.

Theoretical Framework

The Situated Expectancy-Value Theory

The Situated Expectancy-Value Theory (SEVT) delineates why individuals choose their careers as they do. Beliefs about one’s ability to do well in a given career, namely expectancy, and the subjective task values of a career option are proximal psychological determinants of individual career choices (Eccles et al., 1983; Wigfield & Eccles, 2000). Individuals are more likely to take a career that they believe they can do well in, and that they deem as valuable and important to them. The expectancy and subjective task value beliefs are formed based on the individual’s unique characteristics (e.g., gender, race/ethnicity, birth order, temperament) and through the person’s socialization experiences in their sociocultural context over time.

In SEVT, Eccles and Wigfield (2020) specified the inherent comparison among career options in the process of career choices. Among the career options that are available to the individual at a particular time point, the person evaluates each option, with some options affording higher expectancy for success and subjective task values overall than other options. As a result, various career options differ in their likelihood of being chosen based on individuals' relative expectancy for success and subjective task values. This comparison process is embedded in the decision-making process of selecting a career path. When multiple career options are available, the within-person comparison will give rise to a hierarchy of career choices based on the individual's hierarchy of expectancies and STVs for each option. The person might not always create a neatly differentiated ranking in their mind, but they are probably able to report their most and least favored options. When considering whether to change career paths, the choice is between continuing the original career versus switching into a different path.

The Dimensional Comparison Theory

The Dimensional Comparison Theory (DCT, Marsh, 1986; Möller & Marsh, 2013) states that the formation of domain-specific competence beliefs is shaped by a within-person comparison of performances across different domains. An individual will have higher expectancy about their ability in domain A if they perceive themselves doing better in domain A than domain B. As a result, the cross-domain comparison reinforces the relative advantage in domain A and thus leads to the differentiation of the person's expectancy in different domains. Comparison between domains that are similar to each other strengthens the competence beliefs in these domains, where the competence beliefs of dissimilar domains are formed in competition with one another. Prior findings show that physics performance is positively associated with math expectancy, and vice versa, whereas reading performance is unrelated or negatively associated with math expectancy (Gaspard et al., 2018; Marsh et al., 2015). Therefore, differential attitudes about physics and math subjects might lead individuals to switch careers within the STEM field, but the contrast between math and reading may involve changes between STEM and non-STEM fields.

DCT is originally developed to explain the formation of competence-related beliefs. Recent studies have shown some effects on STVs. Math performance negatively relates to reading values, and reading performance negatively relates to math values (Gaspard et al., 2018; Guo et al., 2017; Lazarides & Lauermann, 2019). Individuals knowing that they can do well in a domain are likely to enjoy activities in the domain. Individuals considering a domain important, enjoyable or useful to them are likely to have decent performance in the domain. A handful of studies in recent years aim to bridge SEVT and the DCT by showing that the cross-domain comparison of expectancy and STVs affect career choices (Guo et al., 2017; Lauermann et al., 2015; Nagy et al., 2006). This study extends such investigations to career trajectories.

Math-Reading Comparisons of Achievement and EV Beliefs and Their Influences on STEM choices

Analyses on the implications of the within-person, cross-domain comparison on career choices has accumulated in recent years. Yet, the research is in its beginning stage.

Math and reading achievement

Math performance has been established as an important predictor of STEM course enrollment, major selection, degree attainment, career choices and persistence in numerous studies (Ackerman et al., 2013; Crisp et al., 2009; Crombie et al., 2005; Gottlieb, 2018; Wang, 2013; Watt et al., 2017). Between math and language domains, researchers found that from 10th to 12th grade in high school, higher reading achievement predicted lower intentions to choose math-intensive majors in college and less enrollment in advanced math courses (Nagy et al., 2008; Parker et al., 2012). In contrast, higher math achievement predicted lower likelihood of enrolling in advanced language course (Nagy et al., 2008).

One study (Wang et al., 2013) on the latent profiles of math and reading achievement showed that reading achievement moderated the influence of math achievement on STEM career choices. High school students who achieved high performance in both math and language subjects were *less* likely to work in STEM occupations at age 33 than their peers who had high math achievement and moderate language achievement (Wang et al., 2013), indicating the interactive effect of math and reading achievement on STEM career outcomes. Specifically, the comparative achievement advantage in math relative to that in language domain might be more influential than high math achievement *per se* for STEM choices. In this study, I extended this strand of literature by examining the relation between math and reading achievement and STEM career trajectories. Specifically, I tested both the unique and interactive effects of math and reading performance and STEM attrition and STEM entry.

Math and reading expectancy

Math competence-related beliefs, such as math self-efficacy, math self-concept of ability, math expectancy, have been consistently found to associate with STEM achievement and career choices (e.g., Eccles & Wang, 2016; Parker et al., 2012; Sax et al., 2015; Simpkins et al., 2006). Evidence for the importance of math expectancy on STEM persistence has also been reported. Individuals with greater math expectancy were more likely to carry on STEM careers over time (Ackerman et al., 2013; Dika & D'Amico, 2016; Maltese & Tai, 2011).

Studies based on DCT with expectancy beliefs in math and reading supported the cross-domain effect of math and reading expectancy on STEM career choices. Higher language expectancy predicted lower intention and likelihood to take advanced math courses in high school (Jansen et al., 2021; Nagy et al., 2008). In terms of the choice of college major, higher math expectancy predicts lower likelihood of enrolling in verbal-intensive major in college

(Parker et al., 2012). The cross-domain interaction effect of expectancy beliefs has also been documented. Lauermann and colleges (2015) showed that math expectancy positively related to high school students ’plans to take on math-intensive career, whereas the relation was negative between reading expectancy and the career plans. Moreover, they found a negative interaction effect of math expectancy and reading expectancy on math-intensive career plans, such that the effect of math expectancy on math-intensive career plans was weaker if the students had high reading expectancy. No interactive effect was found for the choices of verbal-intensive career plans. In the present study, I examined whether findings above about the cross-domain effect of math and reading expectancy can be extended to STEM trajectories, in form of both the main effect and interactive effect.

Math and reading values

Math values directly influence STEM major selection and career plans. Students who are interested in studying math take more math courses in high school and are more likely to choose STEM majors in college (Maltese & Tai, 2011; Simpkins et al., 2006; Toh & Watt, 2022). Other value components, such as math utility value and math attainment value, have also been found predictive of STEM career choices (Crombie et al., 2005; Watt et al., 2017).

The effect of cross-domain comparison of values on career outcomes has been found in only a handful of studies. Across math and language domains, higher interest in language predicted less enrollment in advanced math courses (Nagy et al., 2008). Between math and biology, higher interest in Biology predicted less advanced math course enrollment (Nagy et al., 2006). English STV was negatively related to math-intensive career plans (Lauermann et al., 2015). However, findings on the differential effect of subjective task value on STEM career choices are not rare. One study on the association between language STVs and later math course enrollment did not find evidence of a negative association as hypothesized (Jansen et al., 2021). In another study, Lazarides and Lauermann (2019) used cross-lagged models to examine the within and across time association between math utility value and STEM career plans. They only found the cross-domain comparison effect within time (i.e., cross-sectional correlation) but not over time (i.e., longitudinal prediction). Lazarides and Lauermann (2019) also tested the association between interest and STEM career plans, but they did not find any cross-domain effect of interest.

In sum, performances and expectancies in math and reading domains has been found to negatively impact career choices in the other domain. Evidence has also suggested that the influence of math performance or expectancy on STEM career choices would be weakened by high reading performance or expectancy. These findings have been extended to math and reading STVs recently with mixed results. In this study, I used the rationale of this strand of literature to examine the effect of dimensional comparison of math and reading performance and motivational beliefs on movements into and out of STEM careers.

Sociodemographic differences in STEM entry and persistence

Sociodemographic characteristics, such as gender, underrepresented minority (URM) status, and family socioeconomic status (SES), are related to the likelihood of entering or leaving the STEM field.

Gender

Although consistent evidence suggests that women are underrepresented in many STEM fields (e.g., Ceci et al., 2014), less agreement has been reached about to what extent women leave STEM more often than men. One national study on U.S. college students in both two-year and four-year postsecondary institutions showed that a higher proportion of women who declared a STEM major in their first year graduated with non-STEM degrees than men who initially declared a STEM major did (Chen & Soldner, 2013). In another national study on high school students, girls who intended to major in STEM fields more often switched to non-STEM fields in college than boys with the same STEM major plan did (Shaw & Barbuti, 2010). The similar gender differences were observed in boys' and girls' STEM career aspirations during high school (Saw et al., 2018). However, some researchers found the lack of such gender differences in persistence. In one national longitudinal study, Ma (2011) found that college women were just as likely to persist in STEM majors as men did after declaring STEM majors in their first year. Similarly, another national study on college STEM students showed gender similarity in STEM persistence rate (Chen, 2009).

Furthermore, investigations on how much of the gender differences in STEM attrition, when present, could be explained by differences in achievement and motivation has generated mixed findings too. Some studies supported a lack of gender differences after prior math achievement and expectancy were taken into account (e.g., Ackerman et al., 2013; Chen & Soldner, 2013), whereas others provided contradictory evidence (e.g., Ellis et al., 2016; Ma, 2011; Mau, 2003). Therefore, more evidence is necessary to clarify whether men and women differ in STEM persistence, and if they do, to what extent the difference exists net of students' prior performance and motivation. One limitation of these explanatory studies on gender differences in persistence is that math STV has been overlooked. Most of the studies only used math achievement and math competence-related beliefs (e.g., math self-efficacy, confidence in math abilities) to predict STEM persistence, leaving out the important motivational factor of how valuable math is to the individuals as theorized in SEVT (Eccles & Wigfield, 2020; Eccles et al., 1983). Another limitation is that the reading domain has been rarely taken into account. When

STEM attrition is conceptualized in the individual context of the student based on the SEVT and the DCT (Eccles & Wigfield, 2020; Möller & Marsh, 2013), the change in career path involves comparing other career options with those in STEM. Previous findings suggested that girls were more likely than boys to be competent in both math and reading domains (Wang et al., 2013), so performance and motivation in language domain may be particularly influential to explain the potential gender differences in STEM attrition.

URM

Nationally, White and Asian students have been proportionally over-represented in STEM college graduates (National Center for Education Statistics, 2019). Hispanic and Black students leave STEM majors more often than their White and Asian peers (Chen, 2009; Chen & Soldner, 2013; Saw et al., 2018; Shaw & Barbuti, 2010). Disparities in academic preparedness and family SES can explain a substantial amount of the racial/ethnic gap in STEM persistence (Chen & Soldner, 2013). Riegle-Crumb and King (2010) showed that with the same amount of STEM courses and test scores in high school, Black boys would have been twice likely as White boys to choose a Physics/Engineering major in college, and Black girls would have been equally likely as White girls to major in these fields. Similarly, Ma and Liu (2017) found that the racial gap in STEM degree attainment would have been flipped with Black men most likely to earn STEM degrees had they had the same level of family SES and academic preparation as Asian men. One limitation of these studies is the focus on college students. As a result, the findings may be limited to the selected group of students in universities and the process of choosing a college major. In addition, because Black and Hispanic students have a lower college enrollment rate (National Center for Educational Statistics, 2013), the URM students and the non-URM students in a college sample may not be equivalent. To address this issue, I used career aspirations in early adolescence and occupation in mid-20s to obtain a more inclusive sample. Moreover, most of the studies pertained to the selection of STEM majors rather than persistence. In this study, I tested the racial/ethnic differences in STEM career persistence to expand the literature.

Family SES

Family SES is profoundly intertwined with race/ethnicity in the US, so distinguishing the two sociodemographic characteristics in analyses is key to clarifying race/ethnicity differences. More importantly, family SES affects STEM career choices directly or indirectly. National studies showed that students from families of lower SES were less likely than their peers from families of higher SES to choose and graduate in STEM majors (Chen, 2009; Niu, 2017). The SES-based disadvantages manifest in the limited provision of resources and experience that cultivate STEM interest, competence-related beliefs, and achievement (MacPhee et al., 2013; Miller & Kimmel, 2012). Adolescents from disadvantaged backgrounds seldom see STEM careers as a tangible path for their future (Archer et al., 2012). Studies showed that students from families of lower SES were less likely to maintain STEM career aspirations in high school (Saw et al., 2018). In college, first-generation college students switched out of STEM majors more often than continuing-generation college students did (Shaw & Barbuti, 2010). It remains unclear to what extent these differences exist after controlling for students 'STEM motivation and achievement. I aimed to answer this question by testing the unique influence of family SES on STEM persistence in this study.

In sum, the influences of gender, URM status, and family SES on STEM career paths have been supported in previous studies, but more information is needed to understand the ways in which these characteristics influence changes in STEM paths. Some evidence has shown that these sociodemographic characteristics affect STEM attrition in ways additional to their indirect influence on students' STEM achievement and motivation, but findings are mixed. Furthermore, research on STEM entry is still in its early stages. Understanding this trajectory can help expand an understudied career paths into STEM and support students on their way to realizing their STEM career goals.

The Present Study

In the present study, I investigate the sociodemographic, achievement and motivational predictors of changes in STEM career paths from age 13 to age 25. I focused on the association of these predictors with STEM entry and with STEM attrition. I aim to answer two research questions with my analyses:

RQ1: To what extent do sociodemographic characteristics (i.e., gender, URM status and parent education), math and reading performances, and math and reading expectancies and STVs relate to STEM entry?

RQ1a: To what extent do individuals taking the STEM entry path differ from individuals taking the non-STEM path, regarding their sociodemographic characteristics (i.e., gender, URM status and parent education), math and reading performances, and math and reading expectancies and STVs?

RQ1b: To what extent does each of the sociodemographic characteristics (i.e., gender, URM status and parent education), math and reading performances, and math and reading expectancies and STVs uniquely predict STEM entry relative to a non-STEM path?

RQ2: To what extent do sociodemographic characteristics (i.e., gender, URM status and parent education), math and reading performances, and math and reading expectancies and STVs relate to STEM attrition?

RQ2a: To what extent do individuals taking the STEM attrition path differ from individuals taking the STEM persistence path, regarding their sociodemographic characteristics (i.e., gender, URM status and parent education), math and reading performances, and math and reading expectancies and STVs?

RQ2b: To what extent does each of the sociodemographic characteristics (i.e., gender, URM status and parent education), math and reading performances, and math and reading expectancies and STVs uniquely predict STEM attrition relative to STEM persistence?

Hypotheses

Based on studies by Chen and Soldner (2013) and Shaw and Barbuti (2010), I hypothesize that men, non-URM individuals, and individuals from families of higher SES are more likely to persist in and enter STEM than women, URM individuals, and individuals from families of lower SES. However, I hypothesize that these differences will disappear after taking into account of individuals 'performance, expectancy and STV beliefs in math and reading domains, according to the studies by Ackerman and colleagues (2013), by MacPhee and colleagues (2013), and by Riegle-Crumb and King (2010).

Regarding the cross-domain comparisons of performance and motivation, I hypothesize the predictors in math and reading will affect STEM attrition and STEM entry uniquely and interactively. Specifically, I hypothesize that math performance, expectancy, and STV would predict higher likelihood of STEM entry and lower likelihood of STEM attrition, and that reading performance, expectancy and STV will predict lower likelihood of STEM entry and higher likelihood of STEM attrition, based on the studies by Nagy and colleagues (2008), by Simpkins and colleagues (2006) and by Watt and colleagues (2012). In addition, I hypothesize the cross-domain interaction terms between math and reading performance, between math and reading expectancy, and between math and reading STVs respectively, will weaken the positive effect of math performance and motivation on STEM persistence and entry, based on the findings of Lauermann and colleagues (2015) and of Wang and colleagues (2013). That is, these interaction terms will negatively predict the likelihood of STEM entry and positively predict the likelihood of STEM attrition.

Methods

Participants

The same sample in chapter 2 was used in this study. Participants are 1026 adolescents in the original cohort of the Child Development Supplement (CDS) of the Panel Study of Income Dynamics (PSID) launched in 1997 (54% girls; 47% White, 42% Black, 7% Latino, 1% Asian, 3% other; average age in 2002 = 13.08 years old [SD = 1.94]).

Measures

Variables used in logistic regression models include STEM career trajectories, participants 'sociodemographic background, prior achievement, expectancy and STV in math and reading domains.

STEM career trajectories

A myriad of STEM career trajectories between age 13 and age 25 were found in Chapter 2. Two pairs of trajectories were chosen for the purpose of this study. To investigate the decision to enter the STEM field, the trajectory of a non-STEM career aspiration at age 13 followed by a non-STEM employment at age 25 ("no STEM") and the trajectory of a non-STEM career aspiration followed by a STEM employment ("STEM entry") were used. To investigate the decision to leave the STEM field, the trajectory of a STEM career aspiration followed by a

STEM employment ("STEM persistence") and the trajectory of a STEM career aspiration followed by a non-STEM employment ("STEM attrition") were used. The two trajectories in each pair shared the same starting point at age 13, making them developmentally comparable at the beginning of their career paths and thus strengthening the conclusions about predictors of changes in STEM career paths.

Expectancy and STV beliefs

Adolescents' expectancy-value beliefs in math and reading domains were used. They were measured at age 13 at the same time as the career aspirations. Both the expectancy and the STVs were measured with 7-point Likert scale items. Measurements included 6 items on expectancy (e.g., "Compared to most of your other school subjects, how good are you at math?") and 4 items on STVs (e.g., "How much do you like doing math?"). The instruments for math and reading domains matched on their items and response scales. These items were developed by scholars theorizing the SEVT and the Dimensional Comparison theory (Eccles et al., 1993; Marsh, 1990), so the operationalization was closely aligned with the conceptualization of the competence belief and STV constructs (Eccles & Wigfield, 1995; Wigfield & Eccles, 1992). These items have been used in SEVT studies (Lazarides et al., 2021; Simpkins et al., 2006; Watt et al., 2012) as well as the DCT studies (Lazarides & Lauermann, 2019; Wolff et al., 2019) to examine the developmental trajectories of EV beliefs and their association with achievement choice outcomes. The Cronbach's alpha of math expectancy, math STV, reading expectancy and reading STV scales ranged from .69 to .84, indicating satisfactory inter-item reliability of all the scales.

Prior achievement

Adolescents 'achievement in math and reading domains was assessed by the Woodcock-Johnson Test in 1997, five years prior to the measurement of career aspirations and motivational beliefs. The Woodcock-Johnson Test is a set of standardized tests to measure the normative development of children's cognitive abilities and academic achievement (Woodcock et al., 1989). The reading domain consisted of the sections of Letter-Word Identification and Passage Comprehension, and the math domain consisted of the sections of Calculation and Applied Problems. A score for each of the math and reading domains was given based on the number of correct items completed. The scores were standardized with a national average of 100 with a standard deviation of 15. Children's age at the time of testing was taken into account in the scoring protocol. Thus, these measures provide an indication of each child's competence relative to their age mates at that point in time. Evidence from a variety of studies has demonstrated very high across time stability in these assessments (Bornstein et al., 2014; Shull□Senn et al., 1995).

Sociodemographic background

Sociodemographic background measures included gender, URM status, parent education and age. Gender and race/ethnicity were reported in 1997, at the same time as achievement was measured. Age and parent education were collected in 2002, at the same time when adolescents ' first career choice was measured. Gender was a binary variable (0 = male, 1 = female). URM status (0 = non-URM, 1 = URM) was created based on adolescents 'race/ethnicity, with "White", "Asian and Pacific Islander" coded as non-URM, and "Black", "Hispanic", "American Indian", "Alaska Native" and "Other" coded as URM. Parent education was measured as the number of years of formal schooling that adolescents 'parents received. When information of both parents was available, the higher number between the parents was used.

Analyses

Descriptive analyses were conducted as the first step. Group differences in sociodemographic compositions, achievement and motivation between two pairs of trajectories were examined. The first pair included non-STEM and STEM entry trajectories, and the second pair included STEM attrition and STEM persistence paths. Independent t-tests were used for continuous variables, and Chi-square Test of Independence was used for categorical variables.

Logistic regressions were used to test the association between sociodemographic background, achievement and motivation predictors and STEM career trajectories. Two pairs of trajectories were contrasted as the outcome. In the first pair, the STEM entrance trajectory (coded as 1) was contrasted with the "no STEM" trajectory (coded as 0) to examine to what extent sociodemographic, achievement or motivational factors predicted the entrance into the STEM field. In the second pair, the STEM attrition trajectory (coded as 1) was contrasted with the STEM persistence trajectory (coded as 0) to examine factors predicting attritions from the STEM field.

Seven models were tested for each contrast. Model 1 comprised of sociodemographic variables and domain-specific performance. Model 2 added expectancy beliefs in math and reading domains. Model 3 substituted expectancy beliefs with STV beliefs in both domains. Model 4 to 6 tested the cross-domain interaction terms. Model 4 was built on Model 1, with the addition of the interaction between math and reading performance. Model 5 was built on Model 2, with the addition of the interaction between math and reading expectancy. Model 6 was built on Model 3, adding the interaction between math and reading STV. Model 7 included all predictors, which were sociodemographic background, achievement, expectancy and subjective task value in both domains, and the three cross-domain interaction terms. Participants 'age was included in all of the models to control for the multiple cohorts in the original study. Continuous predictors were mean centered before being entered into regression models. Cross-domain interaction terms for achievement, expectancy and subjective task values were created with the centered terms. Multiple imputations and following regression analyses were conducted in Stata 14 SE.

Multiple Imputations

The amount of missing data on predictor variables ranged from 0 to 16 percent of the sample size. As a result of the sample selection criteria of the study in chapter 2, everyone in the sample had a non-missing value on the outcome indicators of STEM career trajectory. Two state-of-art strategies to handle missing data are multiple imputations, and the Full Information Maximum Likelihood (FIML) estimates. Although FIML can be automatically executed in Mplus software when missing values are present in exogenous variables, the combination of binary outcomes and continuous predictors in this study does not fulfill the assumption of multivariate normal distribution of exogenous variables of FIML (Enders, 2001). As an alternative, FIML with Bayesian statistics, which does not require such assumption, was explored. However, model convergence was not reached in several attempts, meaning that the estimates were not reliable. Therefore, FIML was ruled out from consideration.

Variables with missing data were URM status, math and reading achievement, math and reading expectancy and math STV. Two later waves of math and reading achievement, an earlier wave and a later wave of math and reading expectancy-value beliefs, family income and school aspiration (i.e., highest level of schooling/degree desired to have) at age 13 were selected to impute missing values on predictor variables. MI by chained equations was selected compared to

MI with multivariate normal distribution for its accommodation of categorical variables in the model. Diagnostic parameters suggest MI yielded high quality estimates.

Results

Four trajectory groups are shown in Figure 2.1. At age 13, 612 adolescents aspired to non-STEM occupations: 79 percent of them worked in non-STEM jobs by age 25 ("non-STEM path", n = 484) and 21 percent switched to work in STEM jobs ("STEM entry" trajectory, n = 128). A total of 414 adolescents aspired to STEM occupations at age 13: 69 percent left STEM and worked in non-STEM jobs by age 25 ("STEM attrition", n = 287) and 31 percent continued to work in STEM field ("STEM persistence", n = 127).

Group differences in sociodemographic characteristics, achievement and motivation

Descriptive statistics of each trajectory were shown in Table 2.1. Pairwise correlations were shown in Table 2.2.

Non-STEM vs STEM entry

Chi-square Test of Independence (Table 2.1) showed group differences in the gender, χ^2 (1, N = 612) = 9.06, p = .003, Cramer's V = .12, and URM composition, χ^2 (1, N = 611) = 9.63, p = .002, Cramer's V = .13. More women and more URM appeared in the non-STEM group than expected by chance, and these groups were underrepresented in the STEM entry trajectory. The STEM entry group had higher levels of parent education, $t(582) = 2.45$, p = .02, Cohen's d = .25 (non-STEM: M = 13.18, SD = 2.56; STEM entry: M = 13.81, SD = 2.59), math performance, $t(529) = 2.96$, p = .003, Cohen's d = .32 (non-STEM: M = 101.58, SD = 16.46; STEM entry: M = 106.84, SD = 17.42), and lower math STV, $t(610) = 2.39$, p = .02, Cohen's d = .24 (non-STEM: M = 4.67, SD = 1.22; STEM entry: M = 4.38, SD = 1.27), than the non-STEM group.

STEM attrition vs STEM persistence

As shown in Table 2.1, STEM attrition group differed from the STEM persistence group in gender, χ^2 (1, N = 414) = 3.91, p = .05, Cramer's V = .10, and URM composition, χ^2 (1, N = 412) = 18.00, p < .001, Cramer's V = .21. More women and more URM were present in the STEM attrition group, and they were underrepresented in the STEM persistence group. The STEM attrition group had lower levels of parent education, t(384) = 2.49, p = .01, Cohen's d = .28 (STEM attrition: M = 13.17, SD = 2.45; STEM persistence: M = 13.83, SD = 2.14), and math performance, t(336) = 2.47, p = .02, Cohen's d = .29 (STEM attrition: M = 103.54, SD = 17.53; STEM persistence: M = 108.47, SD = 15.48). The STEM attrition group also had higher levels of math STV, t(411) = 2.80, p = .005, Cohen's d = .30 (STEM attrition: M = 4.93, SD = 1.21; STEM persistence: M = 4.56, SD = 1.26), and reading STV, t(412) = 3.91, p < .001, Cohen's d = .42 (STEM attrition: M = 5.33, SD = 1.10; STEM persistence: M = 4.85, SD = 1.25), than the STEM persistence group.

Logistic regressions predicting STEM entry

Consistent across models, gender and URM status were associated with STEM entry relative to a non-STEM path (Table 2.3). Men were nearly two times more likely than women to enter STEM occupations relative to staying in non-STEM field, with other sociodemographic factors, math and English performance, and EV beliefs in math and reading domains held equal. Similarly, with other factors being equal, URM were approximately half as likely as non-URM to enter STEM field. In model 3 and model 6, math STV at age 13 was negatively associated with the likelihood to enter STEM. One-point increase in math STV score predicted 0.19 (1 – 0.81) times decrease of the likelihood to enter STEM. None of the cross-domain interaction terms in performance or EV beliefs were statistically significant.

Logistic regressions predicting STEM attrition

Across models (Table 2.4), URM status was consistently associated with the likelihood of STEM attrition. When sociodemographic characteristics, performance and motivational beliefs were held constant in the model, URM individuals were more than twice as likely as non-URM to leave their STEM aspirations for non-STEM occupations. No achievement, motivational or other sociodemographic factors were statistically significant predictors of STEM attrition.

Inspections into the negative association between math STV and STEM entry

The negative association between math STV and STEM entry, indicating that the more valuable math is to the participants at age 13 the less likely it is for them to switch into STEM field by age 25, contradicted my hypothesis based on the SEVT. The possibility of data error was ruled out after careful examination. Considering that the membership in the STEM entry group is associated with gender and URM status, questions were asked whether gender or URM status can help explain the unexpected pattern. To examine this possibility, the original logistic regression model was run in separate gender and URM status groups with a total of four models, one each for men and women (Table 2.5), for URMs and non-URMs (Table 2.6). The cross-domain interaction term of math and reading STV was omitted from this step of analysis because it was not found to predict the outcome in the original model. The results for gender and URM status subgroups are displayed in Table 3.5 and Table 3.6. Gender subgroup analyses models yield discrepancy in more predictors than expected (Table 2.5). Among women, math STV was not related to the entry into STEM at age 25, but parent education became predictive with marginal statistical significance. The parameter indicates that among women, one year increase in their parents 'education level predicted 1.14 times increase in the likelihood of entering STEM field than staying out of STEM. The pattern is different among men. Math STV was negatively predictive at marginal significance, such that higher math STV at age 13 predicted lower likelihood of entering STEM by age 25. At the same time, URM status became predictive, such that being an URM was associated with less likelihood of entering STEM. Because of these gender discrepancies, a third model with a gender by math STV interaction term was tested. The result showed that math STV was not related to STEM entry, suggesting that the interaction term accounted for some of the covariance between math STV and the outcome.

The same analyses were carried out for URM status subgroups (Table 2.6). The result showed that among URM individuals, math STV was still negatively associated with the likelihood of entering STEM; this association was not found among non-URM people. For non-URM group, gender was predictive such that relative to women, men were twice as likely to enter STEM compared to staying out of STEM. An interaction term between URM and math STV was added to the model, and this term accounted for some of the covariance between math STV and STEM entry.

Although these results suggest that the negative association between math STV and STEM entry did not hold true for everyone, the direction of the association remained negative when it existed. One possibility is the long lag between the math STV measure at age 13 and the differences of job field at age 25. Participants 'math STV might have changed enough over the years so that it did not align with the job outcome a decade later. To examine this possibility, a follow-up wave of math STV measure was used for comparing the means between the non-STEM group and the STEM entry group. The variable was a repeated measure of the math STV items 5 years later when participants reached 18 years of age on average. The group means and the results of the independent t-test within each wave were displayed in Table 2.7. Because of the gender and URM variation found in the logistic regressions, the mean level comparisons were carried out for each of the subgroup as well. Among the whole sample, math STV at age 13 differed between two trajectory groups, such that the non-STEM group (M = 4.67, SD = 1.22) reported higher math STV than the STEM entry group (M = 4.38, SD = 1.27) at age 13. However, this difference did not exist five years later, with two groups having similar level of math STV at age 18 (non-STEM: M = 4.43, SD = 1.35, STEM entry: M = 4.54, SD = 1.35). This result suggests a trend among adolescents in the non-STEM group to lower their math STV over time, and a trend among adolescents in the STEM entry group to increase their math STV over time. The same pattern was found among men and URMs but not among women or non-URMs, corresponding to the group variation in the finding of the negative association between math STV and STEM entry in the logistic regressions.

Discussion

In this study, I aimed to answer "Why do individuals change their career path" through the lens of SEVT and DCT. Based on these theories, I conceptualized changes in STEM career paths, namely STEM attrition and STEM entry, as the result of cross-domain comparisons of achievement, expectancy and STV in math and language domains. These motivational factors are powerful predictors of career choices, which may explain the gender, URM status and family SES related differences in STEM persistence. From my analyses, I found gender, URM status and family SES related differences in STEM attrition and entry as hypothesized. Contrary to my hypotheses, gender and URM status uniquely predicted STEM entry, and URM status uniquely predicted STEM persistence after controlling for the influence of parent education, performance, expectancy and STVs in math and reading domains. Math performance differed between STEM attrition and STEM persistence groups, and between non-STEM and STEM entry groups, but it did not uniquely predict STEM entry or attrition. Contrary to my hypotheses, neither math expectancy nor reading expectancy related to changes in STEM paths. Math STV related to both types of changes in STEM paths but in the opposite direction to my hypotheses. At the same time, reading STV related to but did not uniquely predict STEM persistence. Lastly, none of the cross-domain interactions were predictive of changes in STEM career paths.

Why Some Gender and URM Status Differences Remained Unexplained?

Contrary to my hypotheses, the gender and URM status related differences in STEM attrition and entry were not entirely accounted for by prior performance, expectancy and STV in math and reading domains. Given the same levels of math and reading performances, expectancies and STVs, women and URM individuals were less likely to enter STEM occupations than men and non-URM individuals. Why was this the case considering that two most explanatory motivational factors of career choices, namely expectancy and STV in relevant domains, were taken into consideration? One explanation might be job-specific considerations. The destination of STEM career paths in this study was employment at age 25. Individuals may consider specific aspects of a job that were more detailed than at a domain level when choosing their occupation, and these considerations may vary by gender and URM status. For example, the desire for a flexible work schedule and perceived high time demand were found to predict women's withdrawal from pursuing careers in men-dominated fields from age 18 to age 25 (Frome et al., 2006). Considering that many STEM fields are men-dominated (Ceci et al., 2014), this type of job-specific factors may be related to women's higher likelihood to discontinue their STEM career paths or lower likelihood to switch into the STEM fields. Another possible explanation might be the barriers that women and URM individuals perceived for pursuing STEM careers. When asked about career aspirations at age 13, participants thought about the job they most like to have. The barriers to attaining the career in reality might have been set aside or not foreseen at that time but come into effect in actual job search. The lack of resources and opportunities to get involved in STEM research, others' explicit discouragement from pursuing STEM careers, and the mismatch between women's or URMs' personal beliefs and the cultural values in STEM are examples of such barriers (Guy & Boards, 2019; Strayhorn et al., 2013). Using measures of expectancy and STV measures, with the addition of the cost construct, closer in time to the outcome of employment is one way to study these barriers.

The Limited Influence of Math Performance and Expectancy on STEM Career Changes

In this study, neither math nor reading expectancies related to changes in STEM career paths. Math performance differed between trajectories but did not uniquely predict STEM attrition or entry. Reading performance was not related to any changes in STEM careers. Some prior studies showed that academic expectancy did relate to changes in college-required career aspirations (Gao & Eccles, 2020), and various contextual factors are influential predictors of adolescent's college-related educational trajectory (Messersmith & Schulenberg, 2008). These findings, together with results in this study, may indicate the limited direct influence of expectancy on changes in career path. One possibility might be that expectancy could predict changes in career path without controlling for the effect of performance and STVs. Previous findings on career choices at one point in time showed that STVs was more strongly associated with career choices than expectancy, when tested in separate models (Bong, 2001; Lazarides & Lauermann, 2019; Meece et al., 1990). Considering that prior performance and expectancy were highly correlated (citation), the unique effect of expectancy may be limited after prior performance was controlled for. Regarding changes in career paths, expectancy might play a bigger role in differentiating the starting point and less in later trajectories. In this study, individuals who chose STEM careers at age 13 (i.e., the STEM attrition and the STEM persistence groups) seemed to have higher math expectancy than their peers choosing non-STEM careers at that time (i.e., the non-STEM and the STEM entry group). Therefore, a sufficient level of math expectancy might be necessary for individuals to enter the STEM field but may not guarantee the continuance in the path. The lack of unique predictive power of expectancies might also be due to the insufficient differentiation of the beliefs, as suggested by the weak correlation between the expectancy and performance in the same domain. More studies are needed to replicate the analysis to clarify the role of expectancy in career persistence.

The lack of association between math performance might suggest that prior achievement did not affect changes in STEM career paths directly. As theorized in SEVT (Eccles & Wigfield, 2020; Wigfield & Eccles, 2000), previous achievement influences individuals 'affective experience and general self-schemata, which further influences expectancy and STV beliefs. Individuals may have adjusted their perception of their math and reading abilities based on their performances in these domains, and thus the direct performance on career trajectories was minimal.

The Competent, Resourceful Late Entrants

Contrary to my hypothesis, a negative association between math STV and STEM entry was found. Individuals who switched into the STEM field reported lower math STV at age 13 than individuals who stayed in non-STEM over time. This association held true in the regression analysis. Post hoc inspections into a following wave of math STV pointed to the possibility of changes in math STV over time. Over the period of five years, a trend was found that the math STV seemed to increase among the STEM entry group whereas the math STV seemed to decrease among the non-STEM group. By age 18, the two groups had a similar level of math STV. If this trend continued, the STEM entry group might have higher math STV than the non-

STEM, thus aligning with their choice of occupations by age 25. However, limited by the study design, the sample size of the math STV at age 18 shrank considerably compared to that at age 13. Follow-up studies are necessary to test the conjecture above.

At the same time, the negative association between math STV and STEM entry might shed light on the motivational process of this particular trajectory. Individuals in the STEM entry group seemed to have a comparably high level of parent education and math performance as the STEM persistence group. Thus, the late entry might potentially be due to choices instead of the lack of ability or resources. Follow-up analyses showed a trend of increase in math STV in the STEM entry group, possibly indicating the development of math STVs in the following years. Explorations and specializations of career interest might underlie this delayed increase in valuing of their future career domain. In a previous study, adolescents with late aspirations to college-associated careers similarly had relatively high family SES and academic performance (Gao & Eccles, 2020). More research is called for to further understand this particular career path, and yet the evidence so far suggests choices rather than the lack of choices as the possible explanations. As found in study 1, women who worked in STEM occupations by age 25 were more likely to take the late entry path than expected by chance. Considering that girls were more likely to have high achievement in both language and math domains (Wang et al., 2013), the delayed entry into STEM might just be the time women need before they become motivated to choose the STEM field.

Changes in Career Paths Based on DCT and SEVT

I found that the reading STV differed between STEM attrition and STEM persistence groups, and that the STEM persistence group had lower valuing of reading domains than the attrition group. This finding matches the result of a cross-domain comparison of values between the math and reading domain. However, neither reading STV nor the interaction between math and reading STVs predicted the probability of STEM attrition as hypothesized. One difference between this study and previous studies on the dimensional comparison of motivational belief is the use of regression or SEM approaches. The SEM models, when set up with performances as antecedents, motivational beliefs as mediators and career choices as outcomes (Lazarides & Lauermann, 2019), may be better suited for testing the theorized relationship between constructs, as both the indirect and the direct effects were estimated. The lack of cross-domain association between performance or motivational beliefs and career outcomes might also suggest the limited implications of cross-domain comparison on career outcomes. The cross-domain comparison reflects the use of internal frame of reference to form one's self-concept (Marsh, 1986). This mechanism might be particularly influential for abstract, ambiguous self-perceptions like the self-concept of ability and less pronounced for specific, tangible decisions, such as career choices. Two studies testing the cross-domain influence of motivational beliefs on career outcomes showed null or minimal negative associations (Guo et al., 2017; Lazarides & Lauermann, 2019). More research is needed to examine the implications of cross-domain comparisons on career outcomes.

Why do individuals change their career paths? Findings of this study indicate the changes were made by people in their individual sociocultural contexts. The STEM entry group and the STEM attrition group had different sociodemographic, achievement and motivational profiles. The STEM entry group had one of the highest math performances across the sample, but their math subjective task values were among the lowest. That is, they did not math value as highly as they performed in it, indicating adjustment in their math values in following years. At the same time, the late entry group had high parent education. Taken together, the late entry into STEM domains might signal their explorations of career interest over time. In comparison, the STEM attrition valued math more highly than they performed in the field. Thus, switching out of STEM might result from experiencing setbacks and barriers in STEM domains. How would the changes influence the individuals? How adaptive the changes are to the individual in their context? Prior research shows the failure to meet achievement-related goals during the school-to-work transition was related to higher risk of mental health problem (Nurmi & Salmela-Aro, 2002), underscoring the need to support adolescents and young adults' coping and adaptation when their goals are not met. More research is needed to further understand the implications of these changes on the person's motivation and career outcomes and the precursors to these changes.

The finding also showed that there was a mismatch between performance and STV in the math domain in early adolescence across the four trajectory groups. Looking at how the math performance and STV of each group compared to other groups in the sample, we can see that the non-STEM group and the STEM attrition group valued math more highly than they relatively achieved, and that the STEM entry group and the STEM persistence group performed more highly than they relatively value math. Overall, the correlation between performance and STV in each domain of math and reading was null to small at age 13. In the long run, the career paths seemed to align more with individuals 'relative achievement level. How did the alignment happen? Based on SEVT (Eccles & Wigfield, 2020), individuals 'STV would be likely to become more intertwined with performance and consequently affect the occupational outcomes by age 25. However, more data are needed to understand how the transformation occurs and its implication as STVs involve key beliefs to a person's identity. In particular, the two groups who valued math more highly than they achieved featured an overrepresentation of women and URM individuals, suggesting additional questions of exactly how the precursors and results of the alignment between performance and STVs involve gender- and racial/ethnic- specific factors. This study is the first step in revealing this phenomenon; more research is needed to investigate it in detail.

Limitation and Future Directions

One limitation of the study is the aggregation of STEM careers into one broad categories. The distinction between the health STEM and physics-related STEM careers in Chapter 2 should have been extended to examine to what extent the predictors relate to different STEM domains. The small number of people persisting in health STEM and physics-related STEM careers, less than 40 and 60 respectively, were likely to lead to biased estimates of odds ratio (Bujang et al., 2018; Nemes et al., 2009). In future studies, researchers can use larger samples to study the STEM career trajectories in these fields.

The inspections into the negative association between math subjective task values and STEM entry indicated a cross-over developmental trend of math subjective task values of individuals in the non-STEM career paths and the STEM entry paths. This result underscore the need to use the motivational beliefs in evolvement to understand the changes in career choices. One direction is to identify heterogeneous developmental trajectories of motivational beliefs using techniques such as the mixture growth curve modeling and to test the association between different motivational trajectories and changes in career paths. Due to the limit of our sample, there lacked following measures on math and reading expectancy-value beliefs. In future studies, researchers can expand our research to test this possibility.

Conclusion

In this study, we aimed to answer why people change their STEM career paths by examining the sociodemographic, achievement and motivational precursors of the divergence in

STEM career trajectories. Findings suggest limited influence of math performance and expectancy on changes in STEM career paths, and points to STVs, and potentially STVs in transformation, as the main predictors of late STEM entry. Gender and URM status predicted STEM entry and attrition above and beyond the influence of performance and motivation in math and reading domains, indicating job-specific considerations and potential barriers in fulfilling STEM career goals. Our results revealed the unique achievement and motivational profiles of STEM entrants, indicating a following increase in their math subjective task values to match with their high math performance. More research is needed to understand the process in which this development unraveled and the influential factors of this process. Our finding suggests the limited influence of dimensional comparison in early math and reading achievement and motivation on later changes in career paths. The influence of early expectancy-value beliefs was also limited when sociodemographic factors and achievement was held constant. This result may indicate the need to account for motivational beliefs in its development as the antecedents of changes in career paths.

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Table 2.1

Group differences in sociodemographic composition, achievement and motivation

	n	Women	URM	Parent edu (M[SD])	MPerf (M[SD])	RPerf (M[SD])	MExp (M[SD])	RExp (M[SD])	MSTV (M[SD])	RSTV (M[SD])
Non-STEM path	484	291 (60%)$^{+}$	278 (58%)$^{+}$	13.18 (2.56)^{a}	101.58 (16.46)^{a}	104.75 (17.35)	4.74 (1.07)	5.27 (1.09)	4.67 (1.22)^{a}	5.24 (1.21)
STEM entry	128	58 (45%)$^{-}$	54 (42%)$^{-}$	13.81 (2.59)^{b}	106.84 (17.42)^{b}	106.55 (16.62)	4.68 (1.22)	5.21 (1.08)	4.38 (1.27)^{b}	5.10 (1.14)
Cramer's *V*	--	.12	.13	--	--	--	--	--	--	--
Cohen's *d*	--	--	--	.25	.32	--	--	--	.24	--
STEM attrition	287	150 (52%)$^{+}$	161 (56%)$^{+}$	13.17 (2.45)^{a}	103.54 (17.53)^{a}	106.11 (17.42)	4.88 (1.08)	5.30 (1.10)	4.93 (1.21)^{a}	5.33 (1.10)^{a}
STEM persistence	127	53 (42%)$^{-}$	43 (34%)$^{-}$	13.83 (2.14)^{b}	108.47 (15.48)^{b}	107.28 (15.95)	4.96 (1.11)	5.09 (1.08)	4.56 (1.26)^{b}	4.85 (1.25)^{b}
Cramer's *V*	--	.10	.21	--	--	--	--	--	--	--
Cohen's *d*	--	--	--	.28	.29	--	--	--	.30	.42

Note: URM = underrepresented racial/ethnic minorities. Parent edu = parent education. MPerf = math performance. RPerf. = reading performance. MExp = math expectancy. RExp = reading expectancy. MSTV = math subjective task values. RSTV = reading subjective task values. +/− denotes over-/under-representation based on adjusted standardized residual greater than 1.96 or less than -1.96. a/b denote a statistically significant group mean differences based on Scheffe post hoc test at .05 level.

Table 2.2

Bivariate correlations and descriptive statistics of predictors

	Age	Parent edu	MPerf	RPerf	MExp	MSTV	RExp	RSTV
Age	1							
Parent edu	.02	1						
MPerf	.02	.34***	1					
RPerf	.03	.34***	.66***	1				
MExp	-.16***	.13***	.26***	.10**	1			
MSTV	-.25***	-.11**	-.05	-.15***	.51***	1		
RExp	.06	.06	.05	.27***	-.20***	-.08*	1	
RSTV	.01	-.02	-.08*	.10**	-.09**	.22***	.61***	1
Cronbach's alpha	--	--	--	--	.82	.70	.84	.69
M	13.08	13.33	103.6	105.65	4.8	4.69	5.25	5.2
SD	1.94	2.5	16.92	17.11	1.1	1.24	1.09	1.18

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Parent edu = parent education. MPerf = math performance. RPerf. = reading performance. MExp = math expectancy. RExp = reading expectancy. MSTV = math subjective task values. RSTV = reading subjective task values.

Table 2.3

Estimates of predictors of STEM entry (versus non-STEM path) in a stepwise logistic regression

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
Predictors	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE
Man	1.91*	0.41	1.99*	0.43	1.99*	0.43	1.91*	0.41	2.00*	0.43	1.98*	0.43	2.00*	0.44
Age	0.98	0.05	0.96	0.05	0.94	0.05	0.98	0.05	0.97	0.05	0.94	0.05	0.95	0.05
Parent edu	1.06	0.05	1.07	0.05	1.06	0.05	1.06	0.05	1.06	0.05	1.06	0.05	1.06	0.05
URM	0.56*	0.13	0.55*	0.13	0.60*	0.15	0.56*	0.13	0.55*	0.13	0.60*	0.15	0.59*	0.15
RPerf	0.99	0.01	0.99	0.01	0.99	0.01	0.99	0.01	0.99	0.01	0.99	0.01	0.99	0.01
MPerf	1.01	0.01	1.01	0.01	1.01	0.01	1.01	0.01	1.01	0.01	1.01	0.01	1.01	0.01
MExp			0.86	0.09					0.86	0.09			0.96	0.12
RExp			1.05	0.11					1.06	0.11			1.02	0.13
MSTV					0.81*	0.08					0.81*	0.08	0.83	0.10
RSTV					1.09	0.10					1.07	0.11	1.04	0.13
MPerf * RPerf							1.00	< .001					1.00	< .001
MExp * RExp									1.05	0.09			1.07	0.10
MSTV * RSTV											0.98	0.07	0.95	0.07

Note. In the outcome, STEM entry was coded as 1, and non-STEM path was coded as 0. * $p < .05$, ** $p < .01$, *** $p < .001$. Parent edu = parent education. MPerf = math performance. RPerf. = reading performance. MExp = math expectancy. RExp = reading expectancy. MSTV = math subjective task values. RSTV = reading subjective task values.

Table 2.4

Estimates of predictors of STEM attrition (versus STEM persistence) in a stepwise logistic regression

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
Predictors	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE
Man	0.68	0.16	0.69	0.16	0.74	0.18	0.66	0.15	0.68	0.16	0.74	0.18	0.72	0.18
Age	0.82*	0.05	0.82*	0.05	0.83*	0.05	0.82*	0.05	0.82*	0.05	0.84*	0.05	0.84*	0.05
Parent edu	0.97	0.05	0.97	0.05	0.97	0.05	0.96	0.05	0.97	0.06	0.96	0.05	0.96	0.06
URM	2.59*	0.67	2.52*	0.67	2.12*	0.59	2.61*	0.68	2.53*	0.68	2.11*	0.59	2.13*	0.60
RPerf	1.01	0.01	1.01	0.01	1.01	0.01	1.01	0.01	1.01	0.01	1.01	0.01	1.01	0.01
MPerf	0.99	0.01	0.99	0.01	0.99	0.01	0.98	0.01	0.99	0.01	0.99	0.01	0.99	0.01
MExp			0.98	0.11					0.98	0.11			0.90	0.12
RExp			1.05	0.12					1.04	0.12			0.92	0.14
MSTV					1.09	0.11					1.11	0.11	1.15	0.14
RSTV					1.18	0.13					1.22	0.14	1.23	0.18
MPerf * RPerf							1.00	< .001					1.00	< .001
MExp * RExp									1.03	0.09			1.00	0.10
MSTV * RSTV											1.05	0.07	1.04	0.08

Note. In the outcome, STEM attrition was coded as 1, and STEM persistence was coded as 0. * $p < .05$, ** $p < .01$, *** $p < .001$. Parent edu = parent education. MPerf = math performance. RPerf. = reading performance. MExp = math expectancy. RExp = reading expectancy. MSTV = math subjective task values. RSTV = reading subjective task values.

Table 2.5
Diagnostic analysis of the association between math subjective task value and STEM entry by gender

	Original model			Women (N = 349)			Men (N = 263)			Gender*MSTV Interaction		
	OR	SE	*p*	OR	SE	*p*	OR	SE	*p*	OR	SE	*p*
Man	1.99	0.43	.002							3.43	2.66	.112
Age	0.94	0.05	.301	0.92	0.07	.284	0.99	0.08	.855	0.94	0.05	.289
Parent edu	1.06	0.05	.232	1.14†	0.09	.094	1.00	0.07	.976	1.06	0.05	.233
URM	0.60*	0.15	.044	0.84	0.30	.629	0.40*	0.15	.012	0.59*	0.15	.039
RPerf	0.99	0.01	.217	0.98	0.01	.166	1.00	0.01	.761	0.99	0.01	.222
MPerf	1.01	0.01	.281	1.02	0.01	.142	1.00	0.01	.921	1.01	0.01	.289
MExp												
RExp												
MSTV	0.81*	0.08	.025	0.83	0.11	.167	0.79†	0.11	.077	0.86	0.11	.219
RSTV	1.09	0.10	.376	1.02	0.15	.888	1.14	0.14	.290	1.09	0.10	.372
Men*MSTV										0.89	0.15	.462

Note. In the outcome, STEM entry was coded as 1, and non-STEM path was coded as 0. † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Parent edu = parent education. MPerf = math performance. RPerf. = reading performance. MExp = math expectancy. RExp = reading expectancy. MSTV = math subjective task values. RSTV = reading subjective task values.

Table 2.6
Diagnostic analysis of the association between math subjective task value and STEM entry by URM status

	Original model			URM (N = 332)			non-URM (N = 279)			URM*MSTV Interaction		
	OR	SE	*p*	OR	SE	*p*	OR	SE	*p*	OR	SE	*p*
Man	1.99	0.43	.002	1.65	0.52	.112	2.14*	0.65	.012	1.94*	0.42	.002
Age	0.94	0.05	.301	0.93	0.08	.365	0.97	0.08	.667	0.95	0.05	.339
Parent edu	1.06	0.05	.232	1.06	0.07	.363	1.06	0.08	.397	1.06	0.05	.227
URM	0.60*	0.15	.044							0.54*	0.14	.020
RPerf	0.99	0.01	.217	0.99	0.01	.552	0.99	0.01	.264	0.99	0.01	.250
MPerf	1.01	0.01	.281	1.00	0.01	.898	1.02	0.01	.166	1.01	0.01	.280
MExp												
RExp												
MSTV	0.81*	0.08	.025	0.69*	0.10	.012	0.90	0.11	.393	0.90	0.11	.388
RSTV	1.09	0.10	.376	1.07	0.15	.633	1.10	0.14	.451	1.08	0.10	.389
URM*MSTV										0.77	0.13	.130

Note. In the outcome, STEM entry was coded as 1, and non-STEM path was coded as 0. * $p < .05$, ** $p < .01$, *** $p < .001$. Parent edu = parent education. MPerf = math performance. RPerf. = reading performance. MExp = math expectancy. RExp = reading expectancy. MSTV = math subjective task values. RSTV = reading subjective task values.

Table 2.7

Math STV at age 13 and age 18 of the non-STEM group and the STEM entry group

Table A. Comparisons within gender subgroups

	Everyone				Women				Men			
	Age 13		Age 18		Age 13		Age 18		Age 13		Age 18	
	N	M (SD)	N	M (SD)	N	M (SD)	N	M (SD)	N	M (SD)	N	M (SD)
non-STEM path	484	4.67 (1.22)	92	4.43 (1.35)	291	4.60 (1.26)	54	4.23 (1.32)	193	4.77 (1.15)	38	4.72 (1.36)
STEM entry	128	4.38 (1.27)	29	4.54 (1.35)	58	4.33 (1.29)	12	4.46 (1.28)	70	4.42 (1.26)	17	4.60 (1.43)
Independent T-test	t(610) = 2.39, *p* = .02		t(119) = -.40, *p* = .69		t(347) = 1.49, *p* = .14		t(64) = -.55, *p* = .58		t(261) = 2.17, *p* = .03		t(53) = .28, *p* = .78	

Table B. Comparisons within URM subgroups

	Everyone				URM				non-URM			
	Age 13		Age 18		Age 13		Age 18		Age 13		Age 18	
	N	M (SD)	N	M (SD)	N	M (SD)	N	M (SD)	N	M (SD)	N	M (SD)
non-STEM path	484	4.67 (1.22)	92	4.43 (1.35)	278	4.97 (1.09)	51	4.76 (1.21)	205	4.25 (1.25)	41	4.01 (1.42)
STEM entry	128	4.38 (1.27)	29	4.54 (1.35)	54	4.56 (1.17)	12	4.92 (1.26)	74	4.24 (1.33)	17	4.28 (1.39)
Independent T-test	t(610) = 2.39, *p* = .02		t(119) = -.40, *p* = .69		t(330) = 2.49, *p* = .006		t(61) = -.39, *p* = .70		t(277) = .06, *p* = .96		t(56) = -.66, *p* = .51	

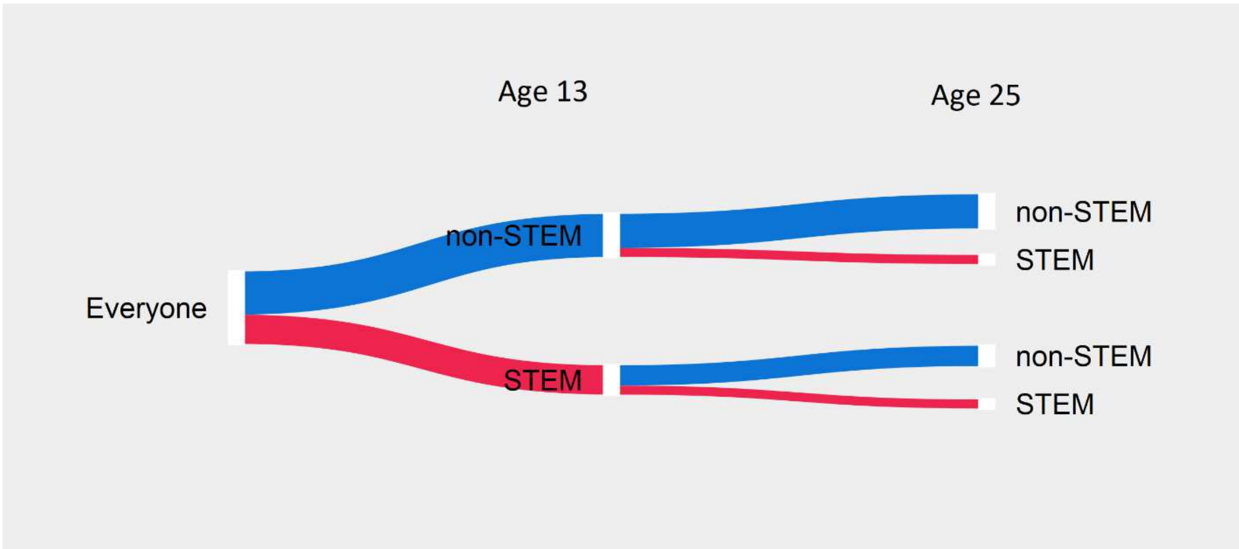

Figure 2.1. STEM career trajectories from age 13 to age 25.

CHAPTER 3

A Mixed-Method Examinations of Situated Expectancy-Value Theory in Students' Open-ended Explanations for STEM Major Plan Changes

Why do students decide to leave or persist in STEM majors? The SEVT delineates the ways that expectancy and subjective task value (EV) beliefs give rise to achievement-related choices (Eccles & Wigfield, 2020; Eccles et al., 1983). Quantitative studies show that students are more likely to persist and have long-term STEM career plans in a field if they can see themselves succeed in the field and perceive STEM major or careers interesting, important, useful and worthwhile to them (Lauermann, Tsai, et al., 2017; Musu-Gillette et al., 2015). Less understood is how often these factors emerge in individuals' decisions in a natural setting. In quantitative studies, participants are prompted to reflect on their EV beliefs with a set of predetermined descriptions. This confirmatory approach is advantageous for testing the theorized relationship between EV beliefs and career choices, but it is limited to understand the decision process. As persistence decisions are actively made by students, what students consider and how they make their decision is central to STEM attrition.

To address this gap in the literature, I investigated why STEM college students want to change their majors using their open-ended explanations. I examined how often students attribute their decisions to various expectancy and subjective task value beliefs. If they do so frequently enough, I then tested whether EV beliefs are linked to students' persistence decisions.

Considering the gendered pattern of STEM attrition (Ma & Liu, 2017; Shaw & Barbuti, 2010), I explored potential differences in men's and women's reasons for their major plan change.

Qualitative Findings on Students' Explanations for STEM Career Choices

Students' perspective about their reasons to choose or persist in STEM careers has been examined in several qualitative studies. Both EV-related reasons and other reasons have been found.

EV-related reasons

Students' confidence to succeed in STEM and the subjective values associated with STEM career choices emerge in students' narratives. All of the EV constructs, expectancy, interest, utility value, attainment value, and cost, have emerged in students' narratives.

Expectancy. In an interview study (DuBow et al., 2016), talented high school girls in computer science field explain why they continue to study in the field in college. They point to their strong sense of competence that were cultivated in prior STEM activities. Similarly, female freshman students in STEM majors attributed their choice of major to their confidence about their math and science ability (Edzie, 2014). They believe they can succeed in their field of study despite challenges.

Interest. Strong Interest, particularly passion, in STEM careers is a consistent theme across multiple studies. Interest in STEM major or careers guide students' decision to continue studying STEM in college, persisting in STEM majors or entering STEM occupations (Appianing, 2017; Bieri Buschor et al., 2014; Fouad et al., 2011; Talley & Ortiz, 2017). When explaining STEM attrition decisions, college students also point to changes in interest, such as being attracted by a non-STEM major or faded passion about their original path (Appianing, 2017).

Utility value. Future career perspectives were important factors of choosing to leave or stay in STEM majors. Students evaluated the extent to which the major affords abundant job opportunities that were stable and well-paid (Appianing, 2017; Bieri Buschor et al., 2014; Edzie, 2014; Fouad et al., 2011). In one study, job-related advantages were the top reasons for female minority students to choose STEM majors in college (Talley & Ortiz, 2017). On average, STEM jobs paid 40% higher than non-STEM jobs (Fayer et al., 2017), so the instrumental value is a clear advantage of STEM majors.

Attainment value. Individuals choose careers that are personally important to them. This value may be expressed as related to different aspects of a person's identity for different individuals. Eccles (2009) argued that individuals, especially adolescents, guide their choices based on their perception of who they are and what kind of person they want to be. This self-image entails various aspects, such as gender and racial/ethnic identities, one's personality and characteristics, terminal values that a person holds central to them (e.g., altruism), things that the person believe they ought to do and or that are proper to do, etc. Attainment value is part of students' decision-making based on prior studies. Many of the studies focused on women in STEM, so gender identity was frequently mentioned in women's explanations. Female role models motivated college students to choose and persist in STEM majors, and the lack of such figures drive female students to question their choices (Appianing, 2017; Bieri Buschor et al., 2014). Among women working in engineering jobs, they experienced both gender-related proud as well as discrimination in their daily experience; both the positive and the negative side of their gender identity affected their choices by leading them to commit or question their career choices (Fouad et al., 2011). Some students expressed a strong commitment to their STEM careers, because they could not envision themselves working outside of the STEM field of their choice (DuBow et al., 2016; Munyaka, 2017). Their field of study was an integral part of their identity. Some students chose STEM because they see a fit between what the field required and their personality (Talley & Ortiz, 2017). Altruistic motive was common reason for women to pursue STEM. They mentioned that their STEM careers could allow them to help others in their profession (Edzie, 2014; Fouad et al., 2011; Talley & Ortiz, 2017). In this case, altruism was the terminal value that were indispensable to the individuals, for both who they were and who they would like to be. In sum, in previous qualitative studies of individuals' STEM career choices, attainment value was frequently mentioned in various forms and aspects. Particularly, it seemed particularly salient and influential for women's decisions.

Cost. Eccles and colleagues (Eccles & Wigfield, 2020; Eccles et al., 1983) theorized that individuals weigh both what they gain and what they have to lose for choosing a career. The types of costs include financial cost, opportunity cost (i.e., the loss of valued alternatives because of choosing one option), effort cost, social cost, and emotional cost (Wigfield et al., 2017). In a focus group study, STEM college students reported the cost of giving up sleep, strenuous emotional struggles, and large amount of effort cost (Zocher, 2020). The high workload of STEM majors cost students time, effort, and leisure (Munyaka, 2017). For women, the demand of caretaking obligations was a prominent aspect of cost (Appianing, 2017; Bieri Buschor et al., 2014; Fouad et al., 2011). One college student explicitly explained that she did not think it was worthy to give up the chance to start a family for pursuing a STEM career (Appianing, 2017). For female engineers, caretaking responsibility was a big factor in their considerations of whether to stay in their position (Fouad et al., 2011).

In sum, the findings above suggest that students explained their STEM choices with EV beliefs: their descriptions of the reasons clearly aligned with the theorization of EV constructs. All of EV constructs appeared in students' narratives. However, these studies are not particularly focused on the SEVT, so investigations about how EV beliefs affect STEM persistence decisions were limited. For instance, it is unclear whether and how often a student considers multiple EV constructs. If students decide to leave STEM, is it caused by declining, rather than elevating, EV beliefs, as suggested by the positive relationship between EV beliefs and choices (Eccles & Wigfield, 2020)? I will address this gap by carrying out a more detailed examination of EV beliefs in persistence decisions, with investigations on the cooccurrence and changes of EV beliefs.

Other reasons

In addition to psychological factors such as EV beliefs, a variety of contextual factors have been found. In previous studies, students mentioned academic and instructional support and social influence.

Academic and instructional support

Instructors are the forefront of students' learning experience. The lack of good relationship with faculty, feeling nervous around intimidating professors, and poor teaching quality could drive STEM students away (Lancaster & Xu, 2017; Talley & Ortiz, 2017). In these studies, students expressed that they felt unsupported when instructors did not make themselves available; large class size and inexperienced teachers also negative affected students' motivation.

Social influence

Influences from parents, family members and peers have been a common theme across studies. STEM students described that their parents motivated them to study STEM majors by creating a stimulating learning environment at home, providing freedom and encouragement for daughters to choose STEM and expecting students to take on lucrative jobs (Bieri Buschor et al., 2014; Talley & Ortiz, 2017). Some students were motivated by the need to make their parents or family members to take pride in the students' achievement (Talley & Ortiz, 2017). Parents could also discourage students from choosing or persisting in STEM, for instance, by explicitly dissuading their child to avoid a STEM major for its the heavy schoolwork (Bieri Buschor et al., 2014), or through the absence of parents' help with homework and exam preparation (Zocher, 2020). Friends and peers can influence students' STEM choices as well, particularly for students from underrepresented racial/ethnic backgrounds. For these students, having a peer group to study together not only offered practical help with their homework and exams but also created a sense of community to keep them motivated (Lancaster & Xu, 2017; Palmer et al., 2011; Zocher, 2020).

The contextual influence from close social networks can indirectly influence individuals' motivational beliefs and career choices (Eccles et al., 1983; Wigfield & Eccles, 2000). Parents, teachers and peers are influential source of social influence on adolescents' STEM motivation and engagement (Kracke, 2002; Lazarides et al., 2017), and participants often tracked the development of their STEM motivational beliefs to the influences from people around them. However, considering that these contextual influences were indirect influences and were not often mentioned in previous qualitative studies, we keep a general category of "other reasons" to accommodate any explanations involving these contextual factors.

Varied reasons for different decisions

Empirical and theoretical evidence suggests that attrition and persistence decisions may be caused by different reasons. In an interview with biology undergraduates, Rosenzweig and colleagues (2021) found that a substantial portion of them change their career plans due to disenchantment of their original path or attraction to a new path. In particular, disenchantment is more likely to be the reason if students want to switch to career plans requiring less education, and attraction is more likely to lead to changes to career plans requiring the same or more education. The finding indicates that the decision process for attrition or persistence might be different. However, in an interview study (Appianing, 2017), the same factor, such as prior performance, seemed affect persistence and attrition decisions in the same way. In this study, we expand evidence in this field by comparing the reasons for moving into STEM majors with the reasons for leaving STEM majors.

Motivation and Persistence in Introductory Chemistry and Physics Classes

Introductory STEM courses are an influential period and context for students' motivation and persistence. It is the primary venue for students to learn about their major in college, especially regarding the content material, workload and learning style (Clark, 2005). Moreover, students get to know about their peers and build their social groups, which can considerably shape their understanding about their future careers and major plan choices (Le et al., 2014). The new academic adjustment in introductory courses often coincide with the transition to college, posing multiple developmental challenges to the students. Prior findings show that students' EV beliefs tend to decline throughout introductory courses (Larose et al., 2006; Young et al., 2018), potentially signaling the influence of the adjustment on students' motivation. Considering the impact of motivational beliefs on students' choice of major (Eccles & Wigfield, 2002, 2020), it is likely that students opt to leave the STEM majors of their choice. In this case, it is particularly useful to understand why students make their choices to identify maladaptive decision-making and impactful practices for promoting persistence. I will focus on students' explanations for the changes in their major plan in introductory courses in my study.

Although the period of introductory courses features the exploration of college majors (Stebleton & Diamond, 2018), the formation of career choices in progress is understudied compared to the finalized choices, such as the major declaration in official registrar records or course enrollment in later years of college (Ashford et al., 2016; Toh & Watt, 2022). If inquired about their major choices, some students in introductory courses might find their decisions premature for official declaration. To improve the fit of the construct operationalization with the particular stage of introductory courses, I measure students' certainty about their major plan to capture STEM major choices in its development.

Gender differences

Traditional gender role socialization lead men and women to consider different aspects for choosing their majors in college. Previous findings show that men college students are more concerned with the status and the financial prospective of their future career as a means to provide for their family (Cattaneo et al., 2017; Mullen, 2014). In qualitative studies, some men explicitly discuss their "breadwinning" obligations and the shame if they fail to fulfill this expectation (Mullen, 2014). On the other hand, women college students are found to choose their major out of interest more often and are less concerned with their future earnings (Mullen, 2014; Quadlin, 2020). However, some researchers reported the lack of such gender differences (Cech, 2016). Considering that STEM occupations are generally better paid than non-STEM counterparts, students who choose to major in STEM might similarly be motivated by the utility value of STEM majors regardless of gender. Another potential gender difference is that women are more likely to choose STEM because of the altruistic values. They perceive it an important terminal value and see health-related STEM careers aligning with this value (Bieri Buschor et al., 2014; Dicke et al., 2019; Edzie, 2014; Talley & Ortiz, 2017). However, most of the findings were reported in quantitative studies with a confirmatory approach, so it is unclear whether the differences spontaneously emerge in students' considerations. Furthermore, evidence is scarce regarding whether expectancy and value beliefs relate to career choices in different ways for men and women. Men and women might only differ in the values they consider with subjective task values similarly relate to persistence decisions. In this study, I will extend this strand of literature by examining the gender differences in the reasons for students' STEM persistence decisions.

The Present Study

In this study, I analyzed students' open-ended explanations for changes in their STEM major plans. The study sample consisted of thousands of students over several years to explore the prevalent and differentiated patterns in students' responses. The analysis narrowed in on the change of certainty in introductory courses, for capturing the role of EV beliefs in the process of decision-making. The link of these changes to explanations were tested to examine the extent to which different decisions (e.g., thinking about joining in versus moving out) depended on different considerations. Lastly, I tested for gender differences in these findings.

To address these gaps in the literature, I investigated the following research questions in this study:

RQ1: What are students' explanations for changes in STEM major plans?

RQ1a: Do students mention EV beliefs in their explanations? If so, how often do they do so?

RQ1b: If EV reasons are mentioned, are decreases in EV beliefs mentioned more often than increases?

RQ1c: How often do students mention expectancy and subjective task value constructs together? When cooccurring, do expectancy and value beliefs affect students' decisions in a corroborating rather than conflicting way?

RQ2: How many students change their major plans by the end of introductory STEM classes in chemistry and physics fields?

RQ3: Are the reasons for persistence decisions and attrition decisions different?

RQ4: Do findings above differ by gender?

Hypotheses

Based on the qualitative findings on students' explanations for their STEM choices (Appianing, 2017; DuBow et al., 2016), I hypothesize that EV beliefs will appear in students ' explanations for their STEM persistence decisions with all five EV constructs to be found. Contextual factors (i.e., social influence from instructors, family and peers) were found in previous qualitative studies when participants were further asked about the formation of their motivational beliefs. Considering that the data in this study was collected in online surveys, I anticipated that contextual factors would be mentioned in only a small number of responses if any.

Among EV-related reasons, I hypothesize that more decreases in EV beliefs will be found than increases, because of the decline of motivational beliefs in introductory STEM courses on the average level (Musu-Gillette et al., 2015). Considering the positive correlations between expectancy and subjective task values in quantitative studies (Lauermann, Tsai, et al., 2017), I hypothesize that expectancy and value beliefs will cooccur in student' explanations and change in the same direction to affect persistence decisions. Taking into account of previous qualitative findings on the differentiated reasons in STEM career choices (Appianing, 2017; Rosenzweig et al., 2021), I hypothesize that students will give different reasons for changing versus keeping their choice of major.

Methods

Participants

Participants were 6,072 undergraduates in introductory chemistry and physics classes in academic years 2017-2018 to 2020-2021 from a large public Hispanic- and Asian-serving (HSI-designated) university in the southwestern U.S. (59% women; 13% European American/White, 28% Latino/a, 25% East Asian, 7% South Asian [e.g., Indian, Pakistani], 25% Southeast Asian/other Asian [e.g., Vietnamese, Pilipino], 2% African America; 49% first-generation college students; $Mean_{\text{age}}$ = 18.84 years old [*SD* = 0.91]). Students were enrolled in introductory chemistry (N = 3,415) or physics (N = 2,657) course sequences that are required for a variety of natural and health science majors in the university. At the end of the classes, students in the classes received an invitation to an online questionnaire about their attitudes about the course, their major and future careers in the field. A $5 gift card was offered for participation in each survey to encourage responses.

Measures

Change in Major Choices

Students were asked "How has this course affected your major choice?" Students chose from three response options: "It made me less certain about my original major", "It had no effect", and "It made me less certain about my original major".

Explanations for Changes in Major Plan

Students were asked "Have your major plans changed since the beginning of the quarter?" (0=no, 1=yes). If students answered yes, they were asked how and why their major plan has changed, with a text-entry box to enter open-ended explanations. This question with branching was used in academic years 2017-2018 and 2018-2019. In academic year 2019-2020 and following years, the branching between the two questions was removed to increase question responses. Thus, students were asked an independent question of how and why their major plans has changed throughout the time of the quarter.

Quantitative Measures of Expectancy-Value Beliefs

The quantitatively measured expectancy and subjective task value beliefs was used to test the replicability of the qualitatively reported beliefs in open-ended explanations. All of the items were measured on seven-point Likert scale (1 = Not at all true, 7 = Very true). The exact same measures were used in the baseline and final surveys. Confirmatory factor analyses were carried out and confirmed that all items under a scale loaded onto one factor.

Expectancy. Expectancy was measured by four items. A sample item was "*I am confident that I will do well in this course*". The Cronbach's α of the scale in the baseline and the final surveys were .86 and .91 respectively.

Interest. Interest was measured by ten items. Sample items include "*I enjoy learning about chemistry/physics*", and "*I think the field of chemistry is very interesting*". One negatively worded item was reversely coded before added to the scale. The Cronbach's α was .91 and .93 in the baseline and final surveys.

Utility value. Utility value was measured by seven items. A sample item was "Chemistry can be useful in my everyday life." The Cronbach's α were .84 and .86 respectively on the baseline and final survey.

Attainment value. Attainment value was measured by four items. A sample item was "*The study of chemistry is personally important to me.*" The Cronbach's α of the scale on the baseline and final survey was .87 and .89.

Analyses

To answer the first question, the frequency and percentage of change in major choices were counted. To examine whether gender was associated with different changes in major choices, a Chi-square Test of Independence was conducted. The standardized adjusted residuals were calculated for each cell to indicate an over- or underrepresentation of a gender group in a given type of responses.

To understand students ’explanations for their persistence decisions, the open-ended responses on the final survey were coded in a *deductive* manner, with a *phenomenological* approach to identify *theoretical categories* (Kuckartz, 2019). A coding scheme was developed with the definition of EV constructs (i.e., expectancy, interest, attainment value, utility value and cost) and other categories. Examples of responses for each category are listed in Table 3.1. The coding scheme was tested by a trained research assistant on a different dataset and revised after the pilot coding. Six categories of responses were finalized: 1) EV-related explanations, 2) other reasons, 3) vague reasons, 4) just describing the changes in major plan without giving explanations, 5) “I don’t know”, and 6) reporting no change in major. These categories are mutually exclusive.

If EV constructs were mentioned, further differentiations were made to identify the kind of EV construct and its change. Coders mark whether expectancy, interest, attainment value, utility value or cost was mentioned. Considering that expectancy and subjective task values jointly influence career choices and that subjective task values have various components (Eccles & Wigfield, 2002), one response was allowed to be marked on more than one EV construct. The total number of value constructs (i.e., interest, utility value, attainment value and cost), as well as the total number of EV constructs, in each response were counted. For each EV concept that was mentioned, coders coded whether the belief was described as increasing or decreasing over time.

Based on the Internal/External Frame of References (Wolff et al., 2019), changes in an EV belief could result from temporal comparisons, comparing with the students' own belief earlier in the quarter, from social comparisons, comparing with other students in the same subject, or from internal comparisons of available options, namely comparing with a different major that the student was considering about. For instance, a student realizing they could do better in the subject than they initially expected would be coded as an increase in expectancy because of temporal comparison. If a student mentioned they found another major more interesting to them, the interest value of their original major would be coded as decreasing. The change in subjective task value were synthesized across four value constructs. Changes in cost beliefs was reversely coded because it represents the sacrifices and burden that is attached to an option (Eccles & Wigfield, 2020). The change in all EV constructs were synthesized in the same way.

The responses were coded by two undergraduate research assistants who were naïve to EV theories prior to this study. I trained them based on a coding scheme with a sample coding sheet using responses from a pilot dataset. A total of 30 responses were randomly sampled for checking the quality of their coding. The inter-rater reliability is .87.

To examine the association between changes in major choices and the explanations for change, a Chi-square Test of Independence, or the Fisher's Exact Test when cell sizes were small, was used. The results could indicate whether students gave different explanations for different changes in major choices (i.e., whether they became more certain about their original major or became less certain about their original major). To test the gender differences in the types of explanations, changes in EV beliefs, the types of combinations of EV beliefs and persistence decisions, a Chi-square Test of Independence was used for each association. A three-way Chi-square Test was carried out to examine whether the relationship between students ' explanations and persistence decisions varies between gender.

Replicability Check of Qualitatively Reported EV Belief Changes

The data collection of the project was part of a random control trial classroom intervention, with one additional survey sent out at the beginning of the classes. The combination of the baseline and the final survey provides a longitudinal measure of students 'motivational beliefs from the beginning to the end of introductory STEM courses. In the two questionnaires, EV beliefs were surveyed in form of repeated measures. They are traditional quantitative measures with Likert-scale items. Constructs included expectancy, interest, attainment value and utility value. This quantitative data provided an excellent opportunity to examine whether students' qualitatively reported EV beliefs changed in the same way as measured by quantitative instruments. For example, did students who reported a decrease in their expectancy in the open-ended responses have lower expectancy scores on the Likert-scale items at the end of the class than at the beginning? Mixed-model Analyses of Covariance (ANCOVA) were carried out to examine this question. Reporting decrease or increase of an EV construct was the between-subject factor in the model, and time (i.e., the baseline and final survey measures) was the within-subject factor. Covariates were gender, intervention condition and subject.

Missing Data

Students were voluntary to fill out the open-ended question about their reasons for changing their majors, so self-selection of participation is a major source of bias. To examine the extent of this bias, missing data analyses was carried out. Students who responded to the open-ended question were compared with students who did not, with regard to their gender, ethnicity, first-generation college-going status, subject (chemistry or physics), treatment condition in a random control trial intervention, the EV beliefs measured by Likert scale items on the same survey. Independent sample T-test was carried out for continuous variables, and Chi-square Test of Independence was used for categorical variables. We found that students who responded to open-ended question to explain changes in their majors had lower scores on expectancy, interest, utility value and attainment value with small effect sizes than non-respondents ($.09 \leq$ Cohen's d $\leq .14$, Table 3.2). Gender, ethnicity, first-generation college-going status or intervention condition were unrelated to question participation (Table 3.2). Nonetheless, course subject was related, such that more chemistry students than expected filled out the question, and fewer physics students than expected answered the question, $\chi^2 = (1, N = 5975) = 5.60$. However, this association was minimal, with a Cramer's V of .03.

Results

Explanations for change in major plan

Regarding the first question, a total of 1309 students gave EV-related explanations, other reasons, vague explanations, or said "they don't know", reported no change in their major plans or just described the change of their major plans without explaining it (Figure 3.1). Sample responses for each category was presented in Table 3.1. The most common responses were reporting no change in major plans (35%, e.g., "*My major didn't change*"), providing EV-related explanations (34%, e.g., "*I lost interest in engineering*", "*I realize I can do more than I think I can*", "*The road is long and the payoff is not that great*") and giving description-only responses (25%, e.g., "*(I) took on a double major*"). EV-related explanations comprised of nearly 90 percent of responses with explanatory information (440 out of 502 responses), more common than other reasons or vague reasons.

Among 38 responses of other reasons, no responses pertained to social influence from instructors, family or peers. Instead, major declaration regulation related reasons was a common explanation. For instance, one student said "*(I) can't get to needed class due to various major restrictions*". Similarly, a student said, "*I didn't pass chemistry so I have to retake*", and another student said "*My gpa is too low*", indicating the requirement of course completion and grades for declaring in their originally intended major. Another type of responses pertained to the barrier to enroll in or complete major-required courses. For instance, a student said "(*my major changed) From PH Science to PH Policy, b/c couldn't fit science classes into my second year*", and another student said "(I) *Can't get to needed class due to various major restrictions*". These regulation-related reasons appeared in nearly half of the "other reason" responses (17 out of 38 responses). Another eight responses related to the need to explore and know more about alternative major options, such as "*I want to see what MSE is like*", and "*I want to look for more options for myself*". Another five students explained that the decision changed because of changes in their perspectives and understanding, such as "*different perceptions on subjects*" and *"New Perspective on Life"*. The rest of eight explanations related to individualized reasons, such as "*financial issues*", or vague reasons, "*The classes I will be taking in my future years at UCI*".

In a closer inspection of EV-related explanations, more decreases than increases were found on expectancy, interest, utility value and attainment value, and more increases than decreases were reported on cost beliefs (Figure 2).

Across the 440 EV-related explanations, 92 of them only pertained to expectancy, 323 subjective task value(s), and 25 included both expectancy and value beliefs (Table 3.3). A predominant portion of EV-related responses contained one EV concept (86% of 440 responses). A total of 60 EV-related responses included multiple EV constructs: expectancy-value combination appeared in 25 of these responses, and multiple value constructs appeared in the rest 35 responses. When the students mentioned expectancy and value constructs together, 24 students reported that their EV beliefs changed in the concordant direction, e.g., both expectancy and subjective task values increasing (in 4 cases) or both decreasing (in 20 cases). One student reported their EV beliefs changing in different directions: the student had a growing interest in their major but found it more difficult than they expected.

Changes in major plan and the association with explanations

By the end of the quarter, 56% students reported no change in their plan of college major. Among the rest of 44% of students, 25% became less certain about their major and 19% became more certain about their major.

Chi-square Test of Independence suggested an association between the change in students' major plan and their explanations for such change, χ^2 (10, N = 439) = 57.41, Cramer's V = .26. Adjusted standardized residuals suggested that students mentioned some reasons more often than expected by chance (Table 3.4). If a student became less certain about their major, decreases in expectancy and decreases in both expectancy and value were mentioned more often than expected by chance. Meanwhile, increases in values were less often the explanation than expected. If a student reported no change in their major plan, an increase in value(s) were more often the reason than expected; decreases in expectancy and value as well as decreases in expectancy were mentioned less often than expected. If a student became more certain in their choice of major, increases in values were attributed to more often than expected.

Ruling Out Differences in Results by Course Subject

In the missing data analyses, course subject was found to relate to whether a student responded to the open-ended question. To examine whether the content of students' responses varied across subjects, Chi-square Tests of Independence were carried out to examine whether course subject was associated with the content of the open-ended responses or with the patterns of EV-related explanations. Results suggested that course subject was related to the content of open-ended responses, χ^2 = (5, N = 1309) = 21.41. Among students who responded to the open-ended questions, more chemistry students than expected gave EV-related explanations, and more physics students than expected said that their major plan did not change. The effect size of this association is small, Cramer's V = .13. Course subject was not related to students' EV-related explanations. Specifically, students in chemistry and physics classes did not differ in how many EV constructs they mentioned, χ^2 = (2, N = 440) = 1.13, or the ways that their EV beliefs changed, χ^2 = (5, N = 439) = 6.79. Therefore, no additional tables were used to present findings in chemistry and physics classes separately.

Gender differences

Gender Differences in the Content of Responses

Findings discussed above varied between gender. Men and women gave different responses to explain changes in their major plans: the most common response among men is reporting no change in their major (40.0%), whereas the most common response among women is giving EV-related explanations (37.0%, Figure 3). Chi-square Test of Independence shows a statistically significant association between gender and the type of responses, χ^2 (5, N = 1284) = 22.45, $p < .001$, Cramer's V = .13. Based on the adjusted standardized residuals, more men than expected gave other reasons, vague reasons or reported no change in their major(s), whereas more women than expected gave EV-related reasons.

Among EV-related explanations, decreases in value(s) were mentioned the most frequently by both men and women (Table 3.5). Increases in one or multiple subjective task value beliefs were the second common type of responses among men, whereas the second common response type for women was decreases in expectancy, χ^2 (5, N = 428) = 11.65, $p = .04$, Cramer's V = .17. More men than expected reported increases in subjective task values, whereas fewer women than expected did so. Men and women reported similar number of EV constructs χ^2 (2, N = 429) = 0.06, p = .97, Cramer's V = .01.

Looking into each of the EV beliefs, men and women reported different changes in their expectancy, χ^2 (1, N = 113) = 4.32, p = .04, Cramer's V = .20, and cost, Fisher's exact test, two-tailed, p = .04 (Figure 4). More women than expected reported a decrease in their expectancy, whereas more men than expected reported an increase in their expectancy. In terms of cost, more women than expected perceived an increase in the cost of pursuing their majors, whereas more men than expected reported a decrease in their perceived cost of the major the change in interest, utility value and attainment value did not vary between men and women.

Gender Differences in Changes in Certainty about Major Plan

By the end of the introductory chemistry and physics classes, men and women had different thoughts about their original major, χ^2 (2, N = 5369) = 80.02, p < .001, Cramer's V = .12. More women than expected said they became less certain about their original major. Meanwhile, more men than expected reported no change in their certainty about their major plan.

Gender Differences in the Association Between Explanations and Changes in Certainty about Major Plan

Men and women gave different attributions for changes in their major plans, χ^2 (10, N = 439) = 54.71, p < .001, Cramer's V = .25 (Table 3.6). Among those becoming less certain about their original major, women attributed it to decreases in their expectancy or decreases in both their expectancy and subjective task values more often than expected; in comparison, men tended to attribute it to decreases in their expectancy only. Among students who perceived no change in their major plans, women explained they had higher subjective ask values about their original major more often than expected, whereas men explained they had higher values or higher expectancy. Among students who became more certain about their original major, men attributed to increases in subjective task values more often than expected, whereas no reasons were particularly more likely to be mentioned by women.

Replicability Check of Qualitatively Reported EV Belief Changes

A mixed-model ANCOVA was carried out for each one of the expectancy, interest and utility value constructs because of sufficient group sizes at both levels of the between-subject factor (reporting increase or decrease of an EV belief). The assumption of homogeneity of variances, which states that the increase group and the decrease group had equal error variance, was tested by the Levene's Test of Equality of Error Variances. Another assumption, which is homogeneity of the variance-covariance matrices, is unique to mixed-model ANOVA/ANCOVA. It assumes that the correlation between the within-subject measures is equivalent across the between-subject groups (Murrar & Brauer, 2018). For instance, the group reporting an increase in interest and the group reporting a decrease in interest should have an equal correlation between the baseline and the final measures of interest. The Box's Test of Equality of Covariance Matrices was used to examine whether this assumption was met. Results showed that both assumptions were satisfied for the three models.

In each model, time was entered as the within-person factor, and group (describing increase or decrease of an EV belief in the qualitative response) was entered as the between-person factor. The interaction effect between time and group was tested. In addition, three interaction effects were entered as control variables: the interaction between time and gender, between time and subject and between time and intervention condition.

Results of the interaction effect between time and group are shown in Table 3.7, with estimated group means. A statistically significant interaction between group and time was found for expectancy, $F(1, 91) = 4.84$, $p = .03$, partial eta squared = .05, and interest, $F(1, 153) = 6.00$, $p = .02$, partial eta squared = .04, but not for utility value, $F(1, 61) = 0.06$, $p = .80$, partial eta squared = .001. The tests indicate that the way that expectancy or interest score changed on the Likert scale measures varied by whether the students reported an increase or decrease of the belief in open-ended responses. Inspection of estimated group means and confidence internals revealed the pattern of the differences. For expectancy, students who described a decline of expectancy in qualitative data had lower expectancy survey score at the end of the class (M = 3.34, SD = 0.15) than at the beginning (M = 4.51, SD = 0.14). Students who described an increase of expectancy in qualitative responses did not have statistically significant changes in their expectancy score from the beginning (M = 4.63, SD = 0.36) to the end of the class (M = 4.54, SD = 0.41). For the interest belief, students describing an increase in qualitative responses showed a trend of increasing interest on Likert scale measures (beginning of class: M = 4.71, SD = 0.21, end of class: M = 4.87, SD = 0.21), and students describing a decrease showed a trend of decreasing interest on survey measures (beginning of class: M = 4.33, SD = 0.13, end of class: M = 3.97, SD = 0.13). However, the changes in the estimated group means were not statistically significant for either group indicated by overlapping confidence internals.

Discussion

In this study, I investigated the reasons or STEM persistence decisions, using students' own explanations for changes in their major plans. As hypothesized, changes in EV beliefs were the most common type of explanation among responses entailing explanatory information. Moreover, changes in subjective task values were mentioned more frequently than changes in expectancy. Major declaration regulations, the need to explore major options and becoming aware of new options were three most common other reasons, and social influences from instructors and family members rarely appeared in the sample. As hypothesized, students gave different explanations for how their major plans changed by the end of introductory STEM classes: students who became less certain tend to attribute their decisions to a decline in expectancy or declines in both expectancy and subjective task values, whereas students who became more certain tend to attribute their decisions to an increase in subjective task values.

SEVT in Naturalistic Career Decision-Making

My findings based on qualitative responses expanded quantitative results on STEM motivation and persistence during early years of college. Some results echo with prior quantitative findings. For example, in this study, subjective task value constructs were more frequent reasons for changes in college major plans than expectancy, suggesting that subjective task values play a bigger role than expectancy when students evaluated their majors in considerations of switching or maintaining their major plans. This message is consistent with previous quantitative findings that career choices were more often associated with subjective task values than with expectancy (Bong, 2001; Lazarides & Lauermann, 2019; Meece et al., 1990). More importantly, my study yielded new findings. First of all, among subjective task value constructs, interest was the most frequently mentioned by students, followed by utility value and attainment value. This prevalence of interest replicates previous findings in qualitative studies (Bieri Buschor et al., 2014; Munyaka, 2017; Talley & Ortiz, 2017). Interest belief is not only intuitive to think of and its prevalence also reflects the predominant cultural ethos of "pursuing your passion" in U.S. universities (Stephens et al., 2012). Students are encouraged by the cultural context to explore and pursue fields of their interest. At the same time, the importance of utility value suggests that students also take into account of the practical value of their college education. The vast majority of utility value explanations pertained to future careers, so the planful alignment between the choice of major and long-term career goals may be potentially adaptive for entering the labor market. Identity-related reasons, which have been a frequent focus of many studies on STEM persistence and attrition (Dou & Cian, 2022; Kim et al., 2018), did not turn out to be a common reason that students in our sample considered. This result was particularly worth noting considering that our sample consisted of a sizable portion of underrepresented racial minority students and first-generation college students. One possible explanation might be students' daily exposure to a diverse student body on campus and in their majors. In this study, European American students took up less than 20 percent of the sample, with comparable portions of Latino students, East Asian students and Southeast Asian students. At the same time, first-generation college-going students comprised nearly half of the sample. Therefore, the reality might have assured underrepresented racial minority students and first-generation students that their social groups are well-represented in STEM classrooms. In this case, the need to identify with a social group in the context (e.g., to identify as STEM students who fit in the STEM classrooms) may not be as strong as in a classroom with less diverse demographics. In addition, the campus bore a comparably diverse student body. As a result, identity-related factors may be present in other aspects of the students' college life and thus less particular to STEM-related career choices. Secondly, I discovered that different EV factors are at play when students considered leaving versus persisting in their chosen major. I found that subjective task value explanations were particularly frequent when students considered entering or persisting in STEM majors, whereas expectancy was particularly mentioned when students considered leaving. Previous quantitative findings on the association between expectancy-value beliefs and career choices revealed uniform associations, such that choices of a particular field depended on the level, not the type, of motivational beliefs (Bong, 2001; Lazarides & Lauermann, 2019; Meece et al., 1990). Our results revealed the differential roles of expectancy and subjective task values in the decisions to leave and to move in/persist respectively. This finding might indicate different targets for efforts to reduce STEM attrition versus to promote STEM entry. If the goal is to attract more students to choose or persist in STEM majors, the finding supports strategies to make the course more valuable to students, such as more interesting, useful, important and/or less costly. If the aim is to alleviate attrition, then the finding suggests maintaining students' confidence to do well in the major. Yet, more research is needed to replicate this finding and explain the psychological mechanisms for this pattern. Another possible explanation for the finding is that individuals with different career trajectories might consider different factors for choosing a major. That is, the finding might pertain less to how one individual makes different decisions but how the subgroup intending to leave and the subgroup intending to persist make decisions. The students who became more certain about their majors might share certain characteristics that lead them to persist by the end of introductory courses and to attribute their choices to values. One such characteristics might be conscientiousness. Findings in counseling psychology showed that individuals with high level of conscientiousness tended to use planful problem-solving strategies to cope with non-interpersonal stresses (DeLongis & Holtzman, 2005). Therefore, conscientious students might be more likely to find out practical, adaptive solutions to handle academic and career-related challenges and thus stay on track with their original major plans. At the same time, higher level of conscientiousness was linked to stronger regulations of achievement behaviors with internal values and interest (Wilmot & Ones, 2019). Therefore, conscientious students might explain their choices with values more often. This explanation needs examination of the causal relationship, but it suggests that the varied explanations for different decisions might be due to between-person differences. This study is limited for distinguishing the within-person and the between-person factors, and more generally, follow-up research is needed to clarify why expectancy and subjective task values differentially relate to in attrition versus persistence decisions.

Major declaration policies, the need to explore major options, and awareness of new major options are other three common reasons. Explanations related to major declaration policies concerns with the time, course history and performance level required for choosing a major. It is worth noting that this policy-related factor appeared in this study but not in previous qualitative studies with participants' retrospective reports. This factor might be regarded as too trivial to ask in interviews, compared with students' motivation, instructional influence and social support. It is also possible that the major declaration policies affect edstudents' on-going persistence decisions more strongly than when students look back on their decisions. Institutions may vary in their regulations about major selection and declaration, so this finding may be specific to our sample. Yet, our finding points to the regulatory power of institution policies on students' changes in their major. The other two reasons reflect the particular stage of career decision-making that students were at in introductory courses. The need to explore major options and the awareness of new major options suggest that the students were gathering information and examining majors that they previously had not known of or considered. They are the two sides of the same coin of career exploration. Based on theories of career development and identity development (Eccles & Wigfield, 2020, Gottfredson, 1981, Marcia, 1980), exploring a variety of career options before committing to a chosen path signals adaptive development. Universities can promote the exploration by providing the time and resources through major declaration policies and career advising.

Contrary to my hypothesis, influences from instructors, family and peers did not appear to be a frequent reason for students' entry or withdrawal from their original major based on the open-ended responses. One explanation might be that the influence of these important socializers affected career decisions through students' domain-specific beliefs, as Eccles theorized in SEVT (Eccles et al., 1983). The affective experience attached to the social interactions might have transformed into the positive and negative attitudes that students hold about an activity or an aspect of a field. In addition, due to the survey data collection method, students were not prompted to further elaborate on how and why their expectancy-value beliefs evolved throughout the course. As a result, the contextual influence did not come across as a common theme as in previous interview studies.

In this study, responses were coded based on a predetermined coding scheme of EV constructs. The goal was to explore the role of motivational beliefs in persistence decisions in qualitative data. Findings about the EV-related explanations in this study are consistent with previous studies on SEVT using quantitative data. Among responses with specific explanations, EV-related reasons took up nearly ninety percent of the answers. The prevalence shows the substantial explanatory power of EV beliefs. In addition, the fact that EV beliefs could be frequently identified in students' daily language suggests the robust ecological validity of these concepts. Students spontaneously described EV beliefs when they were asked to explain their persistence decisions. It shows that the EV concepts were an integral part of career decision-making in its naturalistic setting. These constructs were also identified in previous qualitative studies which did not bear the aim to identify EV concepts (e.g., Edzie, 2014; Fouad et al., 2011). Therefore, it can be concluded that EV concepts substantially cover the beliefs that directly determine career persistence decisions.

Gender differences in Response Pattern, Motivational Changes and Explanations

Overall, women reported negative motivational changes in EV explanations and more withdrawal intention about their major plan than expected by chance. These findings converge with prior literature on gender differences in STEM motivation in introductory courses (Hardin & Longhurst, 2016). Meanwhile, some unexpected gender differences were found. When answering why their major plans changed, women gave more EV-related explanations than expected by chance, whereas men tended to report no change or give no or vague explanations. This difference might be due to women reflecting more often on their personal traits than men do and tend to communicate these thoughts (Belenky et al., 1986; Csank & Conway, 2004). Because EV attitudes are major-specific self-beliefs, women might be more inclined to connect their persistence decisions to these beliefs than men in our study. Data collection methods with more interactions with participants, such as interviews, could be used to prompt self-reflection with men and thus address some of this gender discrepancy in response behaviors.

Men and women also showed nuanced differences in their EV-related explanations. Women reported more decreases in expectancy and more increases in cost than expected by chance but not more decreases in other value constructs. This combination suggests that women found their majors important, interesting and useful as much as men did with similar developmental trends over time, but disproportionally more women became increasingly discouraged about their future success and found their majors increasingly costly during introductory courses. As a result, by the end of the course, the women might be likely to develop a motivational profile with high valuing and low expectancy relative to men. Based on prior findings, this profile was particularly linked to a high level of worry about future performance (Lauermann, Eccles, et al., 2017). Worries about academic performance related to lower academic achievement (Hong et al., 2015), which can further undercut motivation. On average, women experienced less positive affect and stronger withdrawal motivation than men in science classes (Moeller et al., 2015). Findings from this study points to the consequential link among EV motivational beliefs, academic emotion and persistence decisions.

When women and men explain their persistence decisions with EV beliefs, expectancy appear to be more influential for men than women. When explaining why they wanted to change their original major, both men and women tended to point to expectancy with women additionally mentioning the combination of expectancy and subjective task values. Likewise, subjective task value was particularly mentioned when students perceived no change in their major plans, but men additionally mentioned expectancy more often than by chance. Men's tendency to evaluate their future success in their field might be due to the quest for status and power. Men college students in liberal arts college expressed their struggle to find careers that are both lucrative and intellectually fulfilling (Mullen, 2014). These men resolve this dilemma by discontinuing the pursuit of their intellectual interest in choosing major or employment. Researchers can examine the long-term consequences of men's choice to conform to the "breadwinner" role in their career in future research.

Cultural Specificity of Adaptive Career Motives

More discussions have accumulated in recent years to question the generalizability of the common motives of career choices. Some scholars point out that exclusively prioritizing passions may lead to negative career outcomes for first-generation college students. Stebleton (2019) argued that these students are not equipped with the capital that helps to secure a lucrative job when their passion fails to support their living; at the same time, the students often face pressing need to provide for and support their families in various forms. Therefore, it is critical for academic and career advising services to help students make informed decisions to achieve a balance between various needs and motives. Cross-cultural studies between individualistic and collectivistic cultures indicate varied priorities that people place on passion and social obligations. Researchers found that passion was considered problematic and less endorsed by participants as a career motivation in a collectivistic culture, partially because of its conflict with fulfilling social obligations (O'Keefe et al., 2021). This pattern can be understood through the personal and social identities embedded in the attainment value (Eccles, 2009). The pursuit of passion might reflect more of an individualistic motive, which may not align with the person's social roles and responsibilities from a collectivistic perspective. These findings suggests that individuals' career choices are situated in their cultural contexts, so what is considered as adaptive career motives may vary across the cultural backgrounds.

Limitations of Qualitative Survey Responses

In about 25 percent of responses, students only described the ways that their major plans changed without explaining them. More information could have been gathered if these responses had been followed up to prompt explanations. This limitation is caused by the one-directional communication in survey data collection. In the future, researchers can use interviews to ask further questions through conversations. Another limitation of the current question prompt is that the question included both "how" and "why" major plans changed. It can be divided into separate questions to increase responses of explanations.

The response rate on the open-ended question is around 20 percent, causing the lack of representation of the respondent sample. Missing data analyses showed that the participants had lower scores on quantitative measures of expectancy, interest, attainment value and utility value by the end of the course than the non-participants. Therefore, our sample might over-represent students who were thinking about leaving their majors and underrepresent students who considered persisting. Negativity is a common bias in survey reports, such that individuals with negative opinions are more likely to respond to survey questions (Poncheri et al., 2008). Alternative data collection, such as follow-up surveys or interviews with purposive sampling method, can be used to address this limitation.

Conclusion

Using qualitative survey responses, this study provided useful insights about the ways that college students decided on persisting or switching their majors. The findings not only revealed what students considered, but also the inter-relations of these considerations, their relative importance in the decision-making, and their differentiated roles in attrition versus persistence choices. In addition, we showed expectancy beliefs played different roles in men's and women's decisions. Taken together, these results provide a more coherent understanding about the various aspects of why students choose to stay or leave STEM majors.

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Table 3.1
Sample responses of explanations

Construct	Example
Expectancy	“Not sure if I can do well in physics.” “I realized I can do more than I think I can.”
Interest	“I lost interest in engineering.” “I took the class this quarter and I really enjoyed the material more than any of my other courses!”
Attainment value	“I realized I didn't really fit in the health sciences” “I decided that is was not the path for me”
Utility value	“It seems to offer a lot more career opportunities” “I have decided to choose this major so that I can have a good science background to prepare me for medical school”
Cost	“The road is long and the payoff is not that great.” “the classes I’m taking are affecting my mental health.”
Other reasons	“I might not be able to declare into BME due to time restrictions of undeclared.” “I've had the opportunity to explore”
Reason(s) vague	“Realized I don’t want to be a bio major” “Because of Physics”
Only describing major change	“Changing to CsE *(computer science engineering)*.” “Took on a double major”
“I don’t know”	“idk” “I am no longer sure of what I plan to study.”
No change of major	“It doesn’t change.”

Table 3.2
Results of missing data analyses

	Missing sample	Analysis sample	Test statistics	*p*	Effect size
	n	*n*			Cramer's *V*
Women	2731	761	$\chi^2(1, N=5877) = 0.29$	.59	.01
Race/ethnicity			$\chi^2(5, N=5494) = 4.89$	.43	.03
White	561	145			
Latino	1175	339			
East Asian	1071	275			
Southeast Asian/other Asian	1075	325			
South Asian	290	72			
Black	131	35			
First-generation college student	2212	649	$\chi^2(1, N=5855) = 1.24$	.27	.01
Subject			$\chi^2(1, N=5975) = 5.60$	.02	.03
Chemistry	2623	792			
Physics	2032	528			
Intervention condition	2334	655	$\chi^2(1, N=5902) = 0.03$	.86	< .01
EV belief scores	Mean (SD)	Mean (SD)			Cohen's *d*
Expectancy	4.61 (1.48)	4.45 (1.52)	$t(5734)=3.35$	< .001	.11
Interest	4.36 (1.37)	4.24 (1.37)	$t(5733)=2.82$	.005	.09
Attainment value	4.59 (1.48)	4.39 (1.52)	$t(5508)=4.31$	< .001	.14
Utility value	4.91 (1.19)	4.79 (1.21)	$t(5629)=3.10$	.002	.10

Table 3.3

Frequency of various combinations of EV beliefs mentioned in EV-related explanations

Content	Frequency	Percentage
Only pertaining to E	92	21
Decrease in E	79	18
Increase in E	13	3
Only pertaining to V	323	73
Decrease in V	244	55
Increase in V	79	18
Pertaining to both E and V	25	6
Decrease in E and V	21	4
Increase in E and V	3	1
Decrease in E and increase in V	1	1
Including 1 construct	380	86
Including 2 constructs	51	12
Including 3 constructs	9	2
Total	440	100

Note. E = expectancy. V = subjective task values.

Table 3.4

The distribution of EV-related explanations across different types of persistence decisions

Persistence decision	Decrease in E	Increase in E	Decrease in V	Increase in V	Decrease in E & V	Increase in E & V	Total
Less certain about original major	61^{+}	6	134	23^{-}	20^{+}	1	245
No change	12^{-}	7	89	43^{+}	0^{-}	1	152
More certain about original major	6	0	21	13^{+}	1	1	42
Total	79	13	244	79	21	3	439

Note. $^{+}/^{-}$ denotes overrepresentation and underrepresentation of students in a specific cell, with an adjusted standardized residual score no less than 1.96 or no greater than -1.96.

Table 3.5

Frequency of various combinations of EV beliefs mentioned in EV-related explanations

Content	Women	Men	Chi-square Test for gender differences
Only pertaining to E	63 (22%)	27 (18%)	
Decrease in E	57 (20%)	20 (13%)	
Increase in E	6 (2%)	7 (5%)	
Only pertaining to V	199 (71%)	117 (78%)	
Decrease in V	157 (56%)	82 (55%)	χ^2 (5, N=428) = 11.65, p = .04, Cramer's V = .17
Increase in V	42 (15%)$^-$	35 (23%)$^+$	
Pertaining to both E and V	18 (7%)	5 (4%)	
Decrease in E and V	16 (6%)	3 (2%)	
Increase in E and V	2 (1%)	1 (1%)	
Decrease in E and increase in V*	0 (0%)	1 (1%)	
Including 1 construct	242 (87%)	130 (87%)	
Including 2 constructs	32 (11%)	16 (11%)	χ^2 (2, N=429) = 0.06, p = .97, Cramer's V = .01
Including 3 constructs	6 (2%)	3 (2%)	
Total	280 (100%)	149 (100%)	

Note. $^+$/$^-$ denotes overrepresentation and underrepresentation of students in a specific cell, with an adjusted standardized residual score no less than 1.96 or no greater than -1.96.

* Excluded from Chi-square test of gender differences because of limited cell frequency.

Table 3.6

Associations Between EV Explanations and Persistence Decisions Across Gender

A. Men's EV-related explanations across different types of persistence decisions

Persistence decision	Decrease in E	Increase in E	Decrease in V	Increase in V	Decrease in E & V	Increase in E & V	Total
Less certain about original major	18^{+}	1	40	9^{-}	3	0	71
No change	2^{-}	6^{+}	37	21^{+}	0	1	67
More certain about original major	0	0	5	5^{+}	0	0	10
Total	20	7	82	35	3	1	148

B. Women's EV-related explanations across different types of persistence decisions

Persistence decision	Decrease in E	Increase in E	Decrease in V	Increase in V	Decrease in E & V	Increase in E & V	Total
Less certain about original major	41^{+}	5	90	13^{-}	15^{+}	1	165
No change	10^{-}	1	51	22^{+}	0^{-}	0	84
More certain about original major	6	0	16	7	1	1	31
Total	57	6	157	42	16	2	280

Note. $^{+/-}$ denotes overrepresentation and underrepresentation of students in a specific cell, with an adjusted standardized residual score no less than 1.96 or no greater than -1.96. A three-way Chi-square Test of Independence suggested that the gendered pattern in the association between persistence reasons and EV-related explanations is statistically different.

Table 3.7

Mixed-model ANCOVA of the differences in expectancy, interest and utility value between time and group

Qualitatively described changes in EV beliefs	Time 1 Score		Time 2 Score		Interaction Effect in Mixed-model ANCOVA			
	M (SD)	95% CI	M (SD)	95% CI	df	F	*p*	Partial eta squared
Expectancy					1	4.84	.03	.05
Decrease	4.51 (0.14)	[4.24, 4.78]	3.34 (0.15)	[3.03, 3.64]				
Increase	4.63 (0.36)	[3.90, 5.35]	4.54 (0.41)	[3.72, 5.35]				
Interest					1	6.00	.02	.04
Decrease	4.33 (0.13)	[4.07, 4.59]	3.97 (0.13)	[3.71, 4.23]				
Increase	4.71 (0.21)	[4.30, 5.12]	4.87 (0.21)	[4.45, 5.28]				
Utility value					1	0.06	.80	.001
Decrease	5.25 (0.20)	[4.85, 5.65]	4.99 (0.19)	[4.61, 5.38]				
Increase	5.47 (0.24)	[4.99, 5.96]	5.16 (0.23)	[4.70, 5.63]				

Note. Time 1 score = survey scores measured at the beginning of course, Time 2 = survey scores measured at the end of course.

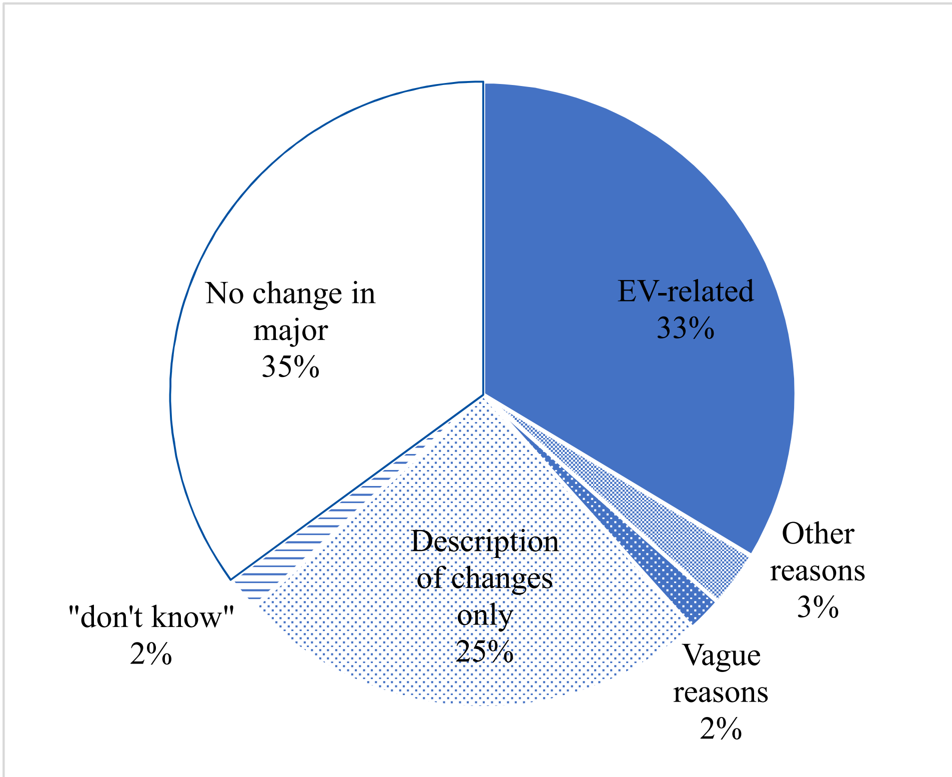


Figure 3.1. Students' responses to why their major plans changed. The total number of responses is 1309.

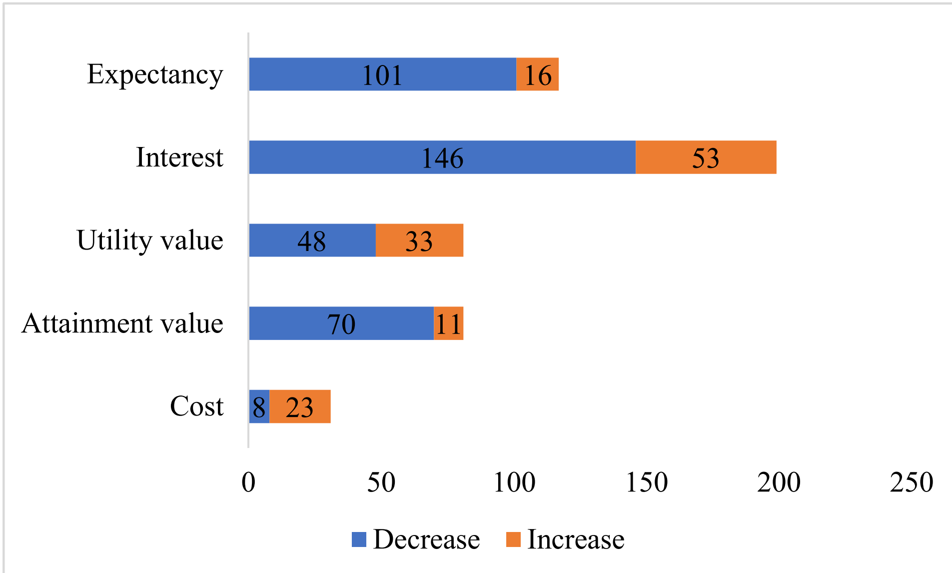
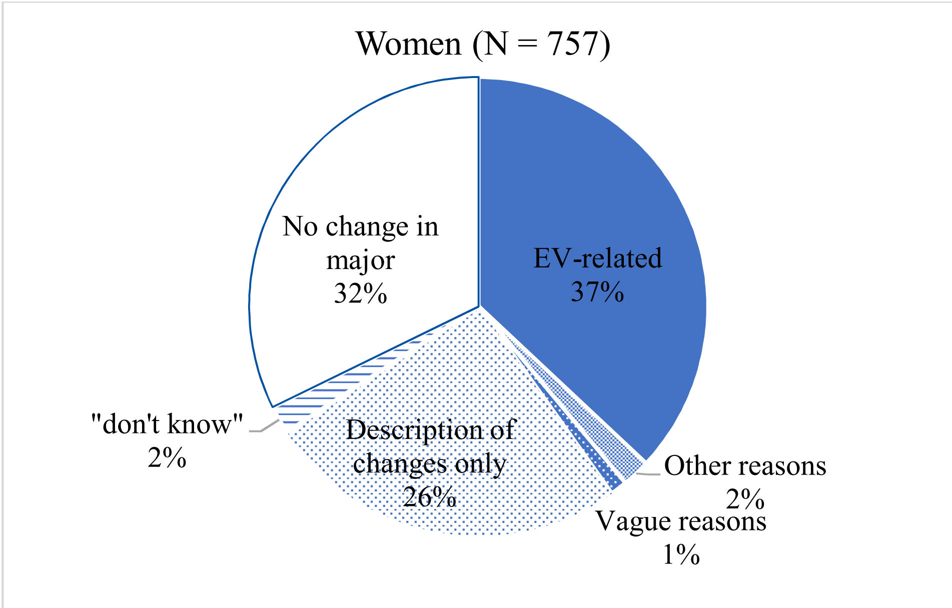


Figure 3.2. EV-related explanations by types of changes. The constructs are not mutually exclusive, so multiple EV could appear together in one response.



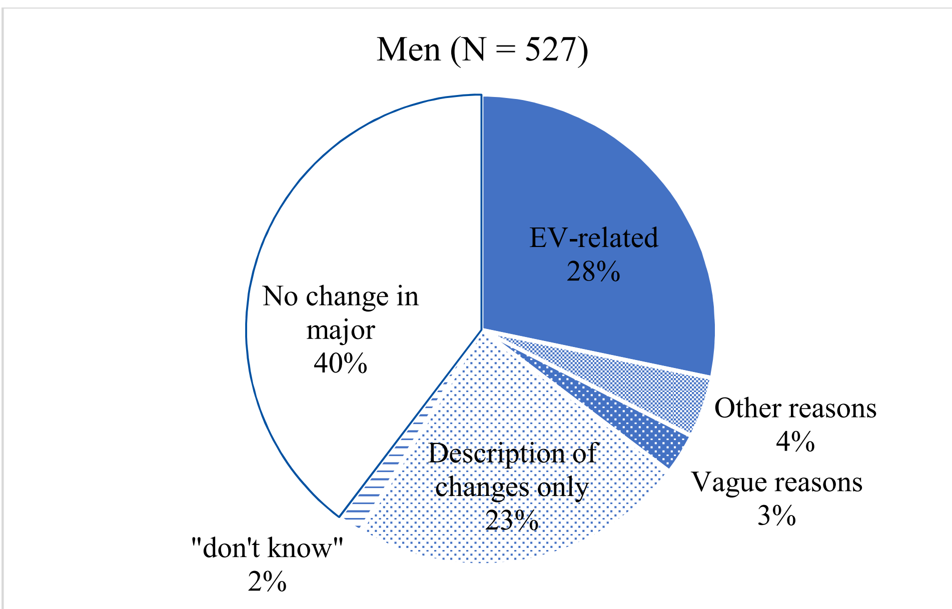


Figure 3.3. Women's and men's responses of why their major plans changed. More men than expected gave other reasons, vague reasons or reported no change in their major. More women than expected gave EV-related reasons.

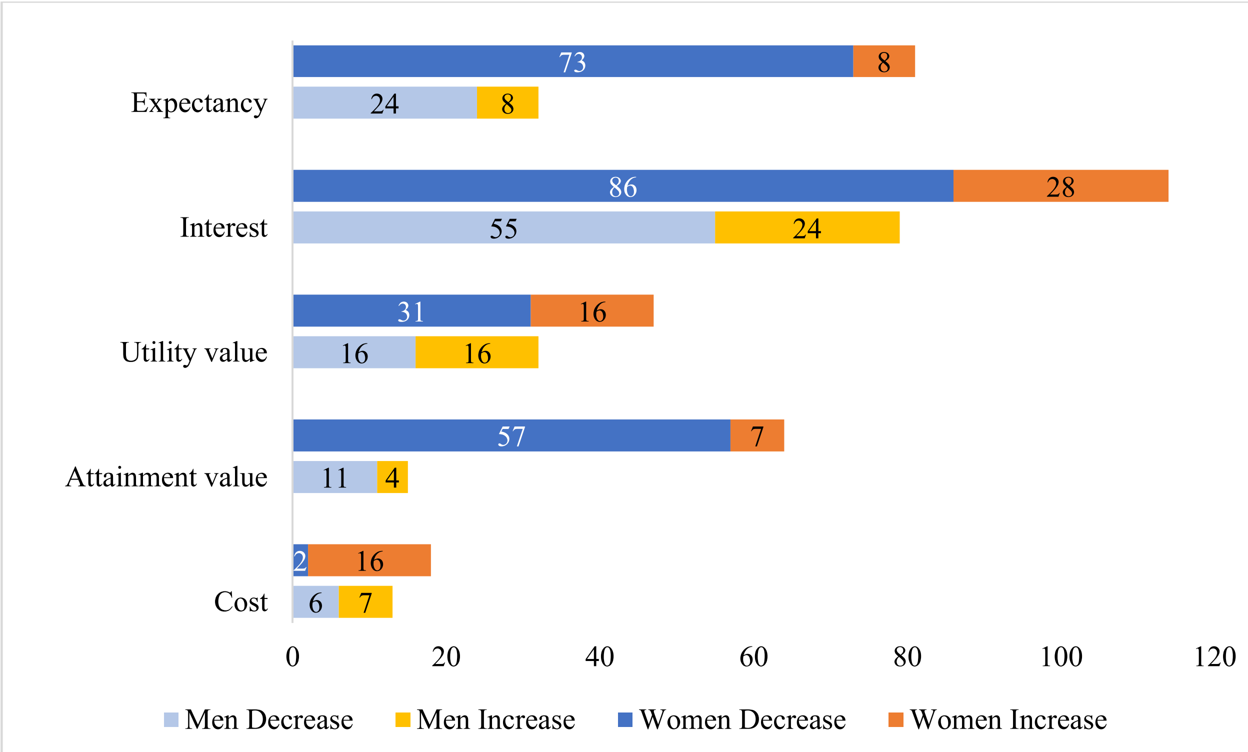


Figure 3.4. Men's and women's EV-related explanations by types of changes. The constructs are not mutually exclusive, so multiple EV could appear together in one response. The distribution of the changes in expectancy and cost differed between gender.

GENERAL DISCUSSION

STEM labor supply is the cornerstone of scientific innovations and advances. Research and policy efforts have been striving to increase the STEM labor supply by patching the "leaky pipeline" of STEM careers. Moreover, the gender differences in STEM participation and attrition have been a critical issue in expanding the STEM labor workforce (Chen & Soldner, 2013; Xie et al., 2015). Men's and women's different career motivation and choices are grounded in the sociocultural influence (Eagly & Steffen, 1984; Eccles, 2011; Simpkins et al., 2015), calling for a gender lens to understand STEM career trajectories. More recently, scholars contend that the "leaky pipeline" metaphor fails to accurately represent diverse STEM career trajectories and stigmatizes individuals leaving the STEM field (Cannady et al., 2014; Metcalf, 2010). This raises the questions of "what do STEM career trajectories look like?" and "why do people change their STEM career paths?". In this dissertation, I aimed to provide evidence to answer these questions by carrying out three studies to describe STEM career paths with gender differences and to explain individual differences in STEM career paths.

Extensive research on STEM career paths exclusively focused on STEM persistence and attrition (e.g., Sadler et al., 2014; Shaw & Barbuti, 2010). Previous studies by Xie and Shauman (2003) shed light on STEM entry as individuals move into STEM careers from previous non-STEM choices. Portraying all existing STEM career paths, including alternative paths leading to STEM occupation, not only reveals the whole picture of STEM career paths but also puts the ongoing discussions about STEM attrition and persistence into a context. For this purpose, in my first study, I described STEM career paths from age 13 and 25 in a national, longitudinal sample across STEM domains. To provide a more comprehensive view, I included the understudied differentiation in education requirement between blue-collar and white-collar STEM careers.

This study expands our understanding of existing STEM career paths and provides the foundation for investigating changes in STEM career choices. In study two and three, I used quantitative and qualitative data to investigate why individuals change their STEM career paths. I conceptualize STEM attrition and entry as changes in a person's career choice and based my studies in the Situated Expectancy-Value Theory and the Internal/External Frame of Reference (Eccles & Wigfield, 2020; Möller et al., 2006; Möller & Marsh, 2013). These studies yielded useful results for the antecedents and motivation of career plan changes in STEM fields. I review the key findings from our three studies and discuss the implications on future research and practices.

Review of Key Findings

A STEM "Highway" With Frequent Exits and Entries Out and into STEM

In study one, the key question we aimed to answer is "what does the STEM 'pipeline' look like?" Our findings indicate that STEM career trajectories resembled a busy highway with individuals entering STEM from various fields and leaving STEM for various destinations at various points in time. This conclusion is drawn from our examinations of four aspects of the STEM career paths: STEM attrition, STEM entry, changes in the size of STEM labor supplies over time, and paths leading to STEM careers. The "pipeline" metaphor highlights the high attrition rate in STEM fields (Chen & Soldner, 2013). Our results support this notion as we found that the attrition rates were higher among STEM careers than among non-STEM careers. However, we discovered that the high attrition rates in STEM did not necessarily associate with a shrinkage of labor supply. This conclusion is drawn from our comparisons between the number of people choosing STEM fields at age 13 with the number of people choosing STEM fields at age 25. There was no sample attritions or additions, so changes in the size of a field resulted from movements of individuals across different fields, instead of leaving or entering the study. We found considerable shrinkage of labor supply in the health STEM and white-collar STEM careers, but a maintenance of size in physics-related STEM fields and an expansion of labor supply in the blue-collar STEM fields. More entry into the STEM field from other fields than attritions was the reason for the maintenance and expansion of physics-related STEM and blue-collar STEM workforce. The prevalence of STEM entry did not support a one-directional, linear career path as implied by the "pipeline" metaphor. Lastly, we investigated the trajectories leading to STEM employment to examine to what extent more presence in a STEM field related to higher likelihood of attaining a STEM occupation. We found that the stereotypical "pipeline" trajectory, with an early commitment followed by persistent choices, was uncommon in most of STEM jobs. It was taken by less than 20 percent of workers in the physics-related STEM field, the blue-collar STEM field, and the white-collar STEM field. However, this trajectory was the most frequent path in the health STEM field, taken by over forty percent of workers. We conjecture that the familiarity of healthcare professions to adolescents and the educational and financial demand of medical school might be relevant to the prevalence of the committed and persistent trajectory unique to the health STEM careers.

From these findings, we conclude that the "pipeline" metaphor is an inaccurate and partial representation of STEM career paths. We found STEM career paths was an open "highway" with people joining the field halfway or returning to the field after a detour in a different field. A linear, one-directional path was infrequent in most STEM jobs. We showed that STEM entry was consequential for the size of labor supply, as much as attrition was. Our study provided a comprehensive picture of the STEM career trajectories to advance our understanding about changes of the STEM workforce throughout the educational and vocational preparation stage.

Gender Similarities in Attrition and Changes of Labor Supply

Gender disparity was at the center of research on STEM attrition and career choices (Eccles, 2011; Xie et al., 2015). Previous research showed that women are more likely than men to leave STEM (Sadler et al., 2012; Shaw & Barbuti, 2010), contributing to the underrepresentation of women in the STEM workforce. Our findings showed gender similarity in attrition rates as well as changes in the size of STEM labor supply. In particular, we found a higher attrition rate among women only in physics-related STEM careers, and a lower attrition rate among women in the health STEM careers. Furthermore, we demonstrated that the STEM labor supply did not shrink more among women. The labor supplies shrank to the similar extent among men and women in health STEM and white-collar STEM fields, expanded among women and shrank among men in the physics-related STEM field, and maintained its size among women in the blue-collar STEM field. Our findings showed that the problems of STEM attrition or shrinkage of STEM labor supply were more severe among women than among men.

Evident Education-based Discrepancies between Blue-collar and White-Collar STEM

Our comparisons of the STEM career trajectories in the blue-collar and white-collar STME careers showed evident influence of educational requirement. The attrition rate and shrinkage of labor supply was higher among white-collar STEM careers than blue-collar STEM careers. At the same time, the entry rate was lower among white-collar STEM careers than blue-collar ones. These findings did not vary between men and women, suggesting a clear influence of education requirement.

Different Sociodemographic, Achievement and Motivational Profiles Between non-STEM and STEM entrants, Between STEM Persisters and Leavers

In study 2, we followed up on the findings in study 1 and compared individuals who changed their STEM career path with their peers who didn't. Among everyone starting with a non-STEM aspiration, those entering the STEM field were less likely to be women, underrepresented racial minorities (URMs), with higher parent education and math performance and lower math subjective task values early on than those who continued in non-STEM careers. Among everyone starting with a STEM aspiration, those leaving the STEM field were more likely to be women, URMs, with lower parent education and math performance, and higher math and reading subjective task values early on than those who persisted in STEM. Early achievement and expectancy in math and reading domains were not uniquely predictive of changes in career path. Men and non-URM individuals were more likely to enter STEM fields given the same parent education, achievement and motivation in math and reading domains; URM individuals were more likely to leave STEM fields when these factors were accounted for. Our results indicate the need to consider job-specific considerations that might relate to the outcome of actual occupation more closely. In addition, our findings suggest shifts in motivational beliefs over the long timespan between the initial aspiration at age 13 and actual occupation at age 25, indicating the role of motivation-in-transformation in changes in career paths.

Changes in Competence-related Beliefs and Subjective Task Values Explained Changes in College Major Plans

In study 3, we coded college students' own explanations for changes in their college major plans. We found that changes in expectancy-value beliefs were the main reasons, with changes in subjective task values mentioned much more often than changes in expectancy. In particular, among students thinking about leaving their original major, disproportionally more students attributed the change to decreases in their expectancy or decreases in both their expectancy and subjective task values; disproportionally fewer students attributed it to increases in their subjective task values. Among students becoming more certain about their original major, disproportionally more students attributed it to increases in their subjective task values.

Contextual and Stage-specific Reasons for Changes in College Major Plans

Among students' giving specific explanations, a small number of students mentioned the influence of major declaration related regulations in the university as main influence of changes in their major plans, highlighting the contextual influence on options that are and are not available to the students. Another type of responses pertained to the need to explore alternative options of major. Because most students in the study were in the first year of their college, they were in the particular stage to explore and learn more about which major they would like to study. Both aspects of these findings point to the situated nature of individuals' career choices, in their external environment and their developmental stage.

Research and Practice Implications

An Updated Landscape of STEM Career Trajectories

Findings from our first and second studies provided an updated landscape of STEM career trajectories. We provided evidence against several aspects of the "leaky pipeline" metaphor, pointing out new directions for research and policy efforts to expand the STEM labor supply and improve the gender balance in STEM workforce. Firstly, we found gender similarity in STEM attrition, regarding the attrition rate, destination of attrition and the trajectory or timing or attrition. This similarity may be the result of decade-long efforts to reduce gender disparity in

STEM attrition. Our results provide substantive evidence for this accomplishment. Secondly, we quantified the changes in the size of the STEM labor supply and narrowed down specific areas in which the labor supply shrank. Namely, the workforce of health STEM careers and white-collar STEM careers shrank considerably from age 13 to 25. This result points out these two subfields needing more research and interventions to increase the STEM labor supply in the future. Thirdly, we found an expansion of women labor supply in physics-related STEM careers, demonstrating a promising ground to further improve women's representation in these men-dominant STEM fields. Fourthly, we suggest that the influential and sizable entry into various STEM fields is another venue through which STEM labor supply and gender imbalance in the workforce can be improved. In particular, the intricate gendered pattern in heath and physics-related STEM field calls for more research to understand men and women's entry and more broadly career development in these professions. Lastly, we identified health STEM as the field in which an early, persistent trajectory with increasingly less entry in later sections of the path was evident. Considering that we found considerable shrinkage of the health STEM labor supply, more investigation is needed regarding to what extent the "pipeline"-like trajectory is related to the shrinkage of the labor supply. Investigations into which aspects and characteristics of the health STEM career drive the shrinkage can also provide useful information for addressing the shrinkage.

Understudied STEM Entry

STEM entrants, people who work in STEM jobs without an early aspiration in the same field, comprised a considerable portion of STEM workers. The large portion of STEM workers suggests that this group are integral to the STEM labor supply as much as, if not more than, STEM persistence. However, in my brief review of the literature, studies on STEM entry were rare compared with those on STEM attrition.

Boosting STEM entry may be a promising way to increase the STEM labor supply. In study two, we found that STEM entrants typically achieved and valued math comparably highly as their STEM persisting peers. It indicates that despite the lack of early aspirations, individuals entering the STEM field at a later time point were competent in STEM field and motivated to pursue STEM careers. Compared with keeping people who are not motivated to pursue STEM careers to stay in the STEM fields, supporting individuals who are motivated in their transition into STEM fields and following career pursuits may be of greater benefit to the STEM entrants, the STEM "leavers" and policymakers. It provides opportunities and support for the STEM entrants as well as the STEM "leavers" to pursue the careers they desire. Currently, the entry into white-collar STEM were less often than entry into blue-collar STEM careers, and the entry into health STEM jobs were small for both genders, indicating challenges and barriers that prospective entrants encounter to transition into the much needed white-collar and health STEM workforce. For policy-making considerations, the alignment of resource and support with individuals' career goals can lead to higher job performance and greater job satisfaction (Kieffer et al., 2004), benefiting the workforce and economy.

Their high math performance and motivation, together with the family resources and support, might be the conducive factors supporting these youths to enter STEM despite the lack of early commitment. Then more questions arise: what makes the students decide to enter STEM at a later time point? The STEM entrants had one of the highest math performances across the four groups, but not the highest math subjective task values. What caused this misalignment? If the entry resulted from that the students later turned to value the math domain which they performed well in, what made this happen? Can researchers and policymakers replicate this process to encourage more STEM-competent adolescents to pursue STEM careers? Answers to these questions can provide innovative perspectives on STEM career trajectories and useful insights for expanding the STEM labor supply.

As discussed in Chapter 3, we believe the STEM entry provides a valuable alternative path to the traditional "pipeline" as successful pathways into STEM. The prevalence of STEM entry provides evidence against the "cumulative advantage" of early STEM career choices (Lent et al., 1994). If STEM career aspirations at age 13 were not necessary for obtaining a STEM career in mid-20s, what is the necessity for successfully entering the STEM field later on? The prevalence of STEM entry among STEM workers indicates much more is to be learned about.

Beyond Women in STEM: Diverse Workforce, Diverse Trajectories

Our findings provide evidence for the limitation of the "cumulative disadvantage" perspective on STEM career trajectories. We showed that a sizable portion of individuals successfully entered STEM careers despite a lack of earlier choices, and that most workers did not take a persistent trajectory to attain their STEM occupation except in health STEM careers. Our findings suggest that the "cumulative disadvantage", perhaps the "cumulative advantage", may be a useful explanation for why people find it easier to continue doing what they have been doing, but the absence of the initial "advantage" does not necessarily set off the negative cycle for people to avoid participating in field. Our findings showed the prevalence of pathways into STEM careers despite the lack of early aspirations. We would like to underscore two important implications form our results.

Firstly, our finding questions the existence and extent of the "disadvantage" or "advantage" between individuals choosing STEM and those choosing non-STEM from early one. Results from the study 2 showed the lack of differences in math competence between individuals choosing STEM and persisted over time and individuals who entered STEM at a later timepoint. This result moved beyond findings on gender similarity in math performance (Hyde & Mertz, 2009) to suggest that the lack of competence not only may not be the reason for the individual differences in STEM career choices at one point in time, but also may not be the reason for the delayed entry or participation in STEM careers. Our finding on the value-driven considerations and contextual influences on students' change of major plans in study 3 supports the multifaceted, and situated framework like the Situated Expectancy-Value Theory (SEVT, Eccles & Wigfield, 2020; Eccles et al., 1983). This perspective points to a shift in the methodological approach beyond a regression-based analysis to test the influence of earlier STEM participation or performance on later participation or choices. Competitive factors, such as change in domain-specific beliefs and values, as well as contextual factors, should be added to the model to specify the scope of each type of factors and compare the size of their influence relative to each other. Moreover, prior participation contains the variation in the domain-specific values and contextual factors at an earlier time, and thus interpreting it as the result of these factors is useful for preventing the oversimplified understanding of the "cumulative disadvantage/disadvantage". The goal of explaining as much as variance in the outcome variable of later STEM participation may lead to mistaking the phenomenon for its cause.

Secondly, our findings questions to what extent promoting a persistent STEM career path is beneficial for expanding the STEM labor workforce. Our findings suggest that the persistent trajectory was found on only a small portion of STEM workers, and paths into STEM careers are very diverse and eclectic. Our findings from the study 2 and 3 suggests that individuals differ in their contextual and developmental coordinate in career developmental trajectories. When some college students were committed to their career choices, other students might have been learning about available options. The discrepancy reflects their differences in prior experience and social constraints (Ek et al., 2021; Stephen et al., 1992), including but not limited to family socioeconomic status, underrepresented racial minority status, etc (Dika & D'Amico, 2016; Perry et al., 2009). Promoting knowledge about STEM careers and providing career exploration resources and activities may benefit everyone in their explorations of career goals, and the advantage of these types of support may be maximized when matched with the developmental stage or individual situation (Eccles et al., 1997; Eccles & Roeser, 2009). Thus, perhaps the best way to expand the STEM labor supply is to provide support for individuals at various stages of career development to follow their career path in their own pace and trajectory.

Using the SEVT and Internal/External Frame of Reference to Understand Career Trajectories

Findings from our study 2 and 3 showed the potential to extend the SEVT and the Dimensional Comparison Theory from career choices at one point in time to career trajectories over time. In study 3, we found that students' attributed changes in their college major plan to expectancy-value concepts. These concepts appeared in most of responses that contained specific explanations, indicating the relevance of the concepts to the decision to change or maintain career choices. Moreover, we found results parallel to previous findings on expectancy-value beliefs in career choices. For instance, our finding that increases in expectancy or subjective task values about the original major were related with students' greater certainty about their original choices of major resembled the positive correlation between expectancy-value beliefs with career choices at one point in time (Simpkins et al., 2006). We also found applicability of the Internal/External Frame of Reference when students described changes in their expectancy-value beliefs. For instance, we noticed the internal comparison among several major options. This is also the within-person comparison described in the SEVT. A major became less desirable to a student when the student became attracted by another major. Thus, the original major shifted to a lower level in the student's hierarchy of available major options. Temporal comparisons of expectancy-value beliefs also appeared in our study, as students mentioned their implicit comparison of their expectancy-value beliefs at the end of the introductory class with those at the beginning of the class. These mechanisms that are relevant to career choices at one point in time were found to involve in decisions about persistence or changes in college major.

At the same time, findings from our second study indicates the need to take into account of the evolvement of expectancy-value beliefs as antecedents of changes in STEM career paths. In our comparison between individuals persisting in STEM and individuals leaving STEM, we found that the non-STEM group had higher math subjective task value than STEM entrants at age 13. Relatedly, we discovered a negative association between math subjective task value and likelihood of switching into STEM careers. Our follow-up inspections suggested that the subjective task value beliefs of the two groups might have developed in a cross-over trend. As adolescents went through school transitions and school to work transitions, their self-perceptions about their domain-specific identity were likely to transform (Jacobs et al., 2002; Wigfield et al., 1991). Therefore, future studies could investigate the developmental trajectories of expectancy-value beliefs using techniques such as growth mixture modeling and test the association between different trajectories of motivational beliefs and changes in career choices. One relevant issue may be the time frame in which expectancy-value beliefs are measured. Studies using the experience sampling method showed that motivational beliefs can be volatile across short periods of time. Therefore, more research is needed to explore at which time scale expectancy-value beliefs should be measured in order to find influences on career outcomes.

Strengths and Contributions of Person-centered Approach to Discover Diverse Career Trajectories

In study 1, we used two person-centered approaches to describe trajectories of STEM career choices and found the STEM entry paths which were relatively understudied. In fact, we learned more about the STEM entry in our analysis with individual career trajectories than from the longitudinal latent class analysis. The latter technique, which extracts numerically representative patterns, was able to find entry into blue-collar STEM careers that were more common but did not show entry into health STEM careers that were of a small quantity. In a special issue of the Journal of Social Issues, Feinstein and Peck (2008) discussed the value of finding the "off-diagonal" trajectories. The "off-diagonal" approaches, in contrast to the numerically common trajectories, such as STEM persistence and attrition in the case of our first study, can provide innovative understanding about the protective/risk factors of the development of a specific behavior. As we demonstrated and discussed in study 2, the STEM entry showed the exceptions or limit of the influence of prior STEM career choices on later choices. These exceptions are useful examples to put existing understanding about STEM career trajectories into a perspective and shed some optimistic light on how people beat the odds. A shift in perspective and even paradigm is thus possible from a "deficit view" to a diversity view. Researchers have cautioned that these exceptions may be idiosyncratic and endogenous (Duncan, 2008). The "off-diagonal" groups may be limited for drawing causal inferences but like case studies and interviews, they can provide useful information on unique and common factors of career development.

Performance-driven, Inflexible Breadwinners

If the gender role socialization discourages some women to pursue their intended physics-related STEM careers, how does it affect men's STEM career? My findings suggest two folds of consequences. The first consequence may be the lack of choices in non-STEM careers. In study two, I found that more men than expected were present in the persistence trajectory in the broad STEM field. This group featured high math performance and low valuing for English. Over time, the lower valuing for English might lead to less participation in language domain (Durik et al., 2006), leading to differentiated math and English performances. The differentiation might have limited restrictions on a man's likelihood to find a well-paid job, such as those in the STEM field, but it may restrict the person's flexibility to adjust to changes in the job market. The findings of Wang and colleagues (2013) showed that adolescents who did well in both math and reading have lower chance of working in STEM fields in adulthood than adolescents who did well in math and moderately in reading, suggesting that the latter group of adolescents might choose STEM because of the lack of choices. Traditional gender role beliefs that men should be the breadwinner may be another reason of the choice. Individuals who endorse such beliefs were more likely to work in STEM jobs in adulthood compared with individuals with equivalent educational attainment (Dicke et al., 2019). Taken these two pieces together, a subgroup of men in the STEM fields might work in a STEM job because it's well paid and does not require strong language skills. Jobs in the manufacturing and transportation industries are examples. These industries might be those at the forefront of the influence of economic fluctuations and technological innovation. The recent COVID pandemic and the competition from the rising technology of automated driving are examples of the impact on the transportation industry. If a family relies on men in these fields as the breadwinner, the impact of an unemployment on income, psychological and physical well-being will be magnified. For instance, researchers pointed to increased male unemployment as one factor for the rise of domestic violence during the COVID pandemic (Krishnakumar & Verma, 2021; Leslie & Wilson, 2020).

The second fold of the consequence is the value conflicts in career choices. Literature documented that men in college face a dilemma between the need to find lucrative jobs to provide for families and their personal interest (Mullen, 2014). Men who prioritize the breadwinner role may enter jobs that do not fit their vocational interest. Such mismatch undermines a person's job satisfaction, job performance and work quality (Earl, 2015; Kieffer et al., 2004), which hinders the fulfillment of the breadwinner role.

In a nutshell, from a few pieces of finding in my study, I believe that the gender role socialization harms career outcomes of men as well. The socialization of gender role beliefs is aimed to fit an individual into a rigid, probably unrepresentative, frame of what a man or women should be like. The benefit of the social influence remains unclear, yet the substantial cost on career outcomes and other aspects falls on every person.

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Appendix A

Missing Data and Participant Exclusion Information.

Reasons for Missing/Exclusion	Frequency
Total participants in CDS 2002’	2907
Not eligible for child interview (i.e., under age 8)	253
Interview incomplete	472
Total interview respondents in CDS 2002’	2182
Not eligible for career aspiration questions (i.e., under age 12)	872
“Don't know”	52
Refuse to answer questions	8
Total participants with concrete responses	1250
Did not participate in data collection at age 25	118
Unemployed at age25 (e.g., disability, housewife/husband, student)	53
No employment information collected due to study design	53
Total participants in Two-wave Sample (age 13 – age 25)	1026
Did not participate in data collection in 2007 or 2009	1
Did not answer career aspiration question in 2007 or 2009	25
Refuse to answer question, “don't know”	21
Data entry error	1
Total Participant in Three-wave Sample (age 13 – age 19 – age 25)	978
No answer for career aspiration in 2005’ or 2007’	100
Don't know/refuse on question in 2005’ or 2007’	10
No answer for career aspiration in 2009’ or 2011’	32
Don't know/refuse on question in 2009’ or 2011’	20
No answer career aspiration in 2005’, 2007’, 2009’ and 2011’	4
Total Participant in Four-wave Sample (Age 13 – Age 18 – Age 21 – Age 25)	812

Appendix B

List of Occupations Present in Reponses with STEM Domain Classifications

2000 Census code	Census occupation title	Category
1	Chief Executives	non-STEM
2	General and Operations Managers	physics STEM
3	Legislators	non-STEM
4	Advertising and Promotions Managers	non-STEM
5	Marketing and Sales Managers	non-STEM
6	Public Relations Managers	non-STEM
9		data entry error
11	Computer and Information Systems Managers	physics STEM
12	Financial Managers	physics STEM
13	Human Resources Managers	non-STEM
14	Industrial Production Managers	non-STEM
15	Purchasing Managers	physics STEM
16	Transportation, Storage, and Distribution Managers	non-STEM
20	Farm, Ranch, and Other Agricultural Managers	health STEM
21	Farmers and Ranchers	physics STEM
22	Construction Managers	physics STEM
23	Education Administrators	non-STEM
30	Engineering Managers	physics STEM
31	Food Service Managers	non-STEM
32	Funeral Directors	non-STEM
34	Lodging Managers	physics STEM
35	Medical and Health Services Managers	non-STEM
36	Natural Sciences Managers	non-STEM
41	Property, Real Estate, and Community Association Managers	physics STEM
42	Social and Community Service Managers	non-STEM
43	Managers, All Other	non-STEM
50	Agents and Business Managers of Artists, Performers, and Athletes	non-STEM
52	Wholesale and Retail Buyers, Except Farm Products	non-STEM
53	Purchasing Agents, Except Wholesale, Retail, and Farm Products	physics STEM
54	Claims Adjusters, Appraisers, Examiners, and Investigators	non-STEM
56	Compliance Officers, Except Agriculture, Construction, Health and Safety, and Transportation	non-STEM
58		data entry error

59		data entry error
60	Cost Estimators	physics STEM
62	Human Resources, Training, and Labor Relations Specialists	non-STEM
70	Logisticians	non-STEM
71	Management Analysts	non-STEM
72	Meeting and Convention Planners	non-STEM
73	Other Business Operations Specialists	non-STEM
80	Accountants and Auditors	physics STEM
81	Appraisers and Assessors of Real Estate	non-STEM
82	Budget Analysts	physics STEM
84	Financial Analysts	physics STEM
85	Personal Financial Advisors	physics STEM
88		data entry error
91	Loan Counselors and Officers	physics STEM
93	Tax Examiners, Collectors, and Revenue Agents	physics STEM
94	Tax Preparers	physics STEM
95	Financial Specialists, All Other	physics STEM
100	Computer Scientists and Systems Analysts	physics STEM
101	Computer Programmers	physics STEM
102	Computer Software Engineers	physics STEM
104	Computer Support Specialists	physics STEM
106	Database Administrators	physics STEM
110	Network and Computer Systems Administrators	physics STEM
111	Network Systems and Data Communications Analysts	physics STEM
120	Actuaries	physics STEM
121	Mathematicians	physics STEM
122	Operations Research Analysts	physics STEM
130	Architects, Except Naval	non-STEM
131	Surveyors, Cartographers, and Photogrammetrists	physics STEM
132	Aerospace Engineers	physics STEM
133	Agricultural Engineers	physics STEM
134	Biomedical Engineers	physics STEM
135	Chemical Engineers	physics STEM
136	Civil Engineers	physics STEM
140	Computer Hardware Engineers	physics STEM
141	Electrical and Electronics Engineers	physics STEM
142	Environmental Engineers	physics STEM
143	Industrial Engineers, Including Health and Safety	physics STEM
144	Marine Engineers and Naval Architects	physics STEM
145	Materials Engineers	physics STEM
146	Mechanical Engineers	physics STEM
150	Mining and Geological Engineers, Including Mining Safety Engineers	physics STEM

151	Nuclear Engineers	physics STEM
152	Petroleum Engineers	physics STEM
153	Engineers, All Other	physics STEM
154	Drafters	physics STEM
155	Engineering Technicians, Except Drafters	physics STEM
156	Surveying and Mapping Technicians	physics STEM
160	Agricultural and Food Scientists	health STEM
161	Biological Scientists	health STEM
164	Conservation Scientists and Foresters	health STEM
165	Medical Scientists	health STEM
170	Astronomers and Physicists	physics STEM
171	Atmospheric and Space Scientists	physics STEM
172	Chemists and Materials Scientists	physics STEM
174	Environmental Scientists and Geoscientists	physics STEM
176	Physical Scientists, All Other	physics STEM
180	Economists	physics STEM
181	Market and Survey Researchers	physics STEM
182	Psychologists	non-STEM
183	Sociologists	non-STEM
184	Urban and Regional Planners	non-STEM
186	Miscellaneous Social Scientists and Related Workers	non-STEM
191	Biological Technicians	health STEM
192	Chemical Technicians	physics STEM
193	Geological and Petroleum Technicians	physics STEM
196	Other Life, Physical, and Social Science Technicians	physics STEM
200	Counselors	non-STEM
201	Social Workers	non-STEM
202	Miscellaneous Community and Social Service Specialists	non-STEM
204	Clergy	non-STEM
205	Directors, Religious Activities and Education	non-STEM
206	Religious Workers, All Other	non-STEM
210	Lawyers	non-STEM
211	Judges, Magistrates, and Other Judicial Workers	non-STEM
214	Paralegals and Legal Assistants	non-STEM
215	Miscellaneous Legal Support Workers	non-STEM
220	Postsecondary Teachers	non-STEM
230	Preschool and Kindergarten Teachers	non-STEM
231	Elementary and Middle School Teachers	non-STEM
232	Secondary School Teachers	non-STEM
233	Special Education Teachers	non-STEM
234	Other Teachers and Instructors	non-STEM
240	Archivists, Curators, and Museum Technicians	non-STEM
243	Librarians	non-STEM

244	Library Technicians	non-STEM
254	Teacher Assistants	non-STEM
255	Other Education, Training, and Library Workers	non-STEM
260	Artists and Related Workers	physics STEM
263	Designers	non-STEM
270	Actors	non-STEM
271	Producers and Directors	physics STEM
272	Athletes, Coaches, Umpires, and Related Workers	non-STEM
274	Dancers and Choreographers	non-STEM
275	Musicians, Singers, and Related Workers	non-STEM
276	Entertainers and Performers, Sports and Related Workers, All Other	non-STEM
280	Announcers	physics STEM
281	News Analysts, Reporters and Correspondents	non-STEM
282	Public Relations Specialists	non-STEM
283	Editors	non-STEM
284	Technical Writers	physics STEM
285	Writers and Authors	non-STEM
286	Miscellaneous Media and Communication Workers	non-STEM
290	Broadcast and Sound Engineering Technicians and Radio Operators	physics STEM
291	Photographers	non-STEM
292	Television, Video, and Motion Picture Camera Operators and Editors	physics STEM
296	Media and Communication Equipment Workers, All Other	physics STEM
300	Chiropractors	health STEM
301	Dentists	health STEM
303	Dietitians and Nutritionists	health STEM
304	Optometrists	health STEM
305	Pharmacists	health STEM
306	Physicians and Surgeons	health STEM
311	Physician Assistants	health STEM
313	Registered Nurses	health STEM
314	Audiologists	non-STEM
315	Occupational Therapists	health STEM
316	Physical Therapists	health STEM
320	Radiation Therapists	health STEM
322	Respiratory Therapists	health STEM
323	Speech-Language Pathologists	non-STEM
324	Therapists, All Other	health STEM
325	Veterinarians	health STEM
326	Health Diagnosing and Treating Practitioners, All Other	health STEM
330	Clinical Laboratory Technologists and Technicians	health STEM

331	Dental Hygienists	health STEM
332	Diagnostic Related Technologists and Technicians	non-STEM
340	Emergency Medical Technicians and Paramedics	health STEM
341	Health Diagnosing and Treating Practitioner Support Technicians	health STEM
350	Licensed Practical and Licensed Vocational Nurses	health STEM
351	Medical Records and Health Information Technicians	non-STEM
353	Miscellaneous Health Technologists and Technicians	health STEM
354	Other Healthcare Practitioners and Technical Occupations	health STEM
360	Nursing, Psychiatric, and Home Health Aides	non-STEM
362	Physical Therapist Assistants and Aides	health STEM
363	Massage Therapists	non-STEM
364	Dental Assistants	health STEM
365	Medical Assistants and Other Healthcare Support Occupations	health STEM
370	First-Line Supervisors/Managers of Correctional Officers	non-STEM
371	First-Line Supervisors/Managers of Police and Detectives	non-STEM
372	First-Line Supervisors/Managers of Fire Fighting and Prevention Workers	non-STEM
373	Supervisors, Protective Service Workers, All Other	non-STEM
374	Fire Fighters	health STEM
375	Fire Inspectors	non-STEM
380	Bailiffs, Correctional Officers, and Jailers	non-STEM
382	Detectives and Criminal Investigators	non-STEM
383	Fish and Game Wardens	health STEM
385	Police and Sheriff's Patrol Officers	non-STEM
386	Transit and Railroad Police	non-STEM
390	Animal Control Workers	non-STEM
391	Private Detectives and Investigators	non-STEM
392	Security Guards and Gaming Surveillance Officers	physics STEM
395	Lifeguards and Other Protective Service Workers	non-STEM
400	Chefs and Head Cooks	non-STEM
401	First-Line Supervisors/Managers of Food Preparation and Serving Workers	non-STEM
402	Cooks	non-STEM
403	Food Preparation Workers	non-STEM
404	Bartenders	non-STEM
405	Combined Food Preparation and Serving Workers, Including Fast Food	non-STEM
406	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop	non-STEM
411	Waiters and Waitresses	non-STEM
412	Food Servers, Nonrestaurant	non-STEM
413	Dining Room and Cafeteria Attendants and Bartender Helpers	non-STEM

414	Dishwashers	non-STEM
415	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop	non-STEM
416	Food Preparation and Serving Related Workers, All Other	non-STEM
420	First-Line Supervisors/Managers of Housekeeping and Janitorial Workers	non-STEM
421	First-Line Supervisors/Managers of Landscaping, Lawn Service, and Groundskeeping Workers	non-STEM
422	Janitors and Building Cleaners	non-STEM
423	Maids and Housekeeping Cleaners	non-STEM
424	Pest Control Workers	non-STEM
425	Grounds Maintenance Workers	non-STEM
430	First-Line Supervisors/Managers of Gaming Workers	physics STEM
432	First-Line Supervisors/Managers of Personal Service Workers	non-STEM
434	Animal Trainers	non-STEM
435	Nonfarm Animal Caretakers	non-STEM
440	Gaming Service Workers	non-STEM
443	Miscellaneous Entertainment Attendants and Related Workers	non-STEM
446	Funeral Service Workers	non-STEM
450	Barbers	non-STEM
451	Hairdressers, Hairstylists, and Cosmetologists	non-STEM
452	Miscellaneous Personal Appearance Workers	non-STEM
453	Baggage Porters, Bellhops, and Concierges	non-STEM
454	Tour and Travel Guides	non-STEM
455	Transportation Attendants	non-STEM
460	Child Care Workers	non-STEM
461	Personal and Home Care Aides	non-STEM
462	Recreation and Fitness Workers	non-STEM
464	Residential Advisors	non-STEM
465	Personal Care and Service Workers, All Other	non-STEM
470	First-Line Supervisors/Managers of Retail Sales Workers	non-STEM
471	First-Line Supervisors/Managers of Non-Retail Sales Workers	non-STEM
472	Cashiers	non-STEM
474	Counter and Rental Clerks	non-STEM
475	Parts Salespersons	non-STEM
476	Retail Salespersons	non-STEM
480	Advertising Sales Agents	non-STEM
481	Insurance Sales Agents	physics STEM
482	Securities, Commodities, and Financial Services Sales Agents	physics STEM
483	Travel Agents	non-STEM
484	Sales Representatives, Services, All Other	non-STEM
485	Sales Representatives, Wholesale and Manufacturing	non-STEM
490	Models, Demonstrators, and Product Promoters	non-STEM

492	Real Estate Brokers and Sales Agents	non-STEM
494	Telemarketers	non-STEM
495	Door-To-Door Sales Workers, News and Street Vendors, and Related Workers	non-STEM
496	Sales and Related Workers, All Other	non-STEM
500	First-Line Supervisors/Managers of Office and Administrative Support Workers	non-STEM
501	Switchboard Operators, Including Answering Service	non-STEM
502	Telephone Operators	non-STEM
510	Bill and Account Collectors	non-STEM
511	Billing and Posting Clerks and Machine Operators	non-STEM
512	Bookkeeping, Accounting, and Auditing Clerks	non-STEM
513	Gaming Cage Workers	physics STEM
514	Payroll and Timekeeping Clerks	non-STEM
515	Procurement Clerks	non-STEM
516	Tellers	non-STEM
520	Brokerage Clerks	non-STEM
522	Court, Municipal, and License Clerks	non-STEM
524	Customer Service Representatives	non-STEM
525	Eligibility Interviewers, Government Programs	non-STEM
526	File Clerks	non-STEM
530	Hotel, Motel, and Resort Desk Clerks	non-STEM
531	Interviewers, Except Eligibility and Loan	non-STEM
532	Library Assistants, Clerical	non-STEM
533	Loan Interviewers and Clerks	non-STEM
534	New Accounts Clerks	non-STEM
536	Human Resources Assistants, Except Payroll and Timekeeping	non-STEM
540	Receptionists and Information Clerks	non-STEM
541	Reservation and Transportation Ticket Agents and Travel Clerks	physics STEM
542	Information and Record Clerks, All Other	non-STEM
550	Cargo and Freight Agents	non-STEM
551	Couriers and Messengers	non-STEM
552	Dispatchers	non-STEM
553	Meter Readers, Utilities	non-STEM
554	Postal Service Clerks	non-STEM
555	Postal Service Mail Carriers	non-STEM
556	Postal Service Mail Sorters, Processors, and Processing Machine Operators	non-STEM
560	Production, Planning, and Expediting Clerks	non-STEM
561	Shipping, Receiving, and Traffic Clerks	non-STEM
562	Stock Clerks and Order Fillers	non-STEM
563	Weighers, Measurers, Checkers, and Samplers, Recordkeeping	non-STEM

570	Secretaries and Administrative Assistants	physics STEM
579		data entry error
580	Computer Operators	physics STEM
581	Data Entry Keyers	non-STEM
582	Word Processors and Typists	non-STEM
584	Insurance Claims and Policy Processing Clerks	non-STEM
585	Mail Clerks and Mail Machine Operators, Except Postal Service	non-STEM
586	Office Clerks, General	non-STEM
590	Office Machine Operators, Except Computer	non-STEM
591	Proofreaders and Copy Markers	non-STEM
593	Office and Administrative Support Workers, All Other	non-STEM
600	First-Line Supervisors/Managers of Farming, Fishing, and Forestry Workers 45-1010	non-STEM
602	Animal Breeders	non-STEM
605	Miscellaneous Agricultural Workers	health STEM
610	Fishers and Related Fishing Workers	non-STEM
612	Forest and Conservation Workers	non-STEM
613	Logging Workers	physics STEM
620	First-Line Supervisors/Managers of Construction Trades and Extraction Workers	physics STEM
622	Brickmasons, Blockmasons, and Stonemasons	non-STEM
623	Carpenters	physics STEM
624	Carpet, Floor, and Tile Installers and Finishers	physics STEM
625	Cement Masons, Concrete Finishers, and Terrazzo Workers	non-STEM
626	Construction Laborers	physics STEM
630	Paving, Surfacing, and Tamping Equipment Operators	non-STEM
632	Operating Engineers and Other Construction Equipment Operators	non-STEM
633	Drywall Installers, Ceiling Tile Installers, and Tapers	non-STEM
635	Electricians	physics STEM
636	Glaziers	non-STEM
640	Insulation Workers	non-STEM
642	Painters, Construction and Maintenance	non-STEM
644	Pipelayers, Plumbers, Pipefitters, and Steamfitters	physics STEM
648		data entry error
651	Roofers	non-STEM
652	Sheet Metal Workers	physics STEM
653	Structural Iron and Steel Workers	physics STEM
660	Helpers, Construction Trades	non-STEM
673	Highway Maintenance Workers	non-STEM
674	Rail-Track Laying and Maintenance Equipment Operators	physics STEM
676	Miscellaneous Construction and Related Workers	physics STEM
682	Earth Drillers, Except Oil and Gas	physics STEM

684	Mining Machine Operators	physics STEM
700	First-Line Supervisors/Managers of Mechanics, Installers, and Repairers	physics STEM
701	Computer, Automated Teller, and Office Machine Repairers	physics STEM
702	Radio and Telecommunications Equipment Installers and Repairers	physics STEM
703	Avionics Technicians	physics STEM
704	Electric Motor, Power Tool, and Related Repairers	physics STEM
710	Electrical and Electronics Repairers, Industrial and Utility	physics STEM
711	Electronic Equipment Installers and Repairers, Motor Vehicles	physics STEM
712	Electronic Home Entertainment Equipment Installers and Repairers	physics STEM
713	Security and Fire Alarm Systems Installers	physics STEM
714	Aircraft Mechanics and Service Technicians	physics STEM
715	Automotive Body and Related Repairers	physics STEM
720	Automotive Service Technicians and Mechanics	physics STEM
721	Bus and Truck Mechanics and Diesel Engine Specialists	physics STEM
722	Heavy Vehicle and Mobile Equipment Service Technicians and Mechanics	physics STEM
724	Small Engine Mechanics	physics STEM
726	Miscellaneous Vehicle and Mobile Equipment Mechanics, Installers, and Repairers	physics STEM
731	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	physics STEM
733	Industrial and Refractory Machinery Mechanics	physics STEM
734	Maintenance and Repair Workers, General	physics STEM
735	Maintenance Workers, Machinery	physics STEM
742	Telecommunications Line Installers and Repairers	non-STEM
752	Commercial Drivers	physics STEM
754	Locksmiths and Safe Repairers	physics STEM
761	Helpers--Installation, Maintenance, and Repair Workers	physics STEM
762	Other Installation, Maintenance, and Repair Workers	physics STEM
770	First-Line Supervisors/Managers of Production and Operating Workers	physics STEM
771	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	physics STEM
772	Electrical, Electronics, and Electromechanical Assemblers	non-STEM
773	Engine and Other Machine Assemblers	physics STEM
774	Structural Metal Fabricators and Fitters	physics STEM
775	Miscellaneous Assemblers and Fabricators	non-STEM
780	Bakers	non-STEM
781	Butchers and Other Meat, Poultry, and Fish Processing Workers	non-STEM
783	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders	non-STEM
784	Food Batchmakers	non-STEM

785	Food Cooking Machine Operators and Tenders	non-STEM
790	Computer Control Programmers and Operators	physics STEM
792	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	physics STEM
795	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	physics STEM
796	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic	physics STEM
800	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	non-STEM
801	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	physics STEM
803	Machinists	physics STEM
804	Metal Furnace and Kiln Operators and Tenders	physics STEM
810	Molders and Molding Machine Setters, Operators, and Tenders, Metal and Plastic	non-STEM
814	Welding, Soldering, and Brazing Workers	non-STEM
815	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	non-STEM
820	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic	physics STEM
822	Metalworkers and Plastic Workers, All Other	physics STEM
823	Bookbinders and Bindery Workers	non-STEM
825	Prepress Technicians and Workers	physics STEM
826	Printing Machine Operators	non-STEM
830	Laundry and Dry-Cleaning Workers	non-STEM
831	Pressers, Textile, Garment, and Related Materials	non-STEM
832	Sewing Machine Operators	non-STEM
835	Tailors, Dressmakers, and Sewers	non-STEM
843	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers	non-STEM
853	Sawing Machine Setters, Operators, and Tenders, Wood	non-STEM
854	Woodworking Machine Setters, Operators, and Tenders, Except Sawing	non-STEM
855	Woodworkers, All Other	non-STEM
860	Power Plant Operators, Distributors, and Dispatchers	non-STEM
861	Stationary Engineers and Boiler Operators	physics STEM
862	Water and Liquid Waste Treatment Plant and System Operators	health STEM
863	Miscellaneous Plant and System Operators	non-STEM
865	Crushing, Grinding, Polishing, Mixing, and Blending Workers	non-STEM
871	Cutting Workers	non-STEM
872	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	non-STEM

873	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	physics STEM
874	Inspectors, Testers, Sorters, Samplers, and Weighers	non-STEM
875	Jewelers and Precious Stone and Metal Workers	non-STEM
876	Medical, Dental, and Ophthalmic Laboratory Technicians	non-STEM
880	Packaging and Filling Machine Operators and Tenders	non-STEM
881	Painting Workers	non-STEM
883	Photographic Process Workers and Processing Machine Operators	non-STEM
886	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders	non-STEM
892	Molders, Shapers, and Casters, Except Metal and Plastic	non-STEM
893	Paper Goods Machine Setters, Operators, and Tenders	physics STEM
895	Helpers--Production Workers	non-STEM
896	Production Workers, All Other	non-STEM
900	Supervisors, Transportation and Material Moving Workers	non-STEM
903	Aircraft Pilots and Flight Engineers	physics STEM
911	Ambulance Drivers and Attendants, Except Emergency Medical Technicians	non-STEM
912	Bus Drivers	non-STEM
913	Driver/Sales Workers and Truck Drivers	non-STEM
914	Taxi Drivers and Chauffeurs	non-STEM
915	Motor Vehicle Operators, All Other	non-STEM
926	Subway, Streetcar, and Other Rail Transportation Workers	non-STEM
930	Sailors and Marine Oilers	non-STEM
931	Ship and Boat Captains and Operators	non-STEM
933	Ship Engineers	physics STEM
935	Parking Lot Attendants	non-STEM
936	Service Station Attendants	non-STEM
951	Crane and Tower Operators	physics STEM
952	Dredge, Excavating, and Loading Machine Operators	physics STEM
956	Hoist and Winch Operators	non-STEM
960	Industrial Truck and Tractor Operators	non-STEM
961	Cleaners of Vehicles and Equipment	non-STEM
962	Laborers and Freight, Stock, and Material Movers, Hand	non-STEM
963	Machine Feeders and Offbearers	non-STEM
964	Packers and Packagers, Hand	non-STEM
965	Pumping Station Operators	physics STEM
972	Refuse and Recyclable Material Collectors	non-STEM
974	Tank Car, Truck, and Ship Loaders	non-STEM
975	Material Moving Workers, All Other	non-STEM
980	Military Officer Special and Tactical Operations Leaders/Managers	non-STEM
981	First-Line Enlisted Military Supervisors/Managers	non-STEM

982	Military Enlisted Tactical Operations and Air/Weapons Specialists and Crew Members	physics STEM
983	Military, Rank Not Specified	non-STEM

Appendix C

Model Fit Indices of LLCA

Table C1

Longitudinal Latent Class Analysis Model Fit Indices for Three-wave Trajectories

Index	2 classes	3 classes	4 classes	5 classes	6 classes	7 classes
		STEM/health STEM/physics STEM				
Entropy	0.644	**0.579**	0.537	0.73	0.564	---
BIC	5084.449	**5063.289**	5105.746	5152.31	5200.142	---
Adjusted BIC	5043.161	**4999.768**	5109.994	5044.326	5069.926	---
LMR (p value)	.0009	**.0001**	.1303	.9517	1	---
BLRT (p value)	< .0001	**< .0001**	. 6667	.375	1	---
		blue-/white-collar STEM/non-STEM				
Entropy	0.548	**0.538**	0.589	0.554	---	---
BIC	7345.869	**7348.982**	7383.073	7444.262	---	---
Adjusted BIC	7285.525	**7256.877**	7259.208	7288.637	---	---
LMR (p value)	.0001	**.0654**	.1986	.9019	---	---
BLRT (p value)	.0001	**< .0001**	< .0001	1	---	---

Table C2

Longitudinal Latent Class Analysis Model Fit Indices for Four-wave Trajectories.

Index	2 classes	3 classes	4 classes	5 classes	6 classes	7 classes
			STEM/health STEM/physics STEM			
Entropy	0.795	0.695	**0.79**	0.828	0.787	0.838
BIC	5669.007	5542.241	**5568.541**	5606.589	5660.288	5711.647
Adjusted BIC	5615.022	5459.675	**5457.395**	5466.863	5491.982	5514.76
LMR (p value)	< .0001	< .0001	**.0001**	.8778	1	1
BLRT (p value)	< .0001	< .0001	**< .0001**	< .0001	1	1
			blue-/white-collar STEM/non-STEM			
Entropy	0.682	0.739	**0.678**	0.693	0.691	---
BIC	8205.834	8120.426	**8107.638**	8166.861	8230.818	---
Adjusted BIC	8126.444	7999.753	**7945.682**	7963.623	7986.297	---
LMR (p value)	< .0001	< .0001	**.0016**	.3513	1	---
BLRT (p value)	< .0001	< .0001	**< .0001**	.0882	1	---