UNDERSTANDING AND INTERVENING IN ACADEMIC DECISIONS THROUGH COURSE INFORMATION PLATFORMS

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

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August 2025

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Cornell University 2025

A central ideal of liberal arts education is to support students in their intellectual exploration and self-discovery beyond the goal of securing employment. In U.S. higher education, this ideal is embodied in the elective curricular model, which encourages students to explore a wide range of disciplines before committing to one. However, in practice, academic decision making under this model is often characterized by overwhelming choices, limited guidance, and decision outcomes that are consequential to timely graduation and career success. Despite these challenges, research on how students navigate academic decisions has been limited, largely due to the lack of tools to observe decision processes at an adequate scale.

This dissertation leverages advances in digital technologies and artificial intelligence to develop course information platforms that can both support and investigate academic decision making. On the one hand, course information platforms can give students access to relevant, accurate, and diverse academic information to inform their decision making. On the other hand, these platforms can collect granular behavioral data on students' decision processes for formal research investigation. The research begins by mapping the landscape of academic decisions in higher education and proposing a new lens for understanding academic decisions as the combination of a learning process and a logistical one. Through a series of empirical studies, it examines how course information tools can be designed to support students' exploration of courses, academic pathways, and career destinations. The findings show that supporting academic exploration is not as simple as making diverse information available; it requires nuanced, research-informed design that helps students make sense of information and make it relevant to their evolving interests and goals. Ultimately, this dissertation highlights the complexity of academic exploration under the elective model and offers actionable insights for the development of academic decision support tools, advising programs, and institutional policies that aim to support diverse and purposeful academic decisions.

BIOGRAPHICAL SKETCH

Youjie (Mina) Chen's research lies at the intersection of education and technology, with a focus on studying how digital systems can address long-lasting educational challenges and adapt to future needs at scale. She employs experimental design, mixed-methods research, and data analytics to generate insights for educators, technology practitioners, and institutional administrators.

To increase the practical impact of her work, Mina has closely collaborated with several organizations and institutional offices. In partnership with the Realizeit Adaptive Learning Platform, she helped establish a behavioral research infrastructure and co-developed interventions tested across diverse institutional settings. At Cornell, she collaborated with multiple offices and led a team of student designers and developers to create *CourseCrafter* and *Pathways*, two campus-wide platforms that support students' academic exploration (around thousands of active users each semester). In the final year of her PhD program, she became a visiting scholar at the Leibniz Institute for Science and Mathematics Education (IPN) and the Heidelberg Institute of Global Health, contributing her expertise in learning analytics to interdisciplinary research projects. This experience has shaped her global perspective on education and deepened her commitment to solving real-world problems through research.

Before beginning her doctoral studies, Mina received a Master's degree in the Learning, Design, and Technology (LDT) program from the Graduate School of Education at Stanford University and a Bachelor's degree in Industrial Engineering from Tsinghua University. She was also the co-founder of an edtech startup that developed AI-powered math tutoring tools for K-12 students in China. Her passion for education began during her undergraduate years and has remained central to her academic and professional journey.

To the soil that gave me roots, and to those who dare to choose the red pill.

ACKNOWLEDGEMENTS

Reaching the end of my PhD journey fills me with a flood of emotions and memories. When I reflect on the ups and downs of the past few years, I'm reminded that it was the many people who supported me have shaped who I am. For that, I am deeply grateful.

My first encounter with education research began at Stanford with my Master's advisor, Professor Mitchell Stevens. I thank him for welcoming me into his lab and introducing me to the study of academic decisions in higher education. My journey would have been completely different without my student mentor, Sebastian Munoz-Najar Galvez, whose kindness and unwavering support shaped how I care for others. I'm also especially thankful to my roommate, Kuangcong Liu, who was my emotional rock as I navigated the cultural transitions of living in the U.S.

During my PhD years, I am most deeply grateful to my advisor, Professor Rene Kizilcec, for his unwavering guidance and for always holding me to the highest standard. He taught me that it's often the last bit of thoughtful paranoia that makes the difference. I feel incredibly fortunate to be among his early students who were able to observe and learn from his meticulous thinking, deep insights, and steady persistence in research. I also thank him for his patience, trust, and openness in encouraging me to explore diverse topics and grow into an independent scholar. I also want to thank my committee members, Professor Malte Jung and Professor Anthony Burrow, for their invaluable support and constructive feedback. They helped me see my work with fresh eyes and pushed me to think a level deeper with provocative questions.

In my research, I've always been drawn to the social impact of academic work. Over time, I've come to appreciate just how much extra effort it takes to turn a rigorously tested idea into something that benefits real people. I'm grateful to Professor Lisa Nishii from the Vice Provost's office of Undergraduate Education, Jessamyn Perlus and Lisa Jensen from the Career Services Office, Ed Dormady and John Udall from Cornell IT, and Rhonda Kitch from the University Registrar. I thank the amazing team that developed *Pathways* and *CourseCrafter*, tools that benefited thousands of Cornell students. This include ZhiYuan Wang, Wentao Guo, Xinyu Gao, Hans Sung, Jay Joo, Sofia Yoon, Bob Zhang, Fynn Datoo, Ian Wilkie Tomasik, Annie Fu, Rebecca Fu, Jennifer Lee, and Martha Brandt.

I'm especially grateful to my labmates at the Future of Learning lab. To Kimberly Williamson, I enjoy every conversation we had and cherish our friendship thoroughly. I thank your support and for expanding my views on equity and culture. To JiYong, for your whimsical spirit and constant kindness. To Scott Allen, for always being happy to have a nerdy conversation together. To Jinsook Lee, for being my lovely mentee and sharing the full emotions of research. I'm also exceptionally lucky to have my cohort. Being admitted together during the pandemic added a new layer of bonding. Roz Thalken and Joy Ming, I'll always cherish our walks around Ithaca and your heartfelt celebrations of my academic milestones. Thank you, Jenny Fu, Serena Guo, and FengYang Lin, for sharing an ear whenever needed. Lastly, a special tribute to Xiaofei Zhou, for going through the PhD journey with me, through high and low. I'm sure we will share more moments in the years ahead.

I'm also truly grateful for all the wonderful colleagues and friends I met during my time in Germany. In Kiel, I deeply appreciated the thoughtful discussions with Professor Olaf Koller and Jenny Meyer. I was especially lucky to share an office with Ronja Schiller and Marlene Steinbach, who made me feel at home from day one. We shared so many fond memories. I thank Anna Hilz for including me in so many moments early on. I thank Chriko Ellersiek for our late-night talks and for being each other's cultural ambassadors. I'm also so lucky to have known Naomi Patricioiu. I'm always reminded of your quiet strength in times of hardship. I still remember the first day I arrived in Kiel, alone in a foreign land, not knowing the language, as the train carried me to the final station on a cold winter night. I had no expectations and no idea of the incredible journey that was about to unfold. In Heidelberg, I'm thankful for the support from Professor Till Barnighausen and Professor Simiao Chen. Till, you made me realize that it's not only possible, but essential, to be both a wise scholar with experiences of working with research a thousand times as well as a curious adventurer like someone who has encountered research for the first time. I thank him for cheering me on at every step and for being my role model. Simiao, thank you for teaching me the importance of integrity, character, and purpose beyond work itself. I also thank all my collaborators, Dr. Torsten Wustenberg, Professor Yingying Wang, Yiwen Fan, Bin Lu, Meng Yuan, Junlai Zhang, Ziyue Zhang, Pascal Geldsetzer, for being in my life just the right time.

Finally, my deepest gratitude goes to my other half and my family. I'm endlessly thankful for having a partner who not only shares my ideals, even when they seem naively ambitious, but also supports me through his quiet actions. Your encouragement is what gives me the courage to start again in times of failure. To my mom, thank you for creating a world of hope and optimism around me, for teaching me to live with truth and integrity from a young age. You shaped the choices that I make in my life. To my dad, to me, you are the embodiment of what it means to be an educator. No matter how busy you are, you're always there for me, encouraging me to look past the surface of experiences. I'm

incredibly lucky to have parents who have shown me, through their everyday actions, what it means to be grounded idealists.

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CHAPTER 1

INTRODUCTION

To its ideal, higher education is regarded as an optimal environment for intellectual exploration, critical reflection, and the pursuit of meaningful aspirations that extend beyond vocational needs. To fulfill this broad educational mission, U.S. higher education widely adopts an elective curriculum model, in which students can explore a diverse array of courses across multiple disciplines before committing to one. This elective model closely aligns with the philosophy that values the breadth of learning before specialization, and the idea that students should develop as holistic individuals rather than merely training them for specific careers [87, 121]. This model is unique compared to the rest of the world, where curricula are much more narrow and prescribed. Many believe that the elective model in U.S. higher education plays a crucial role in fueling critical innovations in the country [77, 196]. Advocates of the model have also highlighted that it better prepares college students to face a future world characterized by complexity, uncertainty, and rapid changes in a global landscape [224].

However, the elective model presents its own set of challenges. The elective model offers students more options and autonomy in their academic decisions in courses, majors and careers, but the abundance of potential options can leave students feeling overwhelmed and uncertain [268]. As a result, prior work shows that students often rely on limited and biased sources of information when making these decisions [256]. Their early decisions in courses can carry consequences in their access to future courses and majors [81]. In many cases, students' decisions are shaped by norms of their immediate social network, which tend to be homogeneous and do not reflect the full range of opportunities available across the university [256, 85, 86]. This reliance can lead students to overlook better-fitting academic paths. More concerningly, the elective model may inadvertently reproduce existing social inequalities [186]. For example, students from underrepresented groups, such as women in Science, Technology, Engineering, and Mathematics (STEM), may switch away from fields after encountering stereotype threat or negative experiences in early gateway courses [60]. Students from less privileged backgrounds often lack access to the same quality of academic and social information upon arrival of the university as their more advantaged peers [94]. Although most universities offer academic advising services, prior work shows that students who stand to benefit the most from such support are also the least likely to seek it out [107]. These compounding challenges highlight the need for more informed, accessible and equitable support to guide students through their academic decision.

Recent advancements in digital technologies, large-scale data collection, and artificial intelligence (AI) have created new opportunities for developing modern course information platforms that both support and study students' academic decisions under the elective model. Traditional course information platforms, offered by most universities, typically allow students to browse course offerings by department and search for courses using course code, keywords in course titles, and instructors. In contrast, modern course information platforms can provide significantly more comprehensive information for students to make decisions, such as students' course reviews and historical enrollment records [297, 226]. By leveraging machine learning algorithms, these platforms can also recommend courses or majors that align with students' interests, as well as help plan academic paths to ensure timely graduation [38, 160, 29]. More importantly, these platforms can capture authentic and granular data on how students engage with information during the academic decision-making process, which was previously unobservable. This creates new opportunities to understand how students make their academic decisions, rather than relying solely on their final decisions [62]. On the one hand, these platforms offer personalized, scalable, and more equitable guidance to support students' academic decision making and facilitate smoother academic progression. On the other hand, they can provide new infrastructures for academic research to gain deeper insights into the students' academic decision-making process. In this dissertation, I will present a series of studies designed to advance the scientific inquiry into how course information platforms can be leveraged both as analytical tools to understand decision-making patterns and as practical intervention tools to support student success under the elective educational environment.

1.1 Research Questions

This dissertation reports studies into how course information platforms can be used as a means to understand and intervene in academic decisions, such as decisions on courses, majors, and career options, under the U.S. elective model. Course information platforms can serve as scalable guidance systems to support students in making informed academic decisions that align with the educational ideal of the elective model. They can also serve as research infrastructures to reveal underlying patterns throughout the academic decision-making process that traditionally cannot be revealed through standard institutional data or research approaches. Specifically, in this dissertation, I investigate these issues through the following questions:

- What are the prevailing approaches and challenges to understanding academic decision making in U.S. higher education? How can insights from supporting students in formal learning contexts inform new directions for understanding and supporting academic decisions? (Chapter 2)
- How can a course information platform (*Pathways*) be designed to support students' interest exploration during academic decision making? How do students perceive and engage with the platform?(Chapter 3)
- How does *Pathways*, a platform that supports academic exploration, influence students' career exploration outcomes? What role do different types of information awareness play in promoting career exploration? (Chapter 4)
- How does a brief, psychologically-precise intervention embedded within a course information platform (*CourseCrafter*) affect interest exploration during course consideration? (Chapter 5)

1.2 Dissertation Outline

This dissertation is structured into six chapters. Chapter 2 first offers an overview of the prevailing theoretical frameworks used to understand the landscape of academic decision making in U.S. higher education. I identify three dimensions, each progressively adding complexity to the previous one. The first dimension examines the academic decisions that students repeatedly make within every single semester, particularly focusing on course decisions at the beginning of each enrollment period. I talk about the diverse factors that contribute to the decisions and dissect the stages that students undergo through the decision-making process. The second dimension expands the investigation to the interdependencies of academic decisions across semesters, which recognizes how early course decisions and experiences accumulate and shape later decisions in courses, majors, and careers. The third dimension recognizes the diversity in students' academic trajectories for academic progression. Recent research highlights the importance of this perspective, in which each student may have multiple viable academic futures for success. Under each dimension, I discuss how modern course information platforms offer unique advantages to understand these complex phenomena and effectively support students. Following this, I introduce a novel theoretical perspective that conceptualizes academic decisions as learning outcomes and borrows insights from research in formal learning contexts. Drawing upon existing literature on psychological interventions in formal education, I explore how such interventions can be integrated into course information platforms and their potential implications. This review informs my research direction and provides a foundation for the broader theoretical framework in my dissertation.

In Chapter 3, I introduce a new course information platform, *Pathways*, which I developed to support academic decision making. The platform emphasizes facilitating exploration of diverse academic pathways through personalized visual representation of archival course pathways based on historical course enrollment data. The goal of the platform is not to prescribe students with optimal decisions through prediction models but to provide students with descriptive information about other students' academic decisions to support their own learning in a constructivist way. To guide the platform's development, I first conducted a formative study through semi-structured interviews with twelve participants in a U.S. research university to understand their primary challenges in exploring their academic interests. I then developed and qualitatively evaluated the platform among fifteen students at the same university. The evaluation showed that students were able to discover diverse pathways relevant to their interests and expressed enthusiasm about continued future use. Additionally, the platform provided new insights into students' academic exploration processes. For example, it reveals that students often struggle to articulate their interests beyond stating their declared or potential majors. Furthermore, although students initially exhibited resistance to actively exploring their interests, their engagement with the tool gradually facilitated new perspectives and deeper reflections about their academic choices.

Chapter 4 builds on the development work presented in Chapter 3 by formally evaluating the *Pathways* platform through a randomized controlled survey experiment involving 234 undergraduate students at the same university. This study focuses on evaluating the impact of the platform on two key indicators of career exploration: self-efficacy in career exploration and behavioral intentions in career exploration. While the overall analysis did not find clear evidence that using *Pathways* significantly increased either outcome across the full sample, exploratory analyses revealed a more nuanced pattern. Specifically, the tool appeared to benefit students who were at a later stage in their career decision-making process. Moreover, students' awareness of official information sources from archival student records and awareness of holistic information that combines academic and career decisions are important predictors of self-efficacy and behavioral intentions. These findings reveal a nuanced view of the potential of digital tools to enhance career exploration outcomes through information support.

While in Chapter 4, the course information tool is viewed as a comprehensive intervention, Chapter 5 shifts its focus to investigating brief, psychological interventions embedded within a course information tool to promote exploration. In this study, I added a purpose reflection prompt into another course information tool that our research team developed, *CourseCrafter*, which allows students to explore courses across departments through search-based navigation. I conducted a randomized controlled field experiment with over 4,000 students at the same university. Results show that a purpose intervention increased students' cognitive engagement in articulating their interests but reduced search activities. By reflecting on their purpose, students became more interested in courses related to creative arts and social change, but less in computer and data science. The findings demonstrate the malleability of students' interests during course exploration and suggest practical strategies to support purpose reflection and guide students toward deliberate exploration of their interests in higher education.

Finally, in Chapter 6, I synthesize insights from the preceding chapters by highlighting overarching lessons learned and outlining recommendations for future research. First, I discuss the critical distinction between what I term the "convenience outcomes" and "learning outcomes" when designing support systems for academic decision making. I explain why convenience outcomes, such as finding courses of interest, are relatively straightforward to facilitate and have been more broadly studied, while learning outcomes, such as exploring interest, pose greater challenges to effectively support. Second, I discuss the challenge to clearly define the outcome measures of academic exploration, and the broader implications of this challenge to promote fundamental educational goals of higher education under the elective model. Last, I discuss the role of course information platforms as part of the institutional infrastructure and provide recommendations for institutions to integrate and sustain advanced course information platforms within their ecosystem to holistically support students in taking diverse academic pathways and fulfilling their purpose in higher education.

CHAPTER 2

LEVERAGING DIGITAL INTERVENTIONS FOR IMPROVED ACADEMIC DECISIONS IN THE LEARNING CONTEXT

This chapter starts with an in-depth background on academic decision making in higher education and the role of course information platforms. Specifically, it organizes this landscape in three dimensions, each adding a layer of complexity to the previous one. The first dimension focuses on academic decisions made within a single semester, outlining the key factors and decision-making processes involved in course selection. The second dimension expands the scope and focuses on the interdependence of decisions on courses, majors, and careers across multiple semesters. The third dimension explains a new theoretical model for academic decision making, the ”pathways” model, which challenges the traditional ”pipeline” model and emphasizes the diversity of students' academic decisions and trajectories. Building on this foundation, the chapter then introduces a new conceptual lens to study academic decision making as a learning process for interests, purpose, and other outcomes central to one's self-discovery. Last, building on this new lens, the chapter draws on intervention studies in formal learning contexts and explores their possibility and benefits to be used in course information platforms to support academic decisions.

2.1 The Landscape of Academic Decision Making in Higher Education

2.1.1 Academic Decisions in a Single Semester

In U.S. higher education, academic exploration is widely encouraged. It is often considered integral to the undergraduate experience, especially in many selective universities that emphasize liberal arts education [87, 219]. Unlike universities in most other countries, where curricula are typically structured with fewer elective options, students in U.S. universities are faced with greater freedoms to choose elective courses and may not be required to choose a major immediately upon arrival at the university. This flexibility introduces additional complexity to the academic decision-making context because students must learn to navigate multiple layers of factors when selecting courses. To unpack this complexity, I will first review the influences and process of course decisions that students face in a single semester.

Many individual factors contribute to students' course decisions. Among them, research consistently shows that personal interest in the course topic is the primary factor [79, 119, 203, 262]. Students are more likely to enroll in courses that align with their interests. Closely intertwined with personal interests are career goals [203, 79]. Students often evaluate whether a course will be relevant to future employment opportunities. Following, students also evaluate their own ability and the difficulty of a course to determine if they feel confident to learn and perform well in it [119, 18, 6].

In addition to these individual factors, instructors and course characteristics also play a big part in students' course decisions. Students tend to favor courses taught by instructors with a good reputation and high teaching quality [79, 263, 46, 230]. Course-specific characteristics include whether the course can be considered to fulfill degree requirements, whether the course is scheduled at a convenient meeting time, and whether the course is offered in a preferred format, such as online or in-person [119, 79].

Importantly, both individual factors and instructor and course-related characteristics can be shaped by broader social and environmental influences. For example, Students often learn about an instructor's reputation, a course's difficulty from their peers [79, 263, 203]. Their interests and career goals can be influenced by their families [262] and academic advisors [138]. Thus, individual factors, instructor and course characteristics, as well as broader social contexts, together can shape a student's course decisions each semester.

In addition to identifying the factors that influence students' course decisions, researchers have also identified the specific stages that students take during the academic decision-making process. Similar to the decision-making process that has been extensively studied in other social science contexts, particularly in consumer behavior research [47], course decisions can be conceptualized as a multi-stage decision-making process of awareness, consideration, and choice [62]. Under this framework, students first create an awareness set, which consists of all the courses they know about. Then they narrow it down to the consideration set, which contains courses that they seriously consider taking. At last, students finalize their choice set, which contains the courses that they select for enrollment.

Applying this model to the academic decision-making process helps researchers reveal where students may be overlooking opportunities. For example, Thompson and colleagues [293] used students' course consideration sets to investigate gendered patterns in STEM enrollment. They found that many students, especially women, may exclude courses from their consideration set if the makeup of these courses has been historically male-dominated. This study shows that gender segregation in courses arises even before the final course decision is made. Similar patterns emerge in studies of major selection. Baker and Orona [23] studied major selection using the multistage decision framework and found that students in some demographic groups were aware of and considered far fewer majors than others, which led to the loss of many possible options in their final choice set. This phenomenon of limited early-stage exploration also applies more broadly to the general student population. Chaturapruek and colleagues [62] found that students only actively consider a small proportion of courses compared to those available at the university (about 2%). These insights underscore the importance of viewing course decisions through a multistage perspective and do not focus exclusively on students' final enrollment outcomes. Expanding students' awareness set and consideration set, especially for those from disadvantaged backgrounds, may offer a crucial avenue for enhanced and equitable access to academic opportunities.

To support students in making informed course decisions at scale, many U.S. universities and research groups have developed course information platforms that help students gain better access to critical course information through multiple stages of their course decisions. A prominent example is the Carta platform at Stanford University [297]. Carta is a course search platform that aggregates and visualizes institutional data, including students' prior course enrollments, course reviews, grade distributions, and workload. By clearly presenting key decision factors, Carta increases information transparency and accuracy to help students make more informed course decisions. A field experiment conducted on Carta reveals that access to grade information on the platform surprisingly lowered students' overall GPA [63]. This finding highlights the nuanced and sometimes unintended consequences that course information transparency can have on student behaviors. The finding also highlights the need for rigorous research to guide the design and implementation of course information platforms to truly benefit students. Another example is the Atlas platform from the University of Michigan [226]. Similar to Carta, when using Atlas, students can search courses and immediately learn detailed course information such as past grade distributions, course enrollment histories, instructor evaluation scores, and so on. Atlas also integrates recommendation algorithms that suggest courses to students that they may not have initially considered. This feature broadens students' awareness and consideration sets for courses, which potentially can create valuable opportunities outside of students' typical academic trajectories. In summary, course information platforms play a critical role in shaping students' semesterly academic decisions by aggregating and presenting accurate information that would otherwise be inaccessible. Without such tools, students often rely on informal sources, such as peers and families, within their social networks, which are often limited and homogeneous social networks [277]. Moreover, advanced searching and personalization features in these platforms can impact how students navigate courses from the initial awareness set to the final choice set.

2.1.2 Academic Decisions across Multiple Semesters

An added layer of complexity in academic decision making is the interdependent nature of course choices across semesters and how course choices can impact major and career outcomes. In particular, although the decision to major in a particular field may appear as a single decision that occurs between the start and the middle of the college experience, it should be more accurately viewed as an iterative process shaped by cumulative experiences taking courses in an elective curriculum [81]. Empirical evidence strongly supports this view by showing how early course decisions matter for major decisions later on. For example, Lang and colleagues [183] reported a strong predictive relationship between students' first enrolled courses and their eventual majors. Similarly, Chaturapruek and colleagues [62] show that the consideration set of courses in students' first term is a strong predictor of their eventual major. These findings collectively suggest that early course choices may set students on particular academic trajectories, either due to pre-existing interests revealed by courses or the influence of initial exposures to courses. Further complicating this relationship is the issue of timing: In a natural experiment using administrative data, Patterson and colleagues [235] found that courses taken during the same semester that a student selects their major have a disproportionately larger impact on major decisions.

While early course decisions impact major decisions, major decisions subsequently also matter for future major transitions and career outcomes. Denice [89] conducted a comprehensive study on major switching and found that major switching is a widespread behavior among college students. Notably, such switching behaviors tend to exacerbate existing gender segregation in academic fields: Women are more likely than men to leave STEM fields after initially selecting them at lower rates than men. Dalberg and colleagues [81] further found that when students switch majors, they tend to move to academically adjacent fields, which also means persistent gender segregation in fields with such issues already. Major decisions not only affect major switching behaviors, but also career outcomes. Majors often serve as signals to potential employers about specific skills and potential fitness for particular jobs. Consequently, different majors can lead to vastly different opportunities in financial returns. The difference in earnings premiums across majors can be almost the same as the earnings gap between a college degree and a high school diploma [7]. This gap even holds after controlling for students' academic performance [13]. Additionally, when a student's major does not match their career goals, it would negatively associate with critical indicators of career development, including self-efficacy, meaningful work, and calling, which is perceiving one's work as originating from an external transcendent source [274]. Together, these findings underscore that major decisions have profound implications, shaping not only students' academic experiences but also their longer-term professional opportunities and personal fulfillment.

As demonstrated above, although the elective curricula create flexibility and benefit academic exploration, they simultaneously introduce significant complexity and interdependence into students' academic trajectories. In particular, it could inadvertently lead to increasingly high-stakes consequences, from individual course decisions to major decisions, and ultimately to career decisions. To address this challenge, a few U.S. community colleges developed the *guided pathways* model, which is designed to improve students' college completion rates and employment prospects [156, 157]. Guided pathways is an institutional reform that organizes programs into broad fields (meta-majors), outlines explicit course sequences, and proactively monitors students' academic progress from an early stage to keep them on track. The essence of the guided pathways is that, compared to the long-standing elective model, students face simpler and more structured academic decisions, as critical interdependencies among courses, majors, and careers are intentionally accounted for in the design. Early evidence from colleges that implement the guided pathways shows notable improvements in students' gateway course completion rates [158]. Ultimately, guided pathways aim to boost college completion rates and reduce equity gaps for students from underrepresented backgrounds [155].

In addition to institutional reforms like guided pathways, course information platforms integrated with the elective curriculum can also play a critical role in mitigating the dependency challenges associated with courses, majors, and careers. With the advancement of AI technologies, intelligent recommendation algorithms have increasingly been used in course information platforms to serve advanced needs beyond providing comprehensive information. AskOski at UC Berkeley is a prominent example of a personalized course information platform [29]. It gathers data on program requirements, course descriptions, class schedules, and historical enrollments. Using machine learning and natural language processing techniques, AskOski can recommend courses for multi-criteria exploration and help students discover viable pathways that fit their academic goals [38, 160].

Besides AskOski, the most common platforms are those that recommend courses to students to reduce college dropout risks [301, 302, 104]. Other platforms focus on addressing course dependencies directly, such as identifying suitable preparatory courses [218], or generating optimal course sequences for academic progression [311]. Moreover, some course information platforms serve to connect courses to relevant majors and career selections. For example, Stein and colleagues developed a system that identifies majors in which students are likely to be of interest and perform well [279]. Su and colleagues developed a personality-driven recommendation system that suggests cross-domain courses and related jobs [284]. Verma and Anika developed a system that recommends elective courses to final-year students so that they can gain skillsets required for their career while preserving their personal interest and preferences [299]. Collectively, these innovative recommendation platforms offer powerful means to support students with personalized guidance to navigate the complexity of interconnected academic and professional decisions.

2.1.3 Diverse Academic Decisions and Diverse Pathways

As demonstrated in the previous two subsections, the elective curriculum model in the U.S. higher education is characterized by complex academic decision-making processes, influenced by multiple factors, and interdependencies of courses, majors, and careers. These characteristics lead students toward diverse academic decision outcomes and varied pathways, as students need to regularly revisit and update their academic interests, goals, and career aspirations. Therefore, traditional measures of student success, such as dropout rates, employability, and income, are not sufficient to represent the full range of valuable outcomes within this system. While these conventional metrics capture standardized notions of success, they fail to recognize that many alternative pathways can also represent meaningful progress. For example, changing majors may represent an intentional switch to a better-fitting major rather than a loss. Additionally, academic exploration and change of pathways contribute to important learning and personal growth, though on the surface, it may seem like a detour to success. Thus, it is important to adopt a perspective that acknowledges the diversity of academic decisions and the legitimacy of varied pathways.

Recent research has started to advocate reframing academic progress from a linear, ”pipeline” metaphor, to a ”pathways” metaphor that can better capture the diversity of student choices and outcomes [175]. The pipeline metaphor assumes predetermined course sequences and casts students as passive objects moving toward one ideal goal. By contrast, the pathways metaphor acknowledges students’ agency and accepts that transitions can be positive steps rather than ”leaks” to be minimized. This paradigm shift enables more inclusive and effective measures of success, as well as fosters educational approaches that better inform student decisions and institutional interventions. Aligning with this shift, recent institutional reforms have adopted new models of student success such as the ”multi-engagement model” [69]. This model explicitly recognizes diverse combinations of academic, extracurricular, and career-related engagement as valid pathways toward student success and promises updated practical methods to inform students’ academic planning.

Crucially, the pathways perspective can be supported through modern course information platforms and analytical approaches. First, these platforms serve as powerful decision-support tools to enable students to discover and pursue diverse pathways. The platforms do so through recommendation algorithms that can present students with diverse courses of interest [232], interactive visualizations that can illuminate unique academic paths [11, 233], what-if scenarios for academic planning that fit their goals [4], and many more. Second, the detailed log data generated by students' interactions with these platforms can offer new insights into the diverse decision processes prior to a decision outcome [62]. Such data can deepen our understanding of the diversity of student experiences beyond standardized institutional data. Finally, course information platforms can serve as critical research infrastructures to enable systematic investigations into supporting students' academic decisions through iterative, low-cost experimentation compared to traditional inquiries. Despite these potential advantages, systematic research that integrates course information platforms with institutional practices is still scarce. Many platforms developed from research labs did not continue to be productionized as institutional resources, with a few exceptions [29, 297, 226]. In this thesis, I aim to bridge this gap by developing academic decision support tools for institutional practices as well as serving as research infrastructures under the pathways paradigm to understand and support diverse academic pathways.

2.2 Rethinking Academic Decision-Making Process As Learning Process

Academic decisions – such as which courses to take, which major to pursue, and which career path to follow – are among the most consequential choices that college students make. These decisions shape not only their educational experiences, but also their timely graduation [22], future academic and career success [117, 288], as well as life satisfaction and personal fulfillment [71, 124].

Academic decisions have been widely studied in the context of sociology, economics, and education, with a focus on the structural and contextual factors that influence them (e.g., [69, 293, 197, 81]). Yet these decision-making processes have been rarely conceptualized as *learning processes*. In college, students are trained to gain knowledge and skills on subject matters, but rarely are there curricula designed on how to make thoughtful and well-informed academic decisions, even though they face challenges and need to navigate the complexity of academic decisions regularly during their college experiences.

Academic decision making can be seen as a form of learning in part because of its outcomes. Broadly defined, learning involves changes in knowledge, skills, beliefs, or dispositions that shape future thoughts and behaviors [42]. From this perspective, the act of choosing courses, majors, and career paths is not merely logistical, it creates both the opportunity and necessity for students to reflect on and develop their interests, purpose, and identity [280]. These outcomes may take the form of discovering a new academic interest, clarifying long-term career aspirations, or cultivating a stronger sense of purpose. These outcomes are especially important during the developmental phase of ”emerging adults”, when students actively explore fundamental questions such as ”who am I?” and ”who do I want to be?” [16, 102]. Academic decision making can contribute to helping students find answers to these questions by requiring them to reflect on their values and capabilities and take ownership of choices that carry lasting consequences for their academic and career directions.

In addition to the outcomes, the process of academic decision-making closely aligns with core principles of constructivist learning. Constructivist theories emphasize that learning emerges through active engagement with one's environment, rather than through passive absorption of information in classrooms [21, 72]. From this perspective, the academic decision-making process is inherently a learning process. Students construct their own interests, purpose, and identities by making choices, experiencing the consequences of their choices, and revising their understanding over time. Framing academic decisions this way allows us to see them not as peripheral to learning, but as central to how students make sense of their educational experience.

The learning involved in academic decision making often relates to beliefs and personal qualities rather than knowledge acquisition [269]. For example, a student who has developed a growth mindset may be more inclined to consider and even enroll in a challenging course, even if their prior performance was not strong [245]. For another example, a student who values intellectual risk-taking or interdisciplinary learning may intentionally explore courses across a wide range of subjects [130, 8]. In both examples, course information platforms can play a dual role in supporting and measuring these forms of learning. For example, the platform may recommend stretch courses based on students' interests and track whether they consider them, as a proxy for growth mindset or intellectual risk-taking. The system can provide students with courses from diverse departments to encourage and measure exploration. While some beliefs or personal qualities can be and have been supported and measured in traditional classrooms (e.g., growth mindset [318, 181]), others are harder and may be uniquely supported and measured in the academic decision-making context (e.g., interdisciplinary exploration). Altogether, recognizing academic decision making as a place for informal learning opens up new possibilities for how we define, support, and assess student learning across the broader educational experience.

While viewing academic decisions as learning outcomes opens up new possibilities, it also comes with limitations. Unlike classroom settings, which are often designed to isolate and measure specific learning outcomes, real-life academic decisions take place in complex, messy environments. Students' course choices are shaped not only by learning-related factors but also by practical constraints, such as major requirements, scheduling conflicts, or financial considerations. These external factors can confound the interpretation of decision outcomes, which makes it difficult to disentangle learning from institutional and other influences. Yet these complexities also make academic decision making a powerful context to understand and support learning because it offers high external and ecological validity. It captures how students navigate authentic, consequential choices that resemble the kinds of decisions they will face beyond college. Traditional classrooms, by contrast, often represent more artificial learning environments removed from the pressures and nuances of everyday life. Therefore, the academic decision-making context could serve as an important learning environment complementary to classrooms in higher education.

So far, little research has been done on using academic choice as a means for learning support and assessment. However, there has been extensive work on promoting students' beliefs and personal qualities through psychologically-precise interventions in the traditional academic setting [303]. In the next section, I will first review how beliefs are shaped under traditional and general educational contexts. I will then explore how students can develop new beliefs and personal qualities during academic consideration and decision making, and how course information platforms can play a part in shaping these beliefs in a long-term and scalable manner.

2.3 Psychological Interventions in Course Information Platforms

As demonstrated in the previous section, learning outcomes supported during the academic decision-making context differ fundamentally from those taught in traditional classroom settings. While classroom instructions primarily target cognitive outcomes, such as the acquisition of knowledge and domain-specific skills, the academic decision-making context aims to foster learning in psychological outcomes. These outcomes often relate to students' motivation, interests, and beliefs about themselves and the world. For example, in the academic decision-making context, students may come to see themselves as more open to academic exploration, learn about a newfound interest, or develop a career aspiration that aligns with a deeper sense of purpose. None of these learning outcomes are cognitive, but instead are rooted in students' evolving self-concepts: the understanding of who they are, who they want to be, and how they situate themselves in the world.

"Wise interventions" are a class of brief interventions that are specifically designed to address these psychology-related needs [305]. They have been applied in traditional classrooms and shown to produce lasting effects across subjects, student populations, and performance outcomes [75, 305, 303]. These interventions typically follow a common structure: The intervention targets a specific psychological mechanism, such as a belief about intelligence (e.g., [313]), belonging (e.g., [304]), or purpose (e.g., [244]). Then the intervention would take the form of a short reading or writing activity, often at a timely moment when students are most receptive to psychological change [74]. For example, a growth mindset intervention may be delivered right before students begin a difficult math course, when they may feel uncertain about their ability to succeed. These interventions are intentionally simple and brief, which allows them to potentially be widely adapted to a variety of scenarios. Wise interventions have been shown effective not just in educational settings [73], but also in other scenarios such as voting brochures [49] and aid delivery websites [291].

So far, little research has explored applying psychological interventions in the setting of academic decision making, despite the theoretical potential. These interventions could be used to support students' psychological needs related to their interests, purpose, and identities. Their attitudinal shifts could be translated into behavioral changes in their academic decisions. In particular, course information platforms can serve as a promising medium to embed such interventions, with four key affordances that make them especially suitable for this purpose. First, as online platforms, they provide a convenient and scalable infrastructure for conducting large-scale randomized controlled trials with low marginal cost compared to traditional offline settings [171]. This makes it possible to evaluate interventions across broad and diverse populations. Prior work in Massive Open Online Courses (MOOCs) has demonstrated this potential: Kizilcec and colleagues scaled up psychological interventions among one-quarter million students to test their effectiveness [173]. Second, modern course information platforms may personalize interventions to increase their effect size by integrating machine learning algorithms. For example, traditional psychological interventions that target student interests typically focus on a single subject in classrooms, such as showing students how a particular class topic has utility value [178, 55]. In the context of academic decision making, students' academic interests are diverse and evolving. Personalized interventions could potentially be tailored to each student's specific interest and guide them to see how their specific interest has utility values to their career goals.

Third, course information platforms could enable researchers to analyze downstream effects of psychological interventions through fine-grained log data they collect. When using a course information platform, students typically go through multiple rounds of interactions: inputting inquiries, receiving algorithmically generated outputs, browsing options, and making new inquiries. Thus, when a psychological intervention is embedded at the start of the user interaction, it would not only shape students' immediate inputs, but also the sequence of outputs and inputs, which reveals what they consider and decide. This setup creates an opportunity to observe what Hecht and colleagues [132] described as the ”domino effect”, wherein a small psychological shift early on triggers a cascade of changes over time. Prior work on utility-value interventions provides evidence for this kind of mechanism with the interventions affecting choices in courses, majors, and career aspirations [55, 128, 258]. Once a utility value intervention helps students see the usefulness of a course subject, they gain more interest in it. Once they become more interested, they may be more likely to take a second course in the same area, and later on major in it. Course information platforms may enrich this process by targeting moments when academic decisions are made. These moments are highly consequential: A student's decision to enroll in a course is often made within a few days during registration, but can determine what they learn for the whole semester, and shape their long-term academic trajectory [183, 62]. Therefore, compared to traditional classroom settings, interventions applied in the academic decision-making setting may offer a unique opportunity to produce lasting impacts. In summary, course information platforms present a promising new context for psychological interventions. Their scalability, capabilities for personalization, fine-grained data collection, and alignment with critical decision points make them a valuable tool for supporting and studying the learning processes embedded in academic decision making.

CHAPTER 3

PATHWAYS: EXPLORING ACADEMIC INTERESTS WITH HISTORICAL COURSE ENROLLMENT RECORDS

The preceding chapter reviews the current landscape of understanding academic decision making in higher education with an emphasis on an emerging "pathways" model and a learning perspective to study and support academic decision making. Building on these insights, this chapter presents the development and evaluation of a course information platform called *Pathways*. *Pathways* leverages historical course enrollment data to help students explore their academic interests by viewing diverse academic pathways of others. The tool is grounded in a constructivist approach to support students in actively constructing their understanding of academic interests through exploratory learning. It is also a tool to support a constructivist style of learning in their academic interest. This chapter details the need-finding process that informed the platform's design and presents evidence on how *Pathways* can help students gain new insights into their interests and possible academic directions.

3.1 Introduction

Each year, thousands of jobs disappear and new industries and occupations emerge [50]. College students are starting careers with rapidly evolving demands due to the transformation of entire industries by digitization and automation [140, 187]. Three out of four US college graduates work in a job that is not even related to what they studied in college [1]. These trends make it more important than ever for college students to actively explore their interests to gain awareness of potential industries to work in and acquire a range of knowledge and skills to adapt to an increasingly complex and rapidly-changing world [101]. To complement a structured curriculum with required courses, the elective choice system in US higher education grants students the freedom to explore a variety of courses during their degree program. The resulting sequence of course enrollments across terms, their *academic pathway*, is a relatively unique reflection of their formal academic experience [22, 14, 62].

Exploring and developing an academic pathway is a *constructivist* learning process and distinct from acquiring skills and knowledge in a specific domain [278, 93]. Transcending the learning that goes on in classrooms, students continuously explore, construct, and reflect on their learning path, as they will continue to do after they graduate. Moreover, pathway exploration and development emphasizes that knowledge is constructed from one's own experience. Students iteratively develop pathways by trying new things themselves, as opposed to being instructed by an expert about the right path. Although many colleges and universities encourage constructivist approaches to learning, most instructor-led curricula tend to provide instructionist classroom learning experiences. The elective curriculum itself provides students with a constructivist learning experience. But to succeed in exploring and developing their pathways, students need appropriate aids and resources to facilitate this type of learning process.

Most students rely on a few sources of information to forge their pathways. Academic advising and counseling have long offered students help with making academic and career decisions through conversations with trained experts. It is a valuable but scarce resource on most campuses. Not all students can have timely access to advisors. Students who might benefit the most are less likely to seek out advising staff, which raises equity concerns [107]. A more widely used source of information on campus is informal conversations with more senior students, but information gathered through this approach is often homogeneous and biased based on a student's social network [277]. Nevertheless, there may still be opportunities to leverage social learning from the academic choices of peers. Historical course enrollment data are usually only accessed by specialized staff and institutional leaders for high-level reports on academic progress, but recently, academic pathway data have been used to generate insights for instructors, students, and members of the research community [11, 231]. We are not aware of any application that provides students with personalized visual representations of archival course pathways, which could convey authentic, temporal information about course and major choices to inform and inspire current students.

We developed *Pathways*, a system to support academic decision making at scale by visualizing campus-wide student pathway data to promote equal access to unbiased information about academic choices. The design of *Pathways* is grounded in psychological theories of interest: interest exploration is a fundamental component in constructivist learning [92]. It is also an important activity for students in the development of their individual and shared values [127, 45] and identities [248] during university education, which are influential throughout students' lives beyond finding a job and other utility-driven choices [91]. *Pathways* uses data storytelling techniques to provide information on course pathways through a series of interactions and visualizations that encourage students to explore. Data storytelling is commonly used in journalism to communicate insights from data with a specific goal [259, 271]. It can help convey complex information and guide exploration in a cognitively well-paced and compelling manner. While we investigate interest exploration among undergraduates, this approach extends to other contexts, including helping working learners navigate their learning journey outside of formal education.

This research makes three primary contributions: first, we develop an interactive and scalable tool that promotes interest exploration and supports academic decision making; second, we present empirical insights into challenges that impede interest exploration during academic decision making; and third, an empirical validation of the tool offers insights into how it supports students in exploring their interests and academic pathways.

3.2 Background

3.2.1 Interest Exploration

Students who start their university education and realize how many options are available to them tend to ponder an important question: what am I interested in? Past research shows that a student's interest significantly contributes to their academic decisions [133] and career choices [179, 282]. Models of interest provide a theoretical foundation to study pathway exploration. The process of constructing pathways can serve as an affordance for students to reflect on their interests.

Past research on the psychological construct of interest distinguishes between situational and individual interest [134, 135]. Situational interest is a psychological state triggered by external cues. Individual interest is a traitlike preference that persists. The model of interest development posits that an individual's situational interest in a topic is first triggered by a particular situation [136, 250]. As they engage with the topic over time, their situational interest transitions into an individual interest that becomes a part of their personal characteristics. The model aligns with a constructivist understanding of interest, because it emphasizes the developmental process of interest instead of considering it to be fixed [92]. Accordingly, we define interest exploration in our research as the intentional effort that a learner puts forth during the initial stage of interest development when situational interest is triggered. Interest can also be triggered when one already has an individual interest [251]. The triggering process can facilitate specific aspects of an established interest to be deepened and evolved. Interest exploration is therefore not constrained to new college students with limited knowledge of what they want to study; it applies to students at all stages of their academic journey.

The design of *Pathways* accounts for the transition state between situational and individual interest for college students. Its goal is to help students not only find pathways based on individual interest, but also, explore situational interest by getting exposed to courses and pathways they would not have known about otherwise.

3.2.2 Digital Tools for Academic Decision Making

Every college and university provides an online course catalog system where students can look up course information. Students can browse courses offered by different departments and search for courses by course code, keywords in the course title, and instructor. The latest generation of course catalog systems, such as *Atlas* at the University of Michigan [226] and *Carta* at Stanford University [297], provide significantly more comprehensive information about courses that draw on data from official registrar records and student evaluations of teaching. These systems display information including grade distributions, official student reviews, estimated time spent on the course, and common courses taken before, with, or after a given course.

In recent years, historical course enrollment data has gained traction as a novel source of information to understand and support academic decision making [280, 159]. They can be used to reveal complex decision patterns that students take for sequential course navigation [11]. Moreover, applying computational methods to these data can suggest relations of courses through co-enrollment records [233, 216], which makes them powerful at course recommendation [231]. The availability of enrollment records at most institutions opens up new opportunities to support students' academic decision making at scale, especially for constructing pathways. For example, Shao and colleagues [273] developed a system that recommends courses across multiple semesters to students for degree planning. We build on prior work in this domain by developing a tool that makes historical course enrollment data accessible and interpretable to students so that they can explore potential pathways.

Most stand-alone, student-facing tools that support academic decision making follow a prescriptive advising model [152]. Crookston [78] describes it as an approach similar to how a doctor would treat a patient. Students receive "prescribed" answers based on practical needs, which tend to concern registration, record keeping, and generating recommendations. For example, one of the most extensive digital advising system can support students in choosing courses and majors, scheduling, and monitoring degree progress [237]. These systems, while important, only in part assist a student's personal pursuit. We opted for a developmental advising model in *Pathways*, which emphasizes helping students become aware of their changing self and realizing their potential [78]. Most academic decision support systems implicitly follow an assumption that interest is stable by treating it as an input for future choice prediction. In contrast, we recognize the changing state of a student's interest. We frame finding pathways as a chance for students to reflect on their changing interests. Moreover, we intentionally do not "prescribe" choices, but create interactive visualizations to encourage students to take on an active role in exploring options.

3.2.3 Data Storytelling

A common concern with data-driven tools that are exploratory in nature is that they are not actionable or interpretable enough to benefit students [76, 309]. Students may get lost during exploration and not be able to extract key insights from the visualizations.

Data storytelling is a powerful technique to communicate complicated information in data and convey ideas to its audience [27, 80, 168]. Specifically, it embeds narrative and structure in a series of data visualizations to highlight insights with an overarching goal [271, 97]. We adopt an "interactive slideshow" framework for data storytelling in *Pathways*, which walks students through steps like a slideshow [308]. The overall story-line is author-driven but with the overarching goal of promoting interest exploration. In each step, it takes a reader-driven approach for students to explore at the level of courses and entire pathways to ensure a high degree of flexibility while following the overarching narrative.

The concept of data storytelling is in popular use today to report news through mass media [123, 57] and it has been adapted to other areas (e.g., business [210, 177]), but few studies have applied it in educational contexts [99]. Chen and colleagues [64] designed narrative slideshows to help educators explore learning patterns in massive open online courses. Martinez-Maldonado and colleagues [211] organized data in layers of storytelling in a multi-modal learning analytics system to explain insights to teachers and students. These studies suggest that data storytelling can be successfully applied in educational settings to improve learning experiences, but more work is needed to develop theoretically grounded and learner-centered systems that demonstrate the effectiveness of data storytelling as a communication technique. We adopt data storytelling as an approach in *Pathways* to promote interest exploration through pathway-finding in a guided manner.

3.3 Formative Study

The process by which students consider courses for enrollment is complex and remains largely unobserved [62]. We therefore conducted a formative study to investigate the following two research questions: What challenges do students face exploring their interests during course consideration? (**RQ1**) How do students identify and develop their interests through courses? (**RQ2**) We will use our findings to draw design ideas that can support students to explore their interest and make academic decisions.

We conducted semi-structured interviews with twelve participants from a

US research university (nine women and three men, nine Asian and three White students, average age 19.8, SD = 0.7). The interview protocol is available on OSF (https://osf.io/g3fdr/). Participants were undergraduate students in various years (one first-year, two second-years, eight third-years, and one fourth-year student) and programs (two in Human Ecology, five in Agriculture and Life Sciences, four in Arts and Sciences, and one in Engineering). To analyze the interview recordings, we used deductive coding based on our two research questions. This led us to two main findings that informed our design decisions.

Finding for RQ1: Students face an overwhelming number of competing factors during course consideration. Participants consider many factors when deciding what courses to take, including interest (12 out of 12 participants), degree requirements (12/12), time schedules (10/12), class capacity (6/12), practical skills to be learned (6/12), instructional style (5/12), workload (5/12), difficulty (4/12), and grades (4/12). Participants felt "overwhelmed" by the many factors they need to consider during course selection. In order to cope, participants postponed consideration of certain factors to subsequent stages of their decision-making process, allowing them to focus on one or two factors at a time. However, the order in which participants considered factors varied. For example, P2 valued timing the most, so she excluded all early morning classes from the start. P8 only considered class difficulty when she made her final decision, whereas P3 considered difficulty from the beginning and only looked into easy classes. It shows that participants have different priorities that, if they dominate over their interest, can limit the scope for exploration. It is therefore important to preserve interest as a priority in students' course consideration process to encourage wider exploration.

Studies of multistage decision-making processes find that people expand their consideration set at an early stage, and then narrow it down in later stages [23, 2, 47]. If a student considers too many competing factors early on, they risk having a small consideration set to start with. One study found that students at one university considered a surprisingly narrow set of courses in their initial course consideration process [62]. Our interview findings suggest that factors such as difficulty can discourage students from pursuing their interests early on, which leads them to consider a narrower set of courses. We therefore intentionally designed *Pathways* as a tool that focuses on students' early decision stages with the goal of expanding students' awareness and consideration of course options to explore more before excluding them from consideration. The primary feature of *Pathways* thus begins with a topic-centered search to give students a space to freely articulate their interests. To prioritize student interest, we intentionally kept the tool simple, omitting features for course planning or course review to avoid cues that highlight other factors, including requirements, scheduling, difficulty, and instructional quality.

Finding for RQ2: Students identify their interests through serendipitous discoveries. Many participants developed a broad sense of their interests from daily interactions with family members (9/12), close friends (4/12), and public media (4/12). In college, taking courses enabled participants to systematically investigate their interests. As a result of taking more and more courses, most participants modified their initial interests or identified new ones (11/12). In retrospect, their interests often changed or developed unexpectedly—for many, a serendipitous experience. For example, P7 was initially interested in food science because "*it sounds cool*". But after taking several relevant courses, she found out that she was not as excited about biology experiments as her peers.

It was then a course in food and consumers that helped her realize that she was actually interested in the marketing side of the food industry, an area she initially had limited knowledge of. In retrospect, P7 identified her new interest through a pivotal course that was broadly related to food. P2 shared a similar experience: she has always been interested in social work for families and children and initially focused on the psychological aspects of this area. But a course about children and the law introduced her to the relevant legal aspects, and she fell in love with it. Although her general interest did not change, her interest developed by exploring different courses about it. These cases highlight how an unexpected shift in a student's interest is often a result of pursuing an existing interest. This finding inspires us to design for serendipitous discoveries in *Pathways* by layering unexpected information on top of expected information.

Prior work on recommender systems developed algorithms that can increase the chance of serendipitous discoveries by adding novelty and diversity in recommendations [58]. This way the recommender system does not generate only relevant information and avoids users being trapped in "filter bubbles". In the context of course recommendation systems, Pardos and Jiang [232] developed an algorithm that returns courses within a student's indicated area of interest but possibly offered by another department that uses different disciplinary vernacular for the same topic in the course description. However, their recommendations do not go beyond a student's stated interest. To recognize potential transitions and developments in a student's interest, *Pathways* aims to generate search results that trigger new situational interest. We developed a serendipity-promoting algorithm that shows both relevant information and diverse-but-irrelevant information to students. However, this approach entails a trade-off: users may be dissatisfied because irrelevant information lowers the perceived accuracy of the search result. Thus, we divided the search results into separate steps, embedding them in the data storytelling framework so that students are gradually guided to more diversified content. We also created explanatory narratives in each step to convey the tool's design intentions to students.

Recommendation algorithms are one way to facilitate serendipitous discovery. Another approach is to use design strategies that can enhance user perceptions of serendipity [242]. In particular, recent studies have argued that serendipity should be conceptualized as an affordance in the design of tools and users should be granted agency to adopt "serendipity strategies" as opposed to serving serendipity "on the plate" [253, 206, 32]. They recommend adding interactions that give users the autonomy to actively explore serendipity. We therefore added an intermediate calibration step in the data storytelling framework to let students calibrate the algorithm and inform the direction of diversity in the final result. *Pathways* positions students as actively seeking out diverse results, rather than being coerced to view content that may not match their interest.

3.4 *Pathways*

The *Pathways* application is an interactive course exploration tool designed to promote interest exploration among college students. Building on our formative study, we designed the system as an exploratory search tool that presents courses and pathways to inspire serendipitous discoveries beyond students' initial interest. We adopted a data storytelling framework to organize the exploration process into three interactive steps, each with a specific sub-goal [254].

The goal of step one (Search) is to have students reflect on what their interests are and be open to all kinds of ideas. The goal of step two (Course Matches) is to support exploration in the student's domain of interest by showing a pool of courses that are independently relevant to their stated interest. The goal of step three (Pathway Matches) is to create serendipitous discoveries in interest exploration by showing pathway visualizations that contain a combination of topics relevant to the student's stated interest and unexpected topics inherent in a given academic pathway. Each step is narrated in an informal style to communicate what is being presented to resemble an informal chat with a mentor. Transitions between steps follow a read-and-proceed interaction paradigm (i.e. students click a button and new content appears below). An overview of the user interface is shown in Figure 3.1 and Figure 3.2. The *Pathways* workflow can be found on OSF: https://osf.io/g3fdr/.

Step 1: Search. First, the student describes their general interests in an open-ended response field (Figure 3.1.a). To underscore the exploratory nature of the tool, we opted for an open-ended prompt ("Describe in a few sentences what you are interested in studying") instead of a series of closed-ended questions about students' departments or majors. While closed-ended responses can provide useful information for inferring interests, they may also limit the expression of ideas to subjects that students are already familiar with or have seen offered at their institution. Below the prompt, a worked example of a lengthy search response is shown to nudge students to write more. A new example response replaces the old one when a student clicks on "Load another example". Below the example response, a large input text box encourages students to reflect.

Step 2: Course Matches. Based on the student's stated interest, the most relevant courses are shown in hexagons and color-coded by the degree of relevance (Figure 3.1.b). The student can filter the courses by credit hours and subject. Course descriptions are shown when the student hovers over a course. If they click on the course, the tool will take them to the institution's official course catalog page with details such as the course description, units, and instructors. The student can save a course to their dashboard if it spurred their interest. All courses shown in this step are directly relevant to the student's stated interest, but the results are not constrained to one department. Thus, the results are more diverse than what the university provides in the course information system, which shows courses by filtering through department categories. This step is intended to be a stepping stone to serendipitous discoveries before showing the student results that extend from their stated interest.

Step 3: Pathway Matches. The student is presented a pool of courses that do not directly match their stated interest but may still be of interest to them (Figure 3.2.a). They are asked to select one or more courses that they find interesting. This is a calibration step for the algorithm to learn about the student's potential interests before pathways are shown. It is also intended to grant students agency to seek out potential interests. Finally, a full pathway visualization of a previous student is shown to the student (Figure 3.2.b). Courses are lined up in hexagons from top to bottom by semester in a chronological order, with "Year 1" to "Year 4" indicated on the left side. This type of temporal visualization depicts how course-taking patterns evolve over time and evokes a personal story for the anonymous student pathway beyond the mere list of courses they took [308]. The hexagonal shapes create a compact layout for the student to view all courses at first sight without the need to scroll much, which conforms

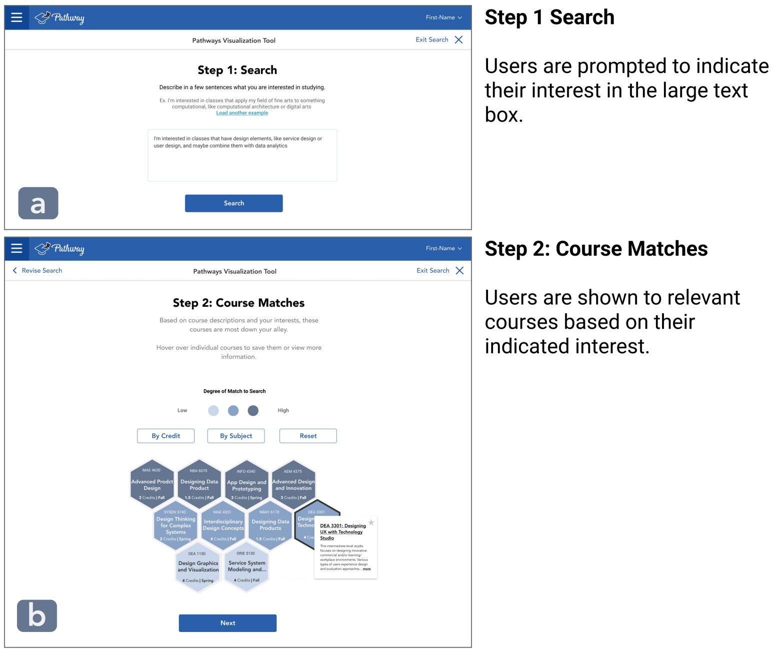

Figure 3.1: *Pathways* user interface (Step 1 and Step 2).

with Mayer's temporal contiguity principle [212]. Courses are color-coded by their subjects to emphasize the diversity of subjects in a pathway. Underneath the visualization, the left/right arrow buttons let the student flip through five pathways. While these pathways contain courses that are relevant to the student's stated interest in the first step and the calibration step, they also contain courses with minimal overlap across pathways to achieve high diversity. The student can save entire pathways or courses of interest into their dashboard.

The Dashboard Page. The exploratory search feature is complemented by a dashboard page where students can browse and manage the list of courses and pathways they saved. Students can also initiate a new search from the dashboard page.

Figure 3.2: *Pathways* user interface (Step 3 and Step 4).

3.5 Algorithm Design Process

This section presents the development of the search algorithm that supports the functions described above. The algorithm operates on an archival, de-identified dataset of historical course enrollments and a dataset of course information that is periodically updated. A known design challenge of smart systems is that the technical feasibility of the algorithm depends on the UX design and dataset characteristics [312, 95]. Following best practices in HCI [36, 37], we conducted design-driven data exploration to guide the algorithm design and match it to our UX design. We also intentionally designed the algorithm to be simple enough to ensure high algorithm interpretability in each step of the results, as well as establish a baseline for future iterations with more complex, intelligent algorithms. We now describe the data we used, how results are generated in steps 2-3, and the design-driven data exploration process that led to the final algorithm design.

In the *Course Matches* step, the model performs single-item recommendation for course items, similar to models for web page searches. The search is performed based on a course information dataset, obtained via an API from the institution's public course catalog with the latest information about all courses on campus. The dataset contains attributes such as course title, course description, instructors, and number of units. We use the course title and description as the course corpus for information retrieval, following these steps: First, the search query from step 1 is preprocessed by spellchecking, lowercasing, lemmatizing, and removing common English stop words as well as specific course-description related stop words such as "course", "teacher", and "instructor". Second, query expansion is performed to improve match quality: if the search query is under 25 words, it is expanded by adding related words from NLTK synsets. Third, the search is performed by computing TF-IDF vectors for unigrams and bigrams found in the query and in the course corpus. We show the top relevant courses to users based on cosine similarity.

In the *Pathway Matches* step, the model recommends a set of pathways composed of courses. The search is performed based on an archival dataset of historical course enrollments for 4,398 students between 2008 to 2019. The data includes all courses that students took each semester until they graduated. It includes nearly all course subjects that a student can take on campus (179 out of 186 subjects offered). Diversity in academic choice patterns can offer valuable insights to current students: instead of only learning about course choices from peers in their social network, students gain equitable access to information about academic decisions of diverse peers. A common challenge with data-driven applications like *Pathways* is that it can be unclear what outputs it will produce in the absence of user input during the initial design phase. We designed our algorithm without knowing what students might write as search inputs. To address this challenge, we created twenty search queries to gain an initial sense of how the algorithm may work. We curated a diverse set of search queries in terms of their subject matter, length, colloquial style, and student motivations. Two example queries we used for testing are *AI for social good* and *I'm interested in classes that apply fine arts to something computational, like computational architecture or digital arts*.

To develop a serendipity-promoting algorithm, we created two metrics to measure both relevance and diversity in the results. We define pathway relevance by the number of relevant courses in a given pathway, where the top 50 courses with the highest cosine similarity are counted as relevant. We then define diversity across pathways by the number of common courses that a set of pathways contain, excluding all relevant courses. The fewer common courses there are, the more diverse the set of pathways is. We aim for an algorithm that achieves high pathway relevance and high diversity across pathways, and we conducted data exploration to understand our dataset in terms of these two metrics.

First, we investigated how many relevant courses a pathway contains for a given search query. We computed pathway relevance for our twenty example

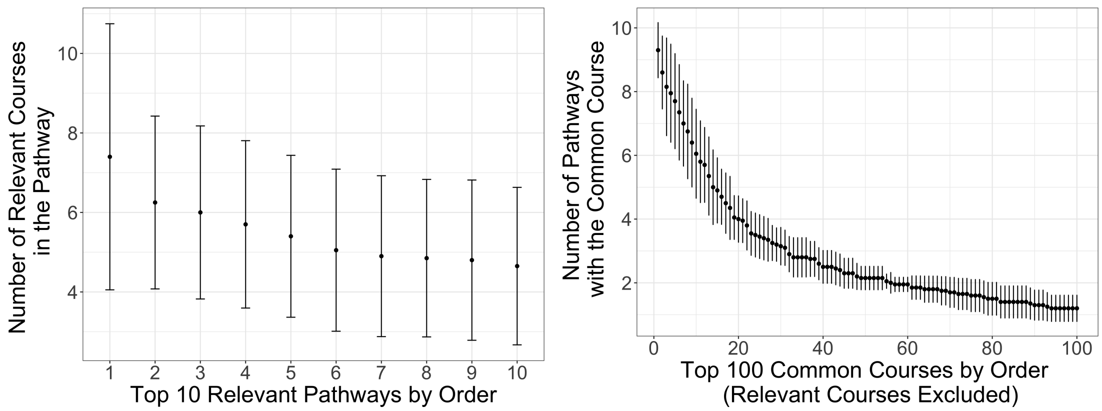

Figure 3.3: Left: Number of relevant courses ($\pm SD$) in the top 10 relevant pathways averaged across all search queries. Right: Number of pathways ($\pm SD$) in the top 100 common courses averaged across all search queries.

search queries and obtained the top ten relevant pathways in order. Figure 3.3.a shows that even the most relevant pathways contain only seven relevant courses on average. Students in our dataset take an average of 43 courses (SD = 8) throughout their undergraduate studies. Thus, at most 16% of courses in a student's pathway are directly relevant to a search query. This implies that even the most relevant set of pathways contains a high proportion of other courses for students to explore. Therefore, for a given search query, we design the algorithm to select the top ten pathways in terms of pathway relevance. This practically guarantees unexpected encounters with courses and topics while maintaining the highest degree of pathway relevance.

Every pathway with high relevance contains irrelevant courses, but it is unclear whether these courses will trigger student interest. We identified and adopted two approaches in our algorithm design to increase the chance that the presented pathway triggers student interest: One approach is to maximize diversity across pathways to broaden the student's exposure to various courses.

The other approach is to prioritize the pathway that contains courses related to the student's potential interest. This raised the question: how many diverse courses are in pathway results for a given query? We computed the number of common courses excluding relevant courses in the top ten relevant pathways for all twenty example queries (Figure 3.3.b). The long tail in the distribution suggests that a large variety of courses are represented in even a small number (10) of pathways. Figure 3.3.b also shows that more than half of the top relevant pathways have approximately 15 courses in common, even after excluding relevant courses that many of these pathways contain. This indicates that common courses are an issue in pathways and may negatively affect the diversity of pathways. However, courses may also be common across pathways because they are good matches for a student's interest, suggesting to students that peers who share their interest mostly took the following set of courses. Therefore, in the calibration step, we ask students to pick courses of interest from a pool of top common courses among their relevant pathways. Based on the student's selection, the algorithm then selects a set of five pathways to achieve the highest diversity across pathways among those with the highest pathway relevance. Pathways are shown to the student in the order that prioritizes those with the most courses of interest selected by the student.

3.6 Evaluation Study

We conducted an evaluation study to test the usability of *Pathways* and to understand academic exploration behaviors. Given that the goal of *Pathways* is to promote interest exploration during academic decision making, we pose the research question (**RQ1**): does *Pathways* support students to explore their interests? We also seek new insights into how interest exploration and academic decision making can be supported using *Pathways* as a research probe [150]. We observe how students react to *Pathways*, and especially to the design strategies we embedded in it, to answer our second research question (**RQ2**): how do students use *Pathways* to explore their interests and academic pathways? Answers to these questions will further our understanding of the needs and desires of students, and generate design ideas for future refinements of *Pathways* and related tools to support academic decision making.

3.6.1 Methods

Participants

We recruited fifteen participants from the university where the tool was developed: eight self-identified women and seven men; eight Asian, five White, one Hispanic, and one Asian-White mixed-race student; three first-year, seven second-year, three third-year, and two fourth-year or above students; three transfer students. Nine participants had already declared a major: four in information science, three in communications, one in applied economics and management, and one in computer science. We use a standard sample size for an initial, exploratory system evaluation in the HCI literature [53].

Procedure

We set up the evaluation study during the course pre-enrollment period, a time when students are highly engaged in academic decisions. The study was conducted one-on-one and online. First, participants were asked to explore *Pathways* for 10-20 minutes while using a think-aloud protocol [154]. Then, the experimenter sent over a short anonymous survey to solicit background information and a quantitative evaluation of *Pathways* to mitigate attitudinal biases that may be induced by the presence of a researcher. Due to connectivity issues, one participant was unable to fill out the survey. In the end, a semi-structured interview was conducted that lasted 20-30 minutes. Participants were asked about their general experience of *Pathways* and their personal interests and academic plans. The study sessions were video recorded, including the think-aloud exploration and semi-structured interview, but excluding the period when participants filled out the survey.

Survey Measures

Participants rated their agreement with seven statements about *Pathways* on a 7-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree, 4 = Neither Agree nor Disagree, 5 = Somewhat Agree, 6 = Agree, 7 = Strongly Agree). The statements (shown in Figure 3.4) are about how well the serendipity-promoting algorithm shows relevant and diverse results (3 items), how the results translated into course discoveries (2), and about future use and recommendation intentions (2).

Interview Protocol and Analysis

In the interview (protocol in OSF: https://osf.io/g3fdr/), participants were asked to compare between *Pathways* and the institution's official course catalog system, *Roster*, that has standard features that most institutions provide today.

Participants were also asked to describe what they would use *Pathways* for. The questions were designed to examine if *Pathways* is an improvement over the most commonly used system in colleges and if participants can discern how *Pathways* is different from a course catalog system. Participants' feedback was contextualized within their stated interests and situation so we can understand how they reached their evaluation of *Pathways* depending on their specific context. This allows us to investigate where *Pathways* was successful and where its limitations lie. We conducted a thematic analysis [43] using the collected recordings. The research team used line-by-line coding and generated memos individually. We analyzed the codes and memos together, looked for patterns across all interviews, and grouped them into themes. During this collaborative analysis, we discussed all key points in the memos for which there was disagreement or which were identified by one but not other researchers. We then reviewed the interview recording and discussed inconsistencies with the themes. Themes that did not contain enough codes for support were removed or combined into other themes. This was an iterative process that lasted until final agreement was reached.

3.6.2 Finding: Performance of *Pathways* (RQ1)

We present findings for RQ1 about how well *Pathways* supports students in exploring their interests. We organize findings into three parts: First, we evaluate if participants perceived the serendipitous-promoting algorithm as generating both relevant and diverse results. Second, we evaluate if the generated results led participants to discover courses that are both interesting and unexpected. Third, we evaluate if students would use the tool in the future and recommend

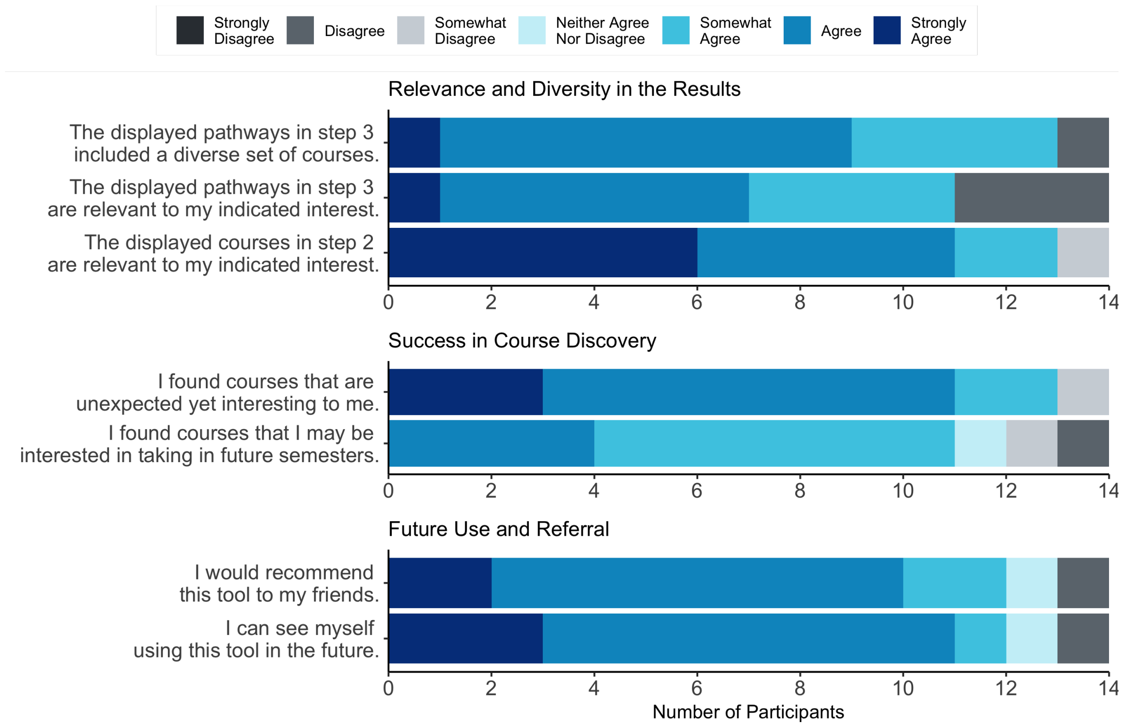

Figure 3.4: Survey responses in the evaluation study (n=14).

it to their peers. We use evidence from the survey (Figure 3.4) and interviews in presenting our findings.

Relevance and Diversity in the Results

We examined participants' subjective evaluation of the results separately in the *Course Matches* step and the *Pathway Matches* step. For the first one, 13 out of 14 participants agreed (Median = 6, SD = 1.2) that the course matches were relevant. When using the tool, all participants saved at least one out of the ten courses to revisit later in their Dashboard. Most participants (10/14) reported that they saw courses related to their interests, including ones they took before, ones they planned to take, and notably, ones that they had not heard of before. This suggests that even a basic relevance match between a participant's search query and course descriptions can increase student awareness of course offerings and create unexpected encounters that may help develop their current interest.

For the *Pathway Matches* step, most participants still agreed that courses were relevant (11/14, Median = 5, SD = 1.7), though the level of agreement was slightly lower than in the *Course Matches* stage. This drop is expected as academic pathways include courses that are not closely related to a participant's indicated interest, which can affect the overall relevance of the result. In fact, 13 out of 14 participants agreed that pathways exposed them to a diverse set of courses (Median = 6, SD = 1.1). These findings highlight the competing goals of closely matching user needs with relevant information and extending beyond user needs with less relevant information. Thus, the inclusion of unexpected results needs to be well-balanced. Overall, the results suggest that *Pathways* presented students with results that balanced relevance and diversity as intended.

Success in Course Discovery

The goal of *Pathways* is to help students find academic interests through viewing relevant and diverse courses. We therefore examined if our approach enabled successful course discovery. Most participants agreed (13/14) that they found courses to take in future semesters (Median = 6, SD = 1.0). Moreover, they also agreed (13/14) that they found courses that are unexpected yet interesting to them (Median = 5, SD = 1.2). This finding is supported by evidence from the interviews. For instance, P12 remarked on how his situational interest was triggered in an unexpected way: *"I didn't even think about (this class) when I was* *initially saying what I was interested in in the first step but it popped up and I was like okay this is something I can see myself doing.*" Overall, the results suggest that *Pathways* was effective in stimulating student interest and creating serendipitous encounters during academic exploration.

Participants also provided feedback on the interaction design and visualizations to discover courses of interest easier. In the calibration step of *Pathway Matches*, five participants commented that they were not interested in any courses presented to them and thus cannot calibrate the algorithm. They therefore suggested adding a "load more" feature to browse through more courses for the calibration step. In the pathway visualizations, three participants raised the concern that color-coding courses by subject makes the pathway too "*noisy*" (P1) or "*distracting*" (P3) because there are too many subjects (Mean = 15 in a pathway, SD = 3.1). They therefore suggested highlighting information in pathways based on broader categories, such as highlighting STEM courses (P13) or courses often taken in the final college years (P6). Additionally, participants appreciated the compactness and sense of liveliness that displaying courses in hexagons evokes, but the constrained width of the hexagon makes course names hard to read and courses of interest less noticeable. P10 suggested that seeing courses as a list may be better. This may be particularly true for the visualization in *Course Matches*, because arranging search results by relevance in a list format is a common design pattern for search engines. Overall, the interviews provided clear feedback for refinements to the visualization for future iterations of *Pathways* to improve its usability.

Future Use and Referral

Most participants (12/14) agreed that they would like to use *Pathways* in the future (Median = 6, SD = 1.3) and would recommend it to friends (Median = 6, SD = 1.3). The interview data offers further insight into their reasons and potential uses. First, participants found it to be a useful, complementary tool to the institution's official course catalog system, *Roster*. Participants described *Pathways* as a way to help them find potential courses of interest, while *Roster* would be used subsequently once they already know what courses to take. P5 explains the difference: "*(With) Roster you had to do the research. This does the research for you.*" Second, participants saw *Pathways* as a tool to improve information equity and mitigate biases, because it allows them to get course-taking advice outside of their social circle: "*I'm actually interested in data science, but like I didn't find any people in the data science field to ask them like which courses are best to learn data analysis.*" (P6). Participants appreciated the ability to gather information that is impartial compared to their friends' point of view: "*If I ask someone else maybe they're more into designs they may recommend design classes but I'm gonna do like front-end and back-end engineering stuff so it's not really that relevant.*" (P13).

Participants came to appreciate connections between courses in academic pathways and engage in longer-term thinking about their academic plans with *Pathways*: "*You can see what courses are used to like built based on higher-level courses. That's definitely something I haven't seen anywhere else.*" (P13). The forward-thinking design of *Pathways* is especially useful to first-year students who may know little about what a four-year degree program entails: "*I think something... you don't realize is you kind of have to have a four-year plan when trying to pick classes, but when you come as a freshman like 'What I think of my four years' is definitely a* *lot.*" (P8). Multi-semester planning is also important to transfer students like P11. She commented that thinking strategically about more than one semester at a time is more common for transfer students, because they have more courses to cover in fewer semesters once they arrive at a new institution.

3.6.3 Finding: Reactions to *Pathways* (RQ2)

This section presents findings related to RQ2 about how students explore their interest and find courses using *Pathways*. We focus on the qualitative evidence from the evaluation study and organize findings around three claims: (1) Students struggle to articulate their interest; (2) Students can be resistant to interest exploration; and (3) Students gain new insights from pathway visualizations.

Students struggle to articulate their interest

Students are asked to indicate their interests in the search prompt on *Pathways*, but when participants faced the large open-ended text box, they expressed a range of attitudes toward it. Half of the participants (7/15) thought the open-endedness of the text box raises uncertainty over how to describe their interest. They also felt reluctant to articulate in full sentences. They would have preferred the search to ask more specific questions that can be answered in short phrases, such as "what major are you interested in" or "what was your favorite class". However, other participants appreciated the large space to be "*wordy*" (P11) about their interests. Participants who overlooked the example queries tended to spend less time thinking about what to write in the search box and typed in keywords such as their majors. Yet participants who closely read through the full-sentence example queries found them extremely helpful as a guide for what to write about and wrote in full sentences. They generally spent more time thinking and wrote more about their interests. This aligns with the design intention of *Pathways* to promote deeper reflection through articulating interests, even if it makes students feel uneasy. What came as a surprise is how much participants relied on example queries not only to determine how much to write in their query but also what to search for. Several participants (5/15) found topics in the example query interesting and decided to search for those or add those to their own interest. This may indicate how students find it taxing to reflect on their interests and rely closely on what is presented as long as it generally aligns with their interest. This also suggests that examples in the user interface can potentially be used as light-touch interventions to influence students' situational interest.

Many participants (9/15) revised their search query after viewing the search results. Among them, four participants realized that the interest that they indicated was too general based on the course results, so they wrote longer sentences to explain their interest. For example, P13 initially only wrote "*security*" in the search prompt, but then added details: "*I'm interested in system security, something in the computational field, and mechanical physics*". This shows how *Pathways* uses course search results to nudge students to reflect on and concretely articulate their interests. Five participants were inspired by search results that were not directly relevant to what they indicated. P10 initially wrote "*I'm interested in classes related to computer science, especially machine learning and human computer interaction. I'm also interested in data science.*", but after seeing a particular pathway, she went back and changed her search query into "*I'm looking for advanced computer science classes relating to computer architecture and robotics.*" This shows how *Pathways* can trigger new situational interest by including seemingly irrelevant information to students. Both cases show how courses and pathways can serve as "tangible objects" that allow students to "play with" their interests and develop a new understanding of it.

Students can be resistant to interest exploration

All participants liked the *Course Matches* feature because it directly connected to their search query, but their attitudes were mixed about the *Pathway Matches* feature. Many participants (10/15) appreciated having *Course Matches* to set the stage for the more complicated *Pathway Matches* to make them "*easy to understand*" (P3). Some (3/15) explored the calibration feature to show different *Pathway Matches*, commenting that it makes pathway visualizations "*versatile*" (P4). However, we also saw that some participants (6/15) were not as enthusiastic and showed confusion or resistance when they were prompted by the calibration feature to explore or when they saw the diverse pathways. We found two reasons for this resistance.

First, some participants (3/15) are open to interest exploration, but only within the bounds of their requirements. They expressed difficulty reconciling the need to satisfy requirements with exploring their interest outside of what is required, describing it as a "*waste of credits*" (P5). For example, P6 tried to recognize which academic major a student pursued based on their pathways, such as "*this person is heavy business*" or "*this is an information science and economics person*"; once identified, P6 would move on to the next pathway until she found one that matched her requirements. While other participants did not consider fulfilling requirements their main priority, many of them (9/15) indicated a desire to see the major of the student whose pathway they were viewing, so that they could determine if the courses they found interesting would also satisfy their own degree requirements. They also expressed a desire for *Pathways* to let them specify their major in the search prompt so that the results could filter out pathways with different requirements. While this suggestion may serve some students' needs, it conflicts with *Pathways*' goal to facilitate broad exploration. P12 commented on the question of whether student major should be reported and incorporated in generating pathway results: "*There are pros and cons. They will filter in more classes in your major but the same time it can be very limiting. There can also be so many pathways that you may not even know you're interested in before and maybe over time you may grow interest in.*"

The other reason that some participants (3/15) chose not to explore is because they believe they had already committed to an interest. P10 expressed that, "*seeing all classes together (in a pathway) takes the focus away from what I'm interested in.*" Because most students formalize their interest in terms of majors and minors, participants behaved differently depending on whether they had already determined a major or minor. For example, P14 is a second-year student who is searching for a minor. He is interested in applying computer science in other disciplines, possibly in linguistics, philosophy, business and education. P14 reported being fascinated by the tool and he spent a long time exploring various outcomes. Participants like P14 mainly used *Pathways* to better understand the academic pathway of prospective majors or minors that they are interested in. However, P12 was less excited about the tool. Even though he is a freshman, he was already determined to declare information science as his major: "*It's a little different for me (than other freshmen) because I kind of already have an idea of what I want to do. [...] I feel like for students who are more undeclared...*

it may be more useful". However, what these participants are often not aware of is that exploration is an ongoing process, even with an established interest. For example, P9 is a fourth-year student majoring in communication and is very open-minded about exploration. She described her motivation for exploration as follows: "*I think this application would be a really cool way to connect to what I'm pursuing for next semester. [...] Like maybe I don't want to just do marketing communications. Maybe I want a photography class. [...] Maybe there is a class that incorporates photography (with communication) but I don't even know and so I think this app being able to connect would be super cool for exploration.*" This case highlights that those who generally enjoy exploration tend to be open to topics that can provide new perspectives on their existing interest even if their interest is well-established.

Students gain new insights from pathway visualizations

When participants browsed through visualizations of different pathways, we were surprised to find that they would extend our working definition of diversity. While we defined diversity only in terms of the variety in course topics across pathways, participants pointed out diversity in terms of when courses were taken, not just what kinds of courses were taken. They noticed many course-taking patterns in the pathways that surprised them because the patterns deviated from their understanding of what a pathway should look like. Specifically, they noted the following unexpected patterns: some students spent the first year primarily taking courses in one field but then transferred to a completely different field in their second year (noticed by P9, P15); some students took an introductory course in an a secondary field in their final year (noticed by P8); some students took courses in topics that look completely irrelevant to their field (noticed by P6, P11, P12, P15); and some students only took three courses in a semester when the usual number is around five (noticed by P11). Many participants expressed surprise and even asked if these pathways were from actual students. Seeing these course-taking patterns broadened participants' understanding to the greater possibilities and options for a pathway.

In addition to noticing different patterns, participants also noticed similarities across pathways. In most pathways, students took courses from a diverse pool of subjects in their early academic years, and later narrowed them down to one or two primary fields. This sends an important message to students: they can take diverse courses early on to explore what works for them, or as P9 put it: "*What this really shows is that all freshmen kind of have a very all-over-the-place schedule cause they're trying to figure things out. No one knows right off the bat that Oh this kid is gonna do CS, this kid is gonna do business. [...] I think a lot of students don't understand is that [...] you should take time to figure things out. Seeing this really motivates you. [...] You can really discover anything.*" The patterns that participants identified in pathway visualizations are not intentionally highlighted in our original design, but they reveal insights that are at the core of what *Pathways* tries to achieve.

3.7 Discussion and Conclusion

We developed *Pathways* to support academic decision making at scale. We adopted a developmental advising approach to encourage students to explore their interests by visualizing past students' course enrollment records, using a data storytelling framework, and a serendipity-promoting algorithm. Our evaluation study shows that *Pathways* can help students discover new courses and potential pathways of interest. We found that many students struggle to articulate their interest, and that presenting courses in the form of pathways can help students formulate and express their interests. We also found that students tend to explore their interests within the bounds of degree requirements, or they view exploration as unnecessary once they declare an academic major. When students explore pathway visualizations, they realize that they can endeavor diverse pathways themselves. The study's findings raise broader theoretical and applied implications concerning academic interest exploration and data communication.

We conceptualize academic decision making as a constructivist learning process that is enabled by the elective system in U.S. higher education. Students need to create academic pathways that not only satisfy degree requirements, but also align with their developing interests and goals. To support this constructivist learning process, we did not design *Pathways* to be an AI "expert" system for academic decision making. Instead, it facilitates learning from peers using minimal AI to select peers who address students' needs. We found students actively reflecting on and evolving their interest in the process of using the tool. Students "observed" the academic decisions of others, represented as pathways, and compared them with their own academic decisions. This demonstrates how *Pathways* supports constructivist learning for academic decisions, and motivates further research into advising tools that support this kind of learning process with a high degree of student agency. Learning to make these decisions is a useful skill for life-long learning and career choices beyond college [255].

We now consider limitations of this research and opportunities for addressing them in future work. First, the historical course enrollment data we used was a sample of undergraduate students at the university that did not include all academic majors. This could have introduced biases, limited the diversity of results, and impeded serendipitous discoveries. While we did not notice problems along these lines, we plan on expanding the data set in future studies. Second, the evaluation study we conducted was in a controlled context rather than a field deployment, which limits the external validity of our findings. Participants used *Pathways* during the pre-enrollment period, but they did not use it "in the wild", which may influence their attitudes and behaviors. Third, the sample of participants was recruited from a channel that reaches a relatively homogeneous sample of students with interests in information science and communication. Their evaluation of the tool and its algorithm may be shaped by their interests. While our sample size is standard for an exploratory study with an initial design [53], the complexity of pathway results might require a larger, more diverse sample to gain generalizable insights about the performance of *Pathways*, and what it tells us about student interest exploration.

Our study reveals unexpected tensions in interest exploration during academic decision making. We were surprised to see how challenging it is for students to articulate their interest in ways other than stating their major. Majors are a useful heuristic for students to think about their interest and it helps students stay focused and graduate on time. The need to pick a major motivates students to explore if their interest fits [275]. Yet majors also constrain interests. We found that students articulate interests in a more nuanced, flexible, and creative way than majors after browsing diverse courses and pathways. Courses and pathways offer students a new channel to envision and develop their interest beyond majors. For today's students, it is especially important to consider interests beyond institutional definitions of academic disciplines (majors/minors), which are broadly defined and less fluid compared to rapidly changing industry demands [24]. How to design prompts and scaffolds to help students learn to articulate their interest warrants further study. Moreover, considering interests beyond one's major can promote exploration after major declaration. Based on prior work on interest development, it is equally important to trigger new situational interest in later interest development stages as it is in early stages [249, 129]. The time of major declaration may separate different stages of interest development: once declared, students have an established interest. We found that only a few students with a declared major continued exploration using *Pathways*, but new situational interest was triggered when they found cross-disciplinary courses that connect back to their established interest. We recommend future research to investigate different types of triggers for different stages of interest development to support sustained exploration.

Finally, our study shows the value of making historical course enrollment data transparent to students. While most advising tools focus on developing prediction models to inform academic decisions [159], *Pathways* demonstrates that descriptive information about other students' choices can be equally, if not more, constructive to support decision making. This approach is extremely scalable because it requires only simple technology and course enrollment data that is available at virtually every university. These data hold valuable information about academic choices and what they entail. But how to strategically surface this kind of information to students in a meaningful way requires further research. In *Pathways*, we used data storytelling and visualization techniques to let students view and compare choice options across peers. We found that students identify patterns that are instructive to them. They notice that many students do not have a clear academic path in the first terms, and are surprised to discover that academic pathways are much more diverse than they presumed. While we cannot tell why students took certain courses at certain times, the normative message conveyed by these observations is compelling: there is no standard way of creating a pathway and it is normal to take time to figure it out. Prior work suggests that social norms emerge when individuals interact with others [272] and they get reinforced when interacting in a relatively homogeneous group [228]. Our work shows that when students interact with a wider group of students, even by viewing their pathways asynchronously online, they are encouraged to update their normative beliefs and explore options that could better suit their needs. Tools like *Pathways* provide channels to convey academic norms with authentic data. We call for more research on students' exploration and decision making to build a science of academic pathways.

CHAPTER 4

SHOWING AUTHENTIC EXAMPLES OF ACADEMIC AND CAREER TRAJECTORIES TO INFLUENCE COLLEGE STUDENTS' CAREER EXPLORATION

In the previous chapter, I introduced a course information platform called *Pathways* to support students' academic exploration and presented qualitative evidence of its benefits. This chapter takes a step further by evaluating *Pathways* through a randomized controlled experiment. The goal is to assess if and how a *Pathways* approach, presenting accurate, holistic, and diverse academic information, affects students' career exploration outcomes. The insights from this chapter will better help us understand the role of information support in academic exploration, and provide important implications for institutional administrators to integrate existing digital resources with traditional career services, creating a more comprehensive support system for students.

4.1 Introduction

Career exploration is instrumental for undergraduate students to make good career decisions. Through career exploration, students reflect on their interests and goals, gather information about potential occupations, and learn to choose a future career path [190, 283]. Career exploration can also enhance students' career decision self-efficacy [67, 68] and their readiness to make career decisions [176]. Additionally, through this process, students can develop more coherent interests and career goals [105, 265], as well as clearer career identities [202, 240].

Career exploration is relevant to students not just upon graduation but also as they start their college program. Many students enter college feeling uncertain about their future plans and need to actively explore them [182, 286]. In the early phase of exploration, the immediate task of selecting courses for next-semester enrollment and declaring a major becomes the primary focus. However, students often overlook how their initial academic decisions are consequential to the range of future career paths available to them [60, 280]. This lack of awareness highlights the essential need for academic planning to be considered in parallel with career exploration. Career exploration and academic planning are intertwined processes that can support each other to facilitate a smooth transition from college education to future careers.

Social Cognitive Career Theory (SCCT), one of the most widely used frameworks in the literature, underscores the importance of contextual affordances to promote career exploration [191, 193]. Contextual affordances are environmental factors that can be experienced as supporting or hindering career outcomes. Past research has focused on one type of contextual affordance: social support, such as parental support and counseling guidance (e.g., [67, 109, 252]. Social support is a significant positive predictor of career exploration [67, 185], partly because it can help individuals obtain career-related information that they otherwise would not know about [185]. This suggests that information support, as a component of social support, may independently affect career outcomes, but this idea has not been empirically tested in the prior literature [112]. Understanding the impact of information support is increasingly important as digital tools can offer information separately from traditional social support networks, such as parents, peers, and career counselors. Extensive information about academic options, skills, and careers can be found online. The availability of information could make information support tools play a valuable role in career decision making, but it could also lead to information overload and misinformation for job seekers. This dilemma presses the need for reliable, unbiased, and representative information to support career exploration and to understand how different approaches to information provision may afford better career exploration.

The current study focuses on information that is commonly provided through peer support, namely the decisions that previous students have made. This kind of peer information is influential to students' academic and career decisions [54, 208, 241], but students typically receive this information through word-of-mouth which limits the reliability and representativeness of the information [167, 144]. To address this limitation, this study evaluates an information support tool that leverages official registrar data on archival student course enrollments and post-graduation career destinations collected across campus. The tool provides students access to de-identified information on past students' academic and career decisions that is more reliable and representative. However, this kind of information support also raises questions about how information should be presented to students to optimally support their career decisions. In this study, through a randomized controlled experiment, we examine how this information support tool impacts students' career exploration outcomes (RQ1), and how students' awareness of different information sources is associated with career exploration (RQ2).

4.2 Background

4.2.1 Perspectives on Career Decision Making

The literature on career decision making distinguishes two theoretical perspectives: the content-based perspective and the process-based perspective [146]. The content-based perspective is primarily concerned with the outcome of career decisions, especially optimizing the person-environment (P-E) fit (e.g., [143]). This P-E fit is optimized by assessing an individual's traits and aligning them with the characteristics of potential work environments. In contrast to the content-based perspective, the process-based perspective focuses on the decision-making process itself as the outcome of interest (e.g., [116, 165]. This process encompasses the sequential stages of collecting information, engaging in self-discovery, and evaluating options to make a good career choice [113].

The content-based perspective has received significant attention in the literature. It encouraged research on personality and ability assessments and promoted the development of tools to help students and workers find a good career match (e.g., [15, 88, 201]. However, given its focus on finding the right career match at a given point in time, it does not attend to the dynamic and continuous processes involved in career decision making. The process-based perspective has received growing attention for its relevance to the modern job market characterized by frequent career transitions and transferable skill sets [118, 238]. It offers a framework for understanding how individuals navigate their career choices and what guidance could assist them at different stages of the process [110, 111]

In this research, we adopt the process-based perspective as our guiding theoretical framework because it better accounts for the influential role of information in career decision making. The process-based perspective recognizes two informational antecedents that affect the career decision process: the lack (or provision) of information and the use of information [112]. The lack of information is further categorized into three types: internal information about the self, external information about the world of work, and information about the process of career decision making [112]. In our study, we developed an information support tool that gives students access to official information on how students in the past made academic and career decisions. This tool therefore provides them with access to external information about the world of work. When students review the choices made by others, they gain information about potential choices they could make for themselves. Additionally, this tool may indirectly provide them with internal information about the self. When students observe the choices of others and the career consequences of those choices, it may cause them to reflect on their own preferences. Overall, we expect our information support tool to have a positive influence on students' career decision-making process.

4.2.2 The role of information support in career exploration outcomes

Building on the process-based perspective of career decision making, this study focuses on the role of information support in facilitating career exploration. Career exploration, as broadly defined by Zikic and Klehe [321], is “the gathering of information relevant to the progress of one’s career”. This definition of career exploration clearly aligns with the process-based perspective. Indeed, career exploration is not only a prerequisite for matching individual preferences to suitable jobs, but also an adaptive mechanism that helps individuals manage frequent changes in modern working environments [35, 139, 320]. However, few studies have empirically examined the effect of informational antecedents on career exploration from a process-based perspective [161, 180].

In this study, we investigate the effect of information support on two specific career exploration outcomes: self-efficacy in academic planning for career exploration and behavioral intentions for career exploration. Career self-efficacy is one of the most essential and densely studied outcomes in the career literature. In the Social Cognitive Career Theory (SCCT; [188, 189, 195], self-efficacy plays a central role in the dynamics of various internal and external career development factors. Hackett and Betz [126] proposed a distinction of two unique kinds of career self-efficacy that is similar to the two distinct perspectives of career decision making. The content domain of career self-efficacy refers to self-efficacy in specific career fields, and the process domain of self-efficacy refers to self-efficacy in using necessary strategies to perform career decision activities. In our research, we focus on the process domain of self-efficacy, and specifically on the self-efficacy in academic planning for career exploration (i.e., how students plan their academic choices to support their exploration of career options).

Several studies have demonstrated a strong association between general career decision self-efficacy and peer support [70, 176, 307]. In our research context, sharing peers' academic and career choices can reveal how past students successfully navigated their paths. This visibility may give students a sense of peer support, and thus raise their self-efficacy in academic planning for career exploration. Additionally, this information can increase students' understanding of the career consequences of specific academic decisions, which can help them explore potential careers more confidently. Therefore, we hypothesize that the information support tool will increase students' self-efficacy in academic planning for career exploration (H1). Relatedly, past research shows that high self-efficacy in career decisions significantly predicts intentions for career exploration [223] and other proactive career behaviors [141]. Therefore, we also hypothesize that the information support tool will increase students' behavioral intentions for career exploration (H2).

The process-based perspective also recognizes that individuals engage with information in varied ways at different stages in the career decision-making process. Considering the complexity and volume of information involved in career decision making, Gati and Asher [111] proposed the PIC (Prescreening, In-depth exploration, and Choice) model that organizes the process of information gathering and processing for career decisions into three stages. In the prescreening stage, an individual narrows down a list of promising careers for the next stage based on their personal preferences. In the in-depth exploration stage, the individual redirects their attention to getting comprehensive information about the narrowed list of promising career alternatives. Finally, in the choice stage, the individual chooses the most suitable career by considering trade-offs between desirable and undesirable features of career alternatives. We employ the PIC model to identify students' career decision stages and use it as a moderator to investigate how information support may affect career exploration outcomes differently across these stages.

To adapt the PIC model to our study context, we added an initial stage before the prescreening stage, which we refer to as "broad exploration." At this stage, individuals broadly explore to develop an expansive list of potential careers. Expanding the breadth of options is a common step identified in general decision-making processes. Individuals face trade-offs between exploring broadly and exploring in-depth during information searches in constrained settings [217]. For the subsequent career decision stages, we refer to each stage in line with our study context as "narrowing down", "close comparison", and "decided." Using this adapted version of the PIC model, we speculate that an information support tool may be most beneficial to students in earlier career decision stages (i.e., broad exploration and narrowing down). The information support tool systematically provides students with a variety of information on potential career options and the corresponding academic pathways based on their interests. Such access enables students to discover new career possibilities and expand their list of potential careers. By integrating career information with academic plans, students can evaluate their preparedness for a career's academic prerequisites. This may help students narrow down their list of career options to align with their current academic standing. In contrast, we expect the information support tool to be less beneficial to students in later career decision stages, because their focus shifts to introspection about their preferences, abilities, and personalities [112]. They may also seek more contextual information about the career options, such as financial implications and advancement opportunities, which falls beyond what the information support tool provides.

4.2.3 Information awareness in career decision making

Students' information awareness about potential career options is a critical antecedent for their career exploration. From a process-based perspective, students who are aware of more and different types of options are likely to make better career decisions [112]. The concept of awareness has been formally studied in the general decision making literature, which proposes a funnel model of choice [62, 142, 229, 276]. The model characterizes choice alternatives into three sequential sets that reduce in size: the awareness set, the consideration set, and the choice set. A person starts their choice process not with the set of all alternatives available (often referred to as the universal set), but with the set of alternatives that they are aware of [221]. Then they reduce the awareness set to the consideration set by evaluating the suitability of potential career options [120]. Finally, the person narrows the consideration set down to a small set of final choices.

Technology as a medium for accessing information is likely to influence the awareness set, both in terms of the overall options and the types of options that are available. For example, in the context of online dating, dating applications can shape someone's awareness set by offering features that allow filtering of potential matches (e.g., by age or gender) [48]. Filters reduce the selection of profiles that are presented, which effectively reduces the awareness set of possible mates. Similarly, in educational settings, course search and recommendation systems play a pivotal role in shaping a student's awareness of available courses to enroll in [62]. These systems use search algorithms to tailor the display of courses based on students' expressed interests. For example, Pardos and Jiang [232] developed a course recommendation algorithm that helps students discover courses of interest that exist across departments, even though the course descriptions use widely different terminologies. This raises students' awareness of a broader variety of course options available to them. Thus, the user interface and algorithmic design of digital tools can have a significant influence on the types of information that shape an individual's awareness set.

In this study, we examine four types of information awareness based on the specific information support tool we designed. First, our tool provides access to *official information* about past students' course enrollments, academic major and minor choices, and the first career destination after graduation. The use of official data sources can substantially increase the reliability of the information presented. This may enhance students' trust in the information and encourage them to consider these academic and career paths more seriously. Prior work on decision making in various contexts has found trust to have a strong influence on decision behaviors (e.g., [59, 170]), especially in high-stake decision contexts like academic and career decisions.

Second, the information support tool is designed to offer *personalized information*. It shows the paths of past students who share similar interests indicated by the current student. Personalization is a common feature in search models that aim to make users aware of information that is relevant to them. Personalized information is shown to help users spend less time on decision making and accept a choice alternative suggested by the relevant content [289].

Third, the algorithm of the information support tool is designed to present *diverse information* about career alternatives, not just the most relevant ones. Search and recommendation algorithms risk creating a "filter bubble" where users see increasingly homogeneous information [39, 222]. This risk can be particularly detrimental to students for career decision making because their understanding of the world of work is still developing. Restricting students' awareness of career options to only familiar ones may hinder them from developing a well-rounded perspective on opportunities available in the world of work. However, presenting information that is overly irrelevant or random could confuse users and reduce the trustworthiness of the tool. To solve this issue, search algorithms have been developed to create "serendipitous" search results that are both relevant and unexpected [10, 58]. In our information support tool, we carefully designed the search algorithm to balance relevance and diversity. This strategy is supported by recent research that shows the importance of diversification in possible career paths for career decisions [115].

Finally, the tool offers *holistic information* by integrating academic decisions with career choices, providing a broader context for each career destination. Academic decisions have been shown to influence career outcomes, including access to further education [294] and job opportunities [267, 151, 294]. By presenting holistic information to students, it helps them understand the connection between their current academic choices to future career paths. It may reduce students' uncertainty about the steps needed to transition from education to the workforce. It may also encourage students to make long-term plans and look beyond their immediate academic choices.

4.3 Methods

4.3.1 Context and Participants

We recruited 234 undergraduate students to participate in a survey-based randomized controlled experiment at a large U.S. research university where our information support tool was developed and made available to all students on campus. The tool allows users to input their interests, and then display a diverse range of academic and career pathways from prior students who share similar interests [65]. We excluded participants from the analysis who were already frequent users of the tool and those who spent less than five minutes in the study, as this is insufficient time to engage with the tool and complete the survey questions. Our final sample consists of 214 students. This group comprised 22.9 % men and 77.1 % women, with a racial breakdown of 50.5 % Asian, 28.0 % White, 7.5 % Hispanic, 5.6 % Black, and 8.4 % with mixed race or ethnicity. Participants were enrolled in various colleges at the university, and most participants (91.1 %) were in colleges that did not require students to declare a major until the second or third year. Participants' academic year distribution was 4.2 % first-year, 33.2 % second-year, 43.5 % third-year, 18.7 % fourth-year, and 0.5 % fifth-year and beyond. This distribution skewed toward upperclassmen, deviating from our initial aim to recruit more underclassmen, who typically face greater uncertainty and have more flexibility in exploring majors and career options.

4.3.2 Procedures

Participants completed the study via an online survey administered on Qualtrics. In the survey, participants were randomly assigned to an intervention condition (N = 110), where they used the information support tool and completed a reflection exercise, or a control condition (N = 104), where they completed a reflection exercise on their major and career interests. In the intervention condition, participants were asked to describe the patterns they observed in alumni's academic paths and career choices in the tool. This writing task was designed to encourage meaningful interaction with the tool. For the control condition, we devised a reflection exercise that requires a similar level of cognitive effort as the intervention reflection. It asked participants to reflect on their interests in potential majors and careers, approaches they took to explore them, and insights they learned through their exploration. After completing the exercise, participants in both conditions proceeded to the online survey to answer a set of questions. All study materials are available online at osf.io/yj7a3/.

4.3.3 Information Support Tool Intervention

The information support tool we used in this study is an interactive search tool that enables users to explore how past students with similar interests made their choices on course, major, and career [65]. The tool operates in several steps to strategically provide users with tailored information. It first asks users to input academic information, including if they have declared a major and what the (intended) major is. Then, users are asked to describe their interests in terms of keywords (e.g., "human-centered design", "natural language processing", and “marketing”; see Figure 4.1). This information is used for the search algorithm to identify alumni with matching academic backgrounds and interests. The tool then shows users a list of courses that match their interest keywords offered by the university and asks them to select those that are relevant. This step helps calibrate the search algorithm to provide results that more accurately reflect the student’s interests in relation to the university’s offerings. Last, the tool displays visualizations of five alumni’s academic pathways (Figure 4.2). Each pathway consists of the person’s major and minor, semesterly course enrollment history, and their first career destination after graduation, which could be an employment destination or a graduate studies program. The course records are retrieved from the university registrar’s office, and the career records are retrieved from the university’s career services office, which conducts a graduation survey. For 26.9 % of alumni, graduation records are missing due to survey non-response. After viewing the search results, students can start a new search with different interest keywords and view alternative alumni pathways.

4.3.4 Measures

Self-Efficacy in Academic Planning for Career Exploration

We adapted the Career Exploration and Decision Self-Efficacy-Brief Decision (CEDSE-BD) Scale [194] into a five-item measure that emphasizes career exploration-focused academic planning (e.g., “I can find courses to gain career-relevant knowledge and skills”). Participants rated each item on a 5-point scale (1 = not confident at all, 2 = slightly confident, 3 = moderately confident, 4 = very confident, 5 = extremely confident). We created a composite score by com-

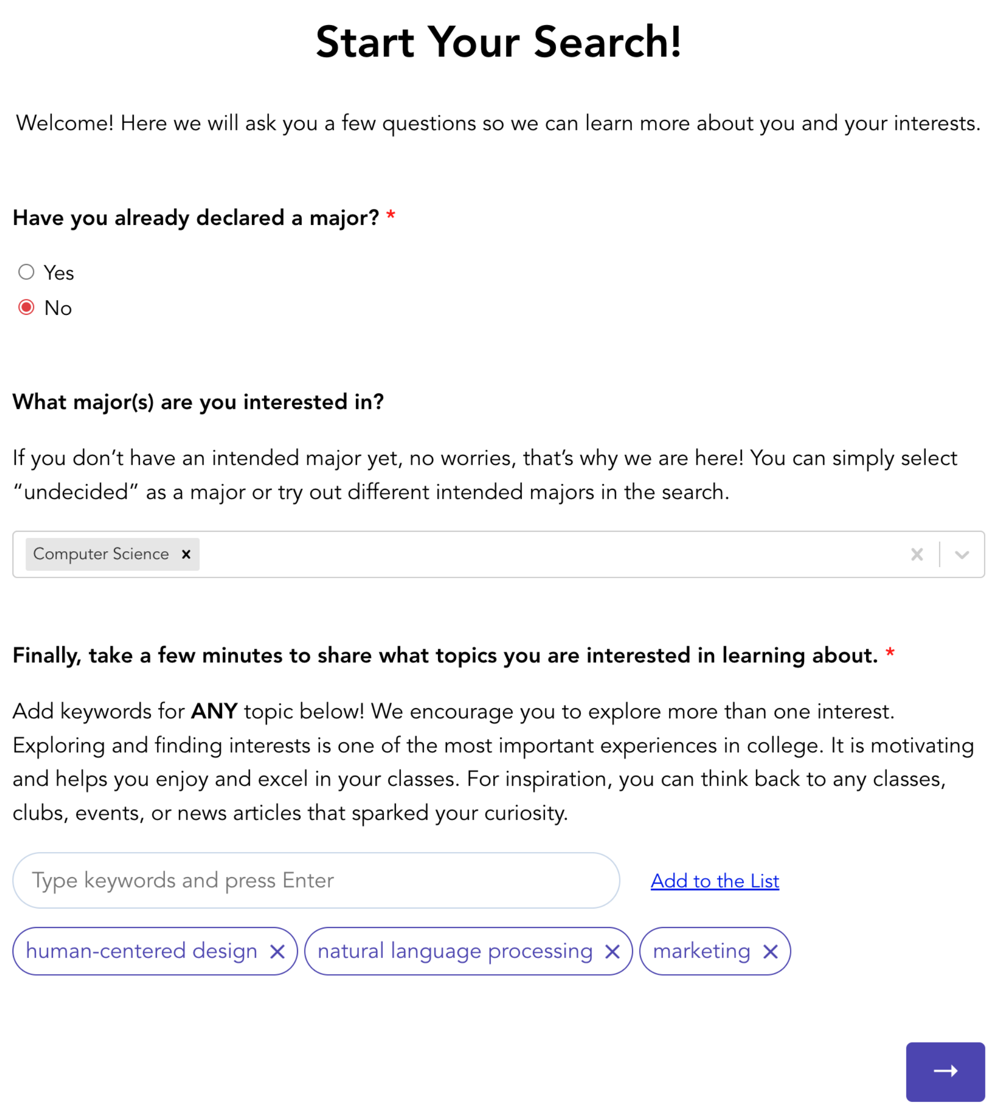

Figure 4.1: Screenshot of the information support tool's search page which shows how students input their academic background and interests.

puting the mean, such that higher values indicate greater self-efficacy (mean = 2.90, sd = 0.99, Cronbach's alpha = 0.91).

Behavioral Intentions for Career Exploration

We adapted the six-item Environment Exploration subscale in the Career Exploration Scale (CES) [283] to measure future behavioral intentions instead of past behaviors (participants answered "How likely or unlikely are you to take the following actions in the next few months?", e.g., "Investigate potential career directions."). Participants rated each item on a 7-point scale (1 = very unlikely, 2 = moderately unlikely, 3 = slightly unlikely, 4 = neither likely nor unlikely, 5 = slightly likely, 6 = moderately likely, 7 = very likely). We created a composite score by computing the mean, such that higher values indicate stronger behavioral intentions (mean = 5.86, sd = 1.04, Cronbach's alpha = 0.78).

Career Decision Stage

Following the PIC model proposed by [111], we developed an item for each career decision stage. Specifically, the response options include: the broad exploration stage, where students try to identify a manageable set of choice alternatives ("I'm exploring potential careers"), the narrowing down stage, where they identify a smaller set of compatible alternatives ("I'm narrowing down the list of potential careers"), the close comparison stage, where they compare the best alternatives ("I'm comparing just a few likely careers"), and the decided stage, where they have made their decision ("I've made up my mind on what career to pursue"). Note that the intervention remains relevant even for students in the final stage because it can help them explore specific occupations or graduate programs in a decided career.

We combined the four stages into two broader stages for analysis. The first two stages are considered the early career decision stage (N = 104), and the latter two stages are the late career decision stage (N = 110). Our choice to collapse the four stages into two (early vs. late) for an exploratory analysis is motivated by the empirical observation that treatment effects are in the same direction within the early and late stages (see Appendix B for analysis results treating the stages as a continuous variable and visualizing group means for each stage). Conceptually, the early career decision stage reflects students who are navigating through a broad set of career options, whether it be expanding or narrowing down their options, while the late career decision stage reflects students who focus on a narrower set of career options, whether it be gathering information about final career options or making up their minds and seeking specific jobs.

Information Awareness

We conceptualized four types of information awareness that students may obtain either through informal approaches, such as asking their upperclassmen, or through the use of the information support tool. Participants rated one item for each type of awareness using a 7-point Likert scale (1 = strongly disagree, 2 = moderately disagree, 3 = slightly disagree, 4 = neither agree nor disagree, 5 = slightly agree, 6 = moderately agree, 7 = strongly agree). The first type is awareness of personalized information sources: "I can find courses and jobs that I didn't know before based on my interest." The second type is awareness of holistic information sources from academic to career choices: "I can tell what courses and majors lead to different careers." The third type is awareness of diverse information sources: "I can find a wide range of potential academic pathways relevant to my interests." The last type is awareness of official information sources: “I can find official information about individual students’ academic and career decisions.”

4.3.5 Analytic Approach

In RQ1, we asked how the information support tool would influence students’ career exploration outcomes. We used linear regression models to examine the causal effect of using the information support tool on the two career-related outcomes: self-efficacy in career exploration-focused academic planning and behavioral intentions for career exploration. First, for confirmatory analysis, we conducted a simple regression analysis for both outcomes with the experimental condition indicator (intervention vs. control) as the only predictor. To test the robustness of our results, we included a set of covariates (participants’ gender, race, academic year, and career decision stage). For non-significant results, we examined the region of practical equivalence (ROPE) under a Bayesian inference framework to obtain a more nuanced understanding of our findings [205, 204]. Next, for exploratory analysis, we added the career decision stage as a moderator of the intervention effect in the regression models. We also conducted mediation analyses with the four types of information awareness as mediators and the two outcome measures.

In RQ2, we asked how students’ awareness of different information sources is associated with career exploration. We used linear regression models to investigate what types of information awareness are significant predictors of the two career-related outcomes. This provides correlational insights about effective ways to design information support tools. The four types of information awareness are entered as predictors for the two career-related outcomes while controlling for the intervention treatment. We confirmed no multicollinearity among the four types of information awareness (all VIF scores are below 2). To test the robustness of our results, we added the same covariates as for RQ1. Furthermore, we fitted the same multiple linear regression models separately for participants in each career decision stage.

4.4 Results

4.4.1 Effects on Self-Efficacy and Behavioral Intentions

We first examined how using the information support tool (the intervention) influenced students' self-efficacy and behavioral intentions. Overall, the tool did not significantly increase self-efficacy ($t(212) = 0.86$, $p = 0.39$, Cohen's $d = 0.06$) or behavioral intentions (t(212) = 0.35, p = 0.73, d = 0.02) across all participants. Figure 4.3 and Figure 4.4 illustrate the mean of the overall effect with standard error bars for each outcome measure by condition. These null results remained robust when controlling for gender, race, academic year, and career decision stage. We used the ROPE method to evaluate the null result: the observed effects are categorized as having "undecided significance" under an expected change of 0.3 points on the Likert scale, which corresponds to a Cohen's d of approximately 0.3 due to pooled SD being close to 1 for both outcomes (self-efficacy: 100 % Credible Interval = [−0.32, 0.58], 90.28 % in ROPE; behavioral intentions: 100 % Credible Interval = [−0.57, 0.66], 95.08 % in ROPE).

Despite no significant main effect, we found evidence that the tool supported students at the late career decision stage (i.e. those who are at the close comparison or decided career stage). For self-efficacy, we found that students' career decision stage significantly moderated the intervention effect (effect of adding the intervention-by-stage interaction to the model: $F(2,210) = 4.19$, $p = 0.04$). Using the full regression model, we found that the intervention significantly increased self-efficacy for students at the late career stage by 13.1 % ($t(210) = 2.04$, $p = 0.04$, $d = 0.19$), while it reduced self-efficacy for students at the early career stage, though not significantly ($t(210) = -0.17$, $p = 0.38$, $d = -0.09$). Figure 4.3 shows this subgroup effect on self-efficacy.

For behavioral intentions, we found a similar moderation effect by students' career stage (effect of adding the intervention-by-stage interaction to the model: $F(2, 210) = 5.59$, $p < 0.01$). Using the full regression model, we found that the intervention significantly increased students' behavioral intentions for career exploration at the late career stage by 7.2 % ($t(210) = 2.13$, $p = 0.03$, $d = 0.24$), but it reduced students' behavioral intentions at the early career stage, though not significantly ($t(210) = -1.70$, $p = 0.09$, $d = -0.15$). Figure 4.4 shows this subgroup effect on behavioral intentions.

To explore the mechanism by which the intervention influenced the self-efficacy and behavioral intentions of students in a late career decision stage, we conducted a mediation analysis [295]. Given that our data collection was cross-sectional, we can obtain causally robust estimates for the intervention effect on the mediator and outcome, but interpretations of the effect of the mediator on the outcome are not causal [281]. We examined the following potential mediators of the intervention effect on these two career exploration outcomes: awareness of personalized information sources, awareness of diversified information sources, awareness of holistic information sources, and awareness of official information sources. We found one of the four potential mediators to be statistically significant for one of the two outcome measures: awareness of official information sources on students' academic and career choices appears to mediate the intervention effect on self-efficacy. This potential mediator accounted for 57.7 % of the variance associated with the treatment effect on self-efficacy (Figure 4.5; average mediation effect: *coef.* = 0.23, $p < 0.01$; average direct effect: *coef.* = 0.15, $p = 0.43$; total effect: *coef.* = 0.38, $p = 0.05$). Thus, brief exposure to the information tool raised students' awareness of official information sources. Students' increased self-efficacy in career exploration may be mediated through their increased awareness of information sources.

4.4.2 Information Awareness As a Predictor of Career Exploration

After the confirmatory analysis of the intervention effects, we conducted an exploratory regression analysis on the survey data to learn more about what factors predict students' self-efficacy and behavioral intentions in career exploration. Our primary interest was in understanding the relationship between the two career exploration outcomes and different types of information awareness. Table 4.1 shows results from two multiple regression models for each career exploration outcome, one focused on awareness of information (i.e., a base model), and another one that adjusted for demographic variables, including gender, race, academic year, and career decision stage (i.e., a full model). All models also controlled for the experimental condition, but it is not the focus of these analyses.

For self-efficacy, students' awareness of holistic information sources and their awareness of official information sources mattered most for enhancing self-efficacy. The strength of the positive associations remained relatively large compared to other variables and was statistically significant even after adjusting for demographic variables. For behavioral intentions, students' awareness of holistic information sources and diverse information sources were robust and marginally significant predictors of behavioral intentions, even when controlling for demographics.

Based on the finding that students' career decision stage moderated the intervention effect in the analysis above, we also investigated predictors of students' self-efficacy and behavioral intentions in career exploration separately for those in their early and late career decision stages. Table 4.2 shows results for the same full regression models as in Table 4.1 but fitted to the subgroups of students who identified with each career decision stage. As expected, based on the findings reported above, the intervention effect was a significant predictor of both career exploration outcomes in the late-stage subgroup.

For self-efficacy, the types of information awareness that mattered the most were consistent with the previous results from the full sample. For both students in their early career decision stage and their late career decision stage, the awareness of holistic information sources and awareness of official information sources were significantly associated with self-efficacy. However, for behavioral intentions, students valued different types of information awareness. For those in their early career decision stage, awareness of holistic information sources significantly mattered for their behavioral intentions, while for those in their late career decision stage, this kind of information awareness did not significantly matter anymore.

4.5 Discussion

This study investigates the effectiveness of showing college students authentic examples of academic and career trajectories to support their career exploration, specifically their self-efficacy in academic planning for career exploration and their behavioral intentions for career exploration. We conducted a randomized online field experiment to test our hypotheses that both career exploration outcomes would be positively impacted by the intervention. However, we did not find significant evidence that the information support tool improved either outcome on the whole. We discuss three potential explanations for why this particular intervention did not significantly impact these outcomes. First, the amount of exposure and engagement with the intervention may have been too low to produce an observable effect. The participants may not have had enough time to meaningfully engage with the information provided by the tool, despite prompting them to write about their insights from using the tool. Students in the intervention group typically spent only 5.2 min (median) using the information tool. This amount of engagement might have been insufficient to influence self-efficacy or behavioral intentions significantly. We expect that providing students with more time to utilize the tool in a natural way, and timing the study to align with academic and career decision periods would increase motivation to use the tool and meaningful engagement with it. For example, embedding the tool into career service seminars related to finding a job or internship could provide a more relevant and impactful experience.

Second, our two key outcome measures may not have captured how reviewing authentic example trajectories benefits students. Our measures were adapted from the Career Exploration and Decision Self-Efficacy-Brief Decision (CEDSE-BD) Scale [194] and the Environment Exploration subscale in the Career Exploration Scale (CES) [283]. These scales have yet to be thoroughly tested in experimental studies with process-based perspective interventions for career decision making. While items in these scales account for the process-based aspect of career decision making [192], they still primarily address content-based outcomes, such as self-efficacy in finding matching information. The process-based approach emphasizes individuals' abilities to proactively make sense of the career decision-making process and the consequences of various career decisions [265, 276]. Process-based interventions can likely enhance students' understanding of the complexity of the world of work. This understanding may not translate into immediate, actionable strategies for finding a matching career, and may even increase students' feelings of uncertainty. As a result, these scales may not have been sensitive enough to capture beneficial changes from a process-based intervention approach [110, 310].

Third, the design of the tool may have failed to convey the potential benefits of reviewing authentic academic and career trajectories. Our exploratory analysis identified types of information awareness that are predictive of higher self-efficacy and behavioral intentions for career exploration. Moreover, our mediation analysis suggested potential explanations for how the tool design did (or did not) convey these types of information awareness. We found two main predictors of higher self-efficacy: awareness of official information about past students' choices, and awareness of holistic information that spans from academic paths to career choices. When students have access to reliable and detailed accounts of others' academic decisions and their career outcomes, instead of fragmented and unreliable information, it can make them feel more confident about their future plans and bolsters their self-efficacy. For behavioral intentions, we found that awareness of diverse information is an important predictor. Awareness of diverse information could inspire students to explore new career paths previously unconsidered, and thus enhance their behavioral intentions for career exploration. Additionally, students' awareness of holistic information is a significant predictor of their behavioral intentions. Holistic representation of information can help students see concrete steps toward a potential career goal, and thus motivate them to engage in career exploration activities. Our exploratory regression analysis shows that these types of information awareness are significant predictors of career exploration outcomes. While the design of our information support tool was intended to enhance all four types of information awareness, we found only one – awareness of official information sources – to be a significant mediator for only one career exploration outcome – self-efficacy — and only for students in their late career decision stage. This pattern of mostly null results suggests that the information provided through the tool did not translate into awareness of this information for most participants. The discrepancy is echoed in technology affordance theory which posits that affordances may be present but not perceived [114]. Users may not perceive an existing technology affordance because they misunderstand the characteristics of the technology [306]. Prior literature provides little insight into the reasons behind the discrepancy between information transparency and information awareness. Nonetheless, Hosseini and colleagues [147] provide some guidance on how to make information transparency produce meaningful results. Their Transparency Depth Pyramid model distinguishes three levels of information transparency in information systems: data transparency, process transparency, and policy transparency. As the level of transparency is progressively addressed, the information becomes increasingly recognized by users. Our information support tool mainly addresses data transparency and process transparency by showing what information is provided (i.e., official information sources) and how the information is provided (i.e., personalized, holistic, and diverse information sources). However, there was a lack of policy transparency, which is about explaining why the information is provided. This gap may have hindered students from fully comprehending and engaging with the information tool. Future designs of such information support tools should explicitly clarify the relevance and purpose of information provision to help students effectively use it for career decision making.

While there was no significant effect overall, our exploration into subgroup effects uncovered that the tool was significantly effective for those in their late career decision stage. These students are comparing a few careers or have decided on their careers and are investigating specific jobs. Contrary to our original hypotheses, the tool did not have a significant effect on students in their early career decision stage. This pattern of exploratory results suggests that students in their late career decision stage are better able to comprehend the utility of the information provided by the tool. One possible explanation is that students in their late career stage are closer to graduation and face more pressure to finalize their career decisions [125]. This may have led them to pay more attention to the information provided by the tool. Additionally, these students may have accumulated experiences and knowledge about academic and career pathways, and thus are better prepared to identify and utilize useful information. Moreover, our exploratory analysis shows that the predictors of information awareness are relatively constant between students at an early and late decision stage. This suggests that the varied impact of the information support tool is less likely due to different types of awareness, but potentially due to different levels of attention and ability to use the information effectively.

The varied impact of information support on students at different career decision stages suggests a need for additional professional support for those in the early stages of their career decisions. For example, the tool can be combined with human advising services, such as university career counseling sessions. Counselors can contextualize and motivate various academic and career trajectories. They can also assist students in identifying the most suitable career options among all options presented by the information support tool. This approach could help students better utilize information support in their decision-making process by simplifying the decision task and reducing the complexity of the choice [66].

Our findings contribute to the literature on career exploration. The most recent comprehensive review of the career exploration literature noted the lack of research addressing causal claims and called for more studies using experimental or longitudinal designs to avoid endogeneity bias [161]. It also argued for research to better understand technology use in career exploration activities, given the increasingly prominent role technology plays in information seeking. Our study responds to both calls by conducting a randomized controlled experiment to understand the causal effects of an information support tool on career exploration. The limited effect that we observed in our study underscores the potential discrepancies between findings based on purely correlational data and those derived from randomized controlled experiments. Our findings underscore the importance of collecting causal evidence to evaluate the impact (or lack thereof) of technologies intended to support career exploration. We suggest that future studies on career decision making adapt outcome measures with better ecological and predictive validity than the ones we used. In fact, a promising direction for future research could be to develop self-report scales that not only measure theoretical constructs but also possess strong predictive validity of consequential behaviors. Our work also extends the literature on the process-based perspective in career decision making. Most prior studies on supporting career exploration adopt the content-based perspective. Individual characteristics, such as preferences, are matched with vocational environments to identify suitable career choices [96, 143, 234]. These interventions were proven effective by providing actionable guidance that helps individuals find matching careers. Process-based perspectives are posited to be more adaptive to the evolving nature of the future of work, where job characteristics are increasingly uncertain and subject to changes [112]. Despite the theoretical appeal of this perspective, the claimed advantages of implementing such approaches remain empirically untested. The lack of significant findings in our study indicates that more empirical work is needed to demonstrate the ostensible benefits of process-based interventions for students. Importantly, the value of the process-based approach may not lie in tangible decision outcomes. Outcome measures may need to focus on the decision-making process itself. This shift in focus makes technological tools critical means to provide a deeper and more accurate understanding of the potential benefits of process-based interventions. Digital tools capture data on decision processes through individuals' digital traces, which offers a direct observation of behaviors related to the decision process. For example, future research can investigate how individuals engage with technology and find previously unconsidered career paths.

This study has several limitations. First, we cannot make causal claims on how different types of information awareness may affect students' career exploration outcomes. Our experiment only allows us to understand the causal effect of the information support tool as a whole. Future studies may design randomized controlled experiments that control for varying technology affordances within an information support tool. This would allow for a better understanding of how particular aspects of information support influence career decision outcomes. Second, the ecological validity of our study is limited as it was conducted as part of an online survey experiment. Participants interacted with the tool mainly for the purpose of the study, and the outcomes were measured by self-report questions. This kind of experiment setup allows for a higher internal validity as it can control for more noise than a longitudinal field experiment. However, it may be limited in reflecting the effectiveness of information support in the real world. Future studies should conduct field experiments, possibly using a randomized encouragement design, to understand the impact of the tool when students engage with it in their actual career exploration process, driven by genuine motivation and need.

4.6 Conclusion

Our study highlights the importance of information support in career decision-making processes. In particular, we demonstrate the nuanced effect of an information support tool on students' self-efficacy and behavioral intentions at different stages of their career exploration journey. Our findings suggest avenues for future research to delve deeper into the mechanisms through which information support influences career exploration outcomes and how technology can be designed to cater to the diverse needs of students at different career decision stages. The insights gained from this research contribute to the academic understanding of information support in decision processes and offer practical guidance for the design and implementation of effective career support tools in educational settings.

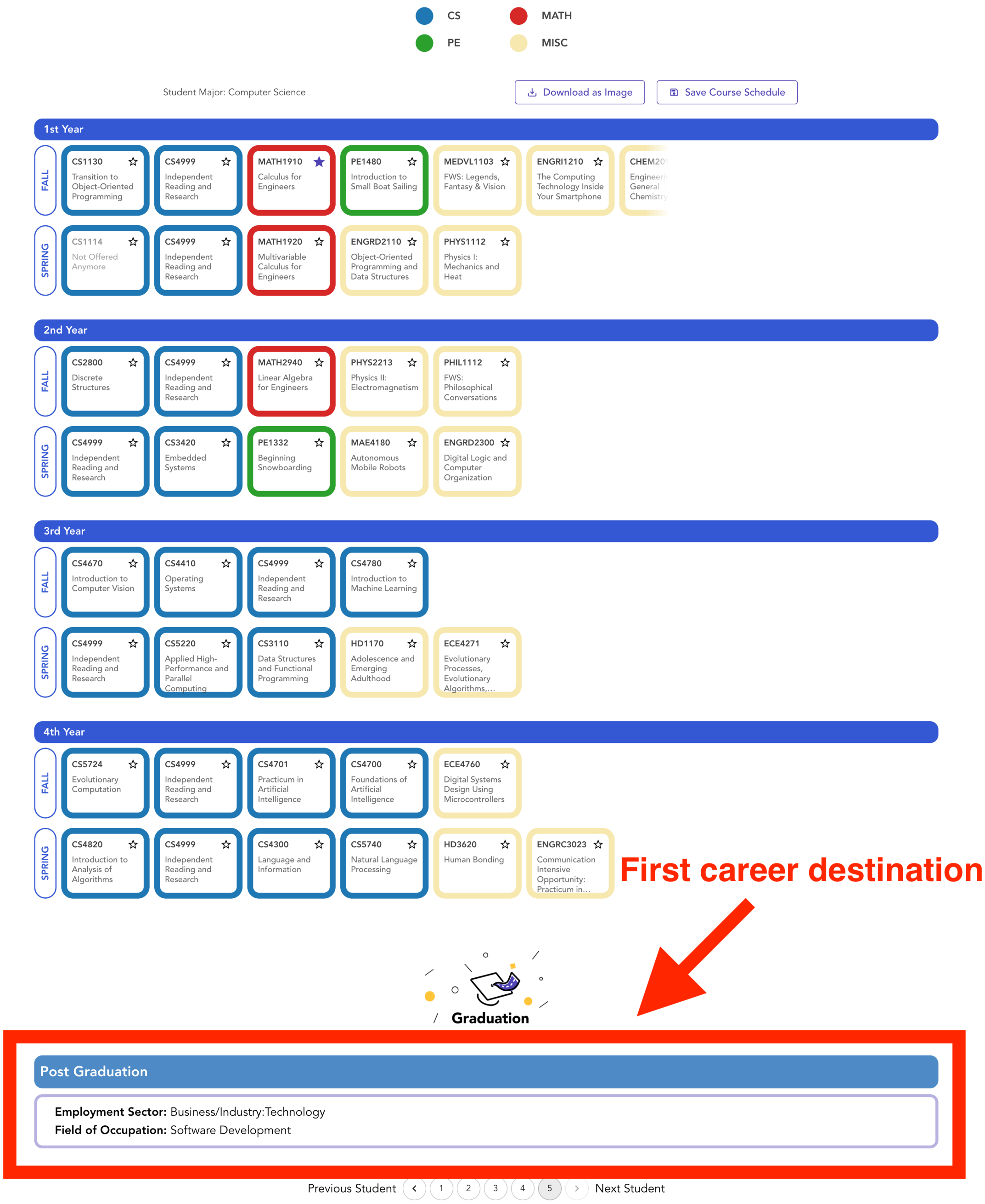

Figure 4.2: Screenshot of the information support tool's results page which shows an academic pathway and first career destination of a student with similar interests who graduated.

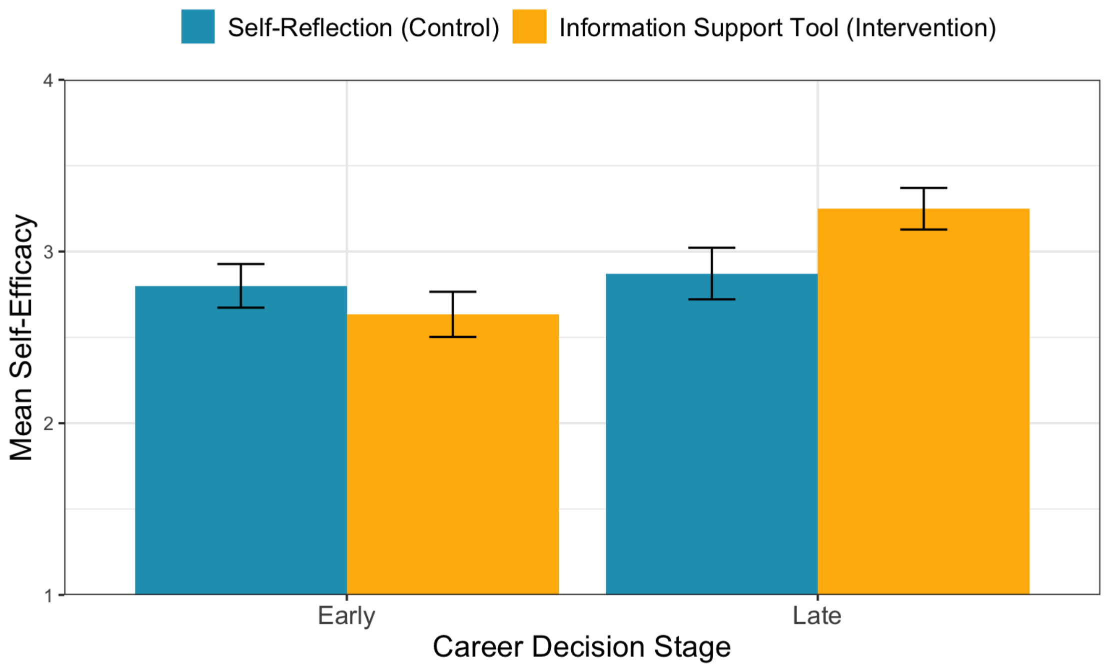

Figure 4.3: Effect on self-efficacy in academic planning for career exploration overall and by career decision stage. Error bars represent 1 standard error above and below the mean.

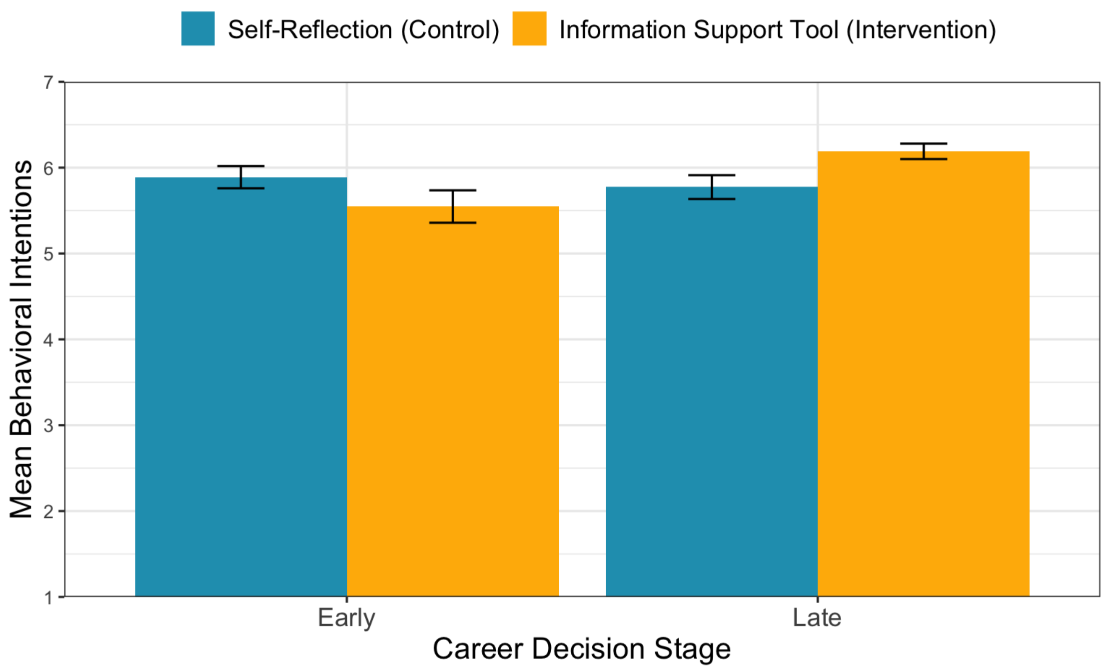

Figure 4.4: Effect on behavioral intentions in career exploration overall and by career decision stage. Error bars represent 1 standard error above and below the mean.

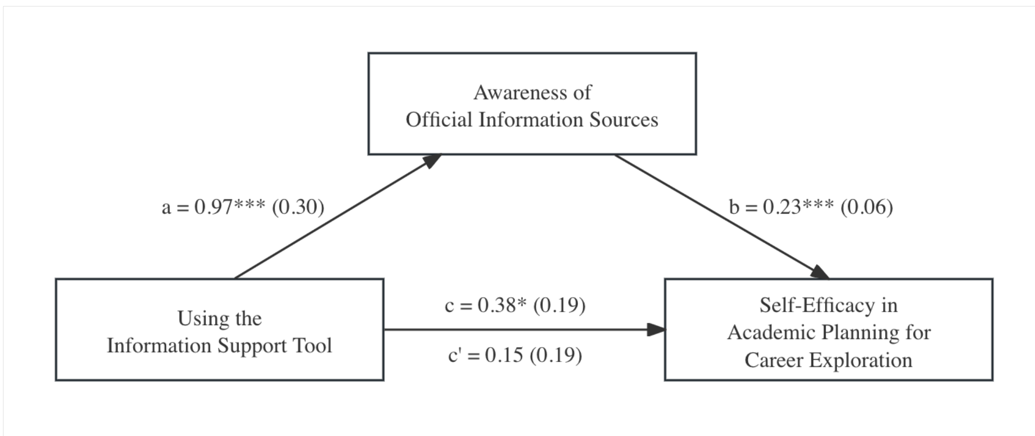

Figure 4.5: Mediation analysis results: awareness of official information sources is a significant mediator of the intervention effect on self-efficacy (analysis for students in the late career decision stage; coefficients are shown with standard errors in parentheses; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$).

Table 4.1: Multivariate regression results using information awareness to predict career exploration outcomes in self-efficacy and behavioral intentions. Coefficients are shown in the table together with standard errors.

	Self-efficacy in academic planning for career exploration		Behavioral intentions in career exploration	
Awareness of personalized information sources	-0.01 (0.05)	-0.05 (0.05)	0.01 (0.06)	0.00 (0.06)
Awareness of holistic information sources	0.16^{***} (0.06)	0.20^{*} (0.05)	0.11^{*} (0.06)	0.11^{*} (0.06)
Awareness of diverse information sources	0.04 (0.05)	0.03 (0.05)	0.14^{**} (0.06)	0.12^{*} (0.06)
Awareness of official information sources	0.15^{***} (0.04)	0.14^{***} (0.04)	-0.01 (0.05)	0.00 (0.05)
Condition: Intervention	0.03 (0.13)	0.05 (0.12)	0.10 (0.15)	0.12 (0.15)
Gender: Female		-0.19 (0.14)		0.05 (0.16)
Race: Asian		-0.34 (0.26)		0.57^{*} (0.30)
Race: Black		0.02 (0.23)		0.19 (0.27)
Race: Hispanic		0.41^{***} (0.14)		0.46^{***} (0.17)
Race: Mixed		0.16 (0.26)		0.73^{***} (0.31)
Race: Other		0.32 (0.36)		-0.25 (0.43)
Academic year: Second-year		-0.07 (0.31)		-0.06 (0.37)
Academic year: Third-year		-0.14 (0.31)		-0.02 (0.36)
Academic year: Fourth-year		-0.20 (0.33)		0.14 (0.39)
Academic year: Fifth-year and beyond		0.73 (0.90)		0.04 (1.05)
Career decision stage: Narrowing down		0.17 (0.17)		0.42^{**} (0.20)
Career decision stage: Close comparison		0.13 (0.19)		0.65^{***} (0.22)
Career decision stage: Decided		0.89^{***} (0.18)		0.54^{**} (0.21)
Intercept	1.23 (0.30)	1.13 (0.44)	4.53 (0.33)	3.96 (0.52)
Observations	214	214	214	214
Adjusted R^2	0.17	0.29	0.06	0.11
F statistic	$F(5,208)=9.47, p<0.01$	$F(18,195)=5.83, p<0.01$	$F(5,208)=3.67, p<0.01$	$F(5,195)=2.50, p<0.01$

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Reference groups for the categorical variables: gender = male, race = White, academic year = first-year, career decision stage = broad exploring.

Table 4.2: Multivariate regression results using information awareness to predict career exploration outcomes in self-efficacy and behavioral intentions by career decision stage. Coefficients are shown in the table together with standard errors.

	Self-efficacy in academic planning for career exploration		Behavioral intentions in career exploration	
	Early career decision stage	Late career decision stage	Early career decision stage	Late career decision stage
Awareness of personalized information sources	-0.04 (0.08)	-0.04 (0.08)	0.04 (0.10)	0.01 (0.08)
Awareness of holistic information sources	0.19** (0.08)	0.25*** (0.07)	0.23** (0.10)	0.07 (0.08)
Awareness of diverse information sources	0.05 (0.08)	-0.01 (0.07)	0.13 (0.10)	0.08 (0.08)
Awareness of official information sources	0.13* (0.07)	0.11* (0.06)	-0.01 (0.09)	-0.03 (0.06)
Condition: Intervention	-0.27 (0.18)	0.39** (0.19)	-0.29 (0.22)	0.50** (0.19)
Gender: Female	-0.23 (0.21)	-0.14 (0.19)	0.13 (0.27)	0.10 (0.63)
Race: Asian	-0.73 (0.53)	-0.27 (0.31)	0.85 (0.67)	0.44 (0.32)
Race: Black	-0.16 (0.32)	0.18 (0.35)	0.43 (0.41)	-0.03 (0.35)
Race: Hispanic	0.31 (0.20)	0.42* (0.22)	0.61** (0.25)	0.09 (0.23)
Race: Mixed	0.01 (0.46)	0.13 (0.33)	0.89 (0.58)	0.58* (0.34)
Race: Other	0.10 (0.62)	0.59 (0.62)	-0.90 (0.79)	0.48 (0.63)
Academic year: Second-year	-0.28 (0.36)	-0.46 (0.87)	-0.32 (0.46)	1.17 (0.89)
Academic year: Third-year	-0.27 (0.36)	0.27 (0.86)	-0.11 (0.45)	0.95 (0.88)
Academic year: Fourth-year	-0.22 (0.42)	0.21 (0.86)	-0.26 (0.53)	1.27 (0.99)
Academic year: Fifth-year and beyond	0.38 (0.93)		-0.37 (1.17)	
Career decision stage: Narrowing down	0.13 (0.18)		0.37* (0.23)	
Career decision stage: Decided		0.81*** (0.18)		-0.07 (0.18)
Intercept	1.47 (0.58)	0.62 (0.99)	3.43 (0.73)	3.81 (1.01)
Observations	104	110	104	110
Adjusted R^2	0.18	0.32	0.19	0.04
F statistic	$F(16,87)=2.40$, $p<0.01$	$F(15,94)=4.36$, $p<0.01$	$F(16,87)=2.49$, $p<0.01$	$F(15,94)=1.29$, $p=0.22$

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Reference groups for the categorical variables: gender = male, race = White, academic year = first-year, career decision stage (early career decision stage sample) = broad exploration, career decision stage (late career decision stage sample) = close comparison; There is no student in the fifth-year and beyond in the late career decision stage sample.

CHAPTER 5

REFLECTION ON PURPOSE CHANGES STUDENTS' ACADEMIC INTERESTS: A SCALABLE INTERVENTION IN AN ONLINE COURSE CATALOG

This chapter continues the investigation of how to support students' academic exploration and self-discovery during academic decision making and introduces the role of purpose. While previous chapters evaluated an entire course information platform as an intervention, this study isolates a brief purpose reflection intervention embedded within a course information platform. The intervention design is inspired by psychologically precise interventions from formal learning contexts. The study also moves a step forward by conducting a large-scale randomized field experiment among students at the present university during course enrollment periods, which provides stronger external and ecological validity than previous chapters. The intervention is low-cost and brief, which makes it potentially adaptable to other platforms beyond the one used in this study. The findings demonstrate the malleability of students' interests during course exploration and suggest practical strategies to support purpose reflection and guide students toward deliberate exploration of their interests in higher education.

5.1 Introduction

Interest exploration is a critical process that college students undertake [106]. It expands students' intellectual horizons and helps them identify specific areas for subsequent interest development. Students who can identify and develop an interest are shown to attend classes more frequently, process instructional content more effectively, and perform better academically [3, 135, 136]. Furthermore, interest exploration is beneficial beyond its immediate developmental effect: It plays an increasingly important role in students' preparation for future career development [163, 287]. Today's students are expected to face future work environments with increasing numbers of career choices and career transitions due to rapid technological advancements, such as large language models, shaping new occupational structures [100]. A willingness to engage in interest exploration is an important facilitator to adapt to the future of work [105]. Thus, supporting deliberate interest exploration in higher education can benefit students to not only achieve academic success but also be prepared for long-term career success.

In U.S. higher education, some institutions encourage interest exploration by offering students a broad range of course options [280]. Students look up course information using online course catalogs to facilitate course enrollment decisions. However, these platforms are not explicitly designed to promote interest exploration and interest-driven course selection. Even though online course catalogs store a complete set of course offerings by its institution, students only view a small fraction of course information based on what they search for. A recent study revealed that students only consider less than 2% of university courses listed on an online course catalog [62]. Despite the prevalence of online course catalogs in universities, there is a limited understanding of how they shape students' access to course information and how they may be better used as a medium to support interest exploration during course selection.

Interest exploration during course selection is a complex process that involves identity and purpose exploration [207]. Students are compelled to not only ask themselves questions like "What do I want to learn?" but more fundamentally, "Why do I want to learn this?" [102, 236]. Reflection on "why" an experience promotes students to engage in exploratory activities [105]. In particular, those who seek purpose through proactive engagement, as opposed to reaction to severe life events, have greater agency and openness to new experiences [137]. Therefore, this research investigates purpose reflection as a catalyst to support interest exploration during course selection. Most prior work that has effectively facilitated purpose reflection among college students required elaborated programs where students participate in face-to-face discussion sessions on purpose (e.g., [51, 239, 292]; but for exceptions, see [244, 314]). Online course catalogs, which are one of the most active and ubiquitous technologically-mediated contexts for academic decision making, have not been studied as a context for purpose reflection.

In the present study, we implemented a purpose reflection intervention by subtly integrating it into the search prompt of an online course catalog to facilitate interest exploration during course selection in higher education. We examined two types of purpose reflections, a self-interest-oriented purpose intervention and a self-transcendent-oriented purpose intervention, to understand how variations of a purpose intervention may influence students to explore their interests in different directions. The findings of this study advance our theoretical understanding of how student interest exploration can be influenced during course selection. It also demonstrates applied strategies for institution policymakers to encourage purpose reflection in an accessible, scalable, and equitable manner through the widely available technology of online course catalogs.

5.2 Literature Review

5.2.1 Online Course Catalogs

Almost every university has an online course catalog that stores official and basic course information to facilitate students' course exploration and selection. New advancements have been seen in online course catalogs in recent years. Some universities have begun to incorporate new types of information into online course catalogs, including course reviews, instructor ratings, student-reported course load, and even student course grades from previous years (e.g., [226, 297]. Other platforms utilize state-of-the-art recommendation algorithms to better match students with courses of interest (e.g., [231]). These innovations have enhanced the utility of online course catalogs to help students navigate courses. They also highlighted the opportunity for researchers to examine the use of online course catalogs and how different types of information influence students' decision making.

Alongside the practical significance of online course catalogs, their methodological advantages for research have gained prominence. Traditionally, phenomena around academic decision making, such as course and major choice, are mainly studied through qualitative or survey methods (e.g., [19, 122, 131]). Online course catalogs have historically not been used for research, only for administrative purposes. In recent years, however, the rise of educational data science has led online course catalogs to become valuable research instruments to collect large-scale authentic data and even run randomized field experiments to answer research questions in education [213].

Compared to previous research methods, they can reveal empirical traces of how students consider course options before arriving at a final decision. For example, by analyzing clickstream data from a university-wide online course catalog, Chaturapruek and colleagues [62] found that the number of courses that students consider is much more restricted than the number of courses offered by the university. Moreover, online course catalogs can incorporate randomized experiments to identify causal relationships during academic decision making with high statistical power and at a low cost. For example, Chaturapruek and colleagues [63] ran a campus-wide randomized field experiment on an online course catalog to examine the effect of varied access to grade information and time commitment information on students' course choices. They found that changes in the type of information presented did not affect the composition of courses that students choose, but access to grade information surprisingly lowered students' overall GPAs. In another example, Yu and colleagues [317] conducted a randomized controlled experiment on an online course catalog to investigate the effect of different course recommendation engines on course choices. The study revealed that a search engine was most effective in promoting serendipitous course discovery when it explains new course recommendations with keywords from courses that a student took before. In summary, these studies demonstrate that online course catalogs can provide new complementary perspectives to understand students' course exploration and selection process. Following this line of research, we conducted a large-scale randomized field experiment through an online course catalog and analyzed variations in students' digital trace data to understand how students explore their interests.

5.2.2 Interest Exploration and Purpose Reflection

We define interest exploration based on the classic interest development model proposed by Hidi and Renninger [136]. Interest exploration is the stage where students explore a range of situational interests that are initially unstable but may potentially become long-lasting individual interests. We thus theorize two mechanisms through which interest exploration may be affected by purpose reflection.

First, purpose reflection may affect interest exploration by helping students develop a clearer understanding of their interests. College students commonly struggle to come up with ideas of what to study during course search and selection, which can prevent them from engaging in interest exploration [65]. Proactive efforts to seek out purpose, such as explicit reflection on purpose, can bring clarity to their purpose and induce concrete thoughts on ways to pursue it [164]. For example, a student may identify that their purpose is to create a more sustainable living space for the next generation. This idea may prompt them to explore interests in environmental engineering or biology, which they may have never realized before reflecting on their purpose. Therefore, a purpose reflection intervention may give students new ideas on what interests to explore and promote students to engage more in interest exploration.

However, the process of reflecting on purpose is not always enjoyable. In fact, previous research shows that engaging in self-exploration of identity and purpose may cause psychological distress [169, 270]. As a result, students may want to avoid feelings of frustration and not engage in purpose reflection. This raises the possibility that a purpose reflection intervention may unintentionally discourage students from exploring their interests during course selection. Given the two possible outcomes, we raise the first research question:

RQ1: How does a purpose reflection intervention impact students' engagement with interest exploration?

A second way that purpose reflection may affect interest exploration is by signaling students' interest-driven motivation. Interest is only one of the many motivators that influence a student's course decision [17, 19, 138]. Other main motivators include fulfilling course requirements, achieving high grades, and managing course workloads [20, 214, 227]. These motivators can sometimes be at odds with each other during course selection. Interest-driven choices may be salient or inconspicuous depending on which motivator is signaled when the individual enters a context [264]. For example, a student may not engage in interest-driven course exploration if they are primed to be overly concerned about their grades. Under such circumstances, reflection on purpose may encourage students to prioritize interest as a factor in making course choices given that reflection on purpose can heighten intrinsic motivation [199]. In particular, having a purpose often leads people to engage in activities they find more personally meaningful [220, 247]. Relatedly, previous interview studies show that when high school students discuss future career interests, they spontaneously tie them to a purpose [149]. Therefore, there is good reason to believe that reflection on purpose may influence students to explore their interests, particularly in areas they find personally meaningful.

What academic areas would an individual find personally meaningful? Here we distinguish areas of interest led by two types of purpose, a self-interest purpose and a self-transcendent purpose. This distinction comes from two streams of research on purpose in the literature. Damon and colleagues [83] define purpose as “a stable and generalized intention to accomplish something that is at once meaningful to the self and of consequence to the world beyond the self.” Embedded in this definition is the emphasis on a self-transcendent element in purpose. That is, a purpose needs to be tied to a desire to contribute to the world other than being of personal interest. Other scholars study purpose that is more broadly defined as a central aim that directs life goals [215, 164, 260], which can be of self-interest as well. Prior research shows that when adolescents talk about their purpose, a self-interest purpose and a self-transcendent purpose are distinguishable, but often coexist [316, 315]. However, there is limited empirical evidence on whether the distinction between a self-transcendent purpose and a self-interest purpose is necessary among college students and whether they may lead to different directions of interest. In this study, we developed two interventions based on these two conceptualizations of purpose to examine if they would cause any difference in students’ interest exploration. Specifically, we ask the following research question:

RQ2: How does reflection on different types of purpose (self-interest purpose and self-transcendent purpose) influence the areas of interest that students explore?

5.3 The Present Study

We investigated the role of purpose reflection in interest exploration during course searches. We developed a low-cost, brief, and scalable approach to facilitate purpose reflection by reframing the course search prompt on an online course catalog that is in regular use by thousands of students at the institution. We examined two kinds of framing messages, one that emphasizes self-interest purpose and one that emphasizes self-transcendent purpose, and compared them against a control condition that did not prompt students to reflect on their purpose.

We first examined how the two purpose reflection interventions may affect students to engage in interest exploration during course search (RQ1). Specifically, we examined the effects on both students' behavioral engagement and cognitive engagement. These two dimensions of engagement are conceptually different but related [28]. For example, a student may not show behavioral engagement in a classroom by not raising their hand, but they may engage cognitively by thinking about the questions that the teacher raised. Measuring both behavioral and cognitive engagement can help us better explore the specific mechanisms for a purpose reflection intervention to be effective [12]. Based on our literature review, we remain agnostic as to whether a purpose intervention will positively or negatively affect students' engagement in either dimension. It is also possible that the intervention does not have any effect on students' engagement at all given that the intervention is brief and subtle.

We then examined how purpose reflection may affect the areas of interest that students explore (RQ2). We hypothesized that students who were given either a self-interest purpose intervention or a self-transcendent purpose intervention would be more interested in areas that can be associated with their own purpose compared to a control condition. Specifically, in the self-interest purpose intervention, students may explore areas of interest that support purpose towards the self, such as "to enjoy". In the self-transcendent purpose intervention, students may explore areas of interest that support their purpose towards others, such as "to help others" or "to protect the planet." To systematically categorize students' areas of interest and formulate hypotheses, we apply topic modeling to students' course search queries across all three conditions (see Methods for details). This data-driven approach is agnostic to the areas students might be interested in. We identified five areas of interest: (1) business, (2) computer and data science, (3) creative arts, (4) social change, and (5) all other areas of interest.

Following the topic modeling results, we formulated hypotheses for the first four specific areas of interest. First, we hypothesized that a purpose intervention would cause students to be less interested in business and in computer and data science. This is grounded in prior literature on purpose, which suggests that purpose is generally tied to more intrinsic than extrinsic motives such as financial gain or status [316, 315]. Even though areas of computer and data science and business can be intrinsically self-fulfilling and create benefits for others, they are often viewed as areas that lead to high-paying jobs [31]. Second, we hypothesized that the self-interest purpose intervention would increase students' interest in creative arts, because self-interest purpose emphasizes intrinsic motives towards the self, such as studying an area that is personally enjoyable. The creative arts are often associated with play and enjoyment [9, 266]. Third, we hypothesized that the self-transcendent purpose intervention would increase students' interest in social change, because self-transcendent purpose emphasizes intrinsic motives towards others, such as studying in an area that benefits the community. These three hypotheses guide our examination of how academic interests may be affected by purpose reflection during course searches.

5.4 Methods

5.4.1 Context and Participants

The research is conducted using an online course catalog platform at a large and selective land-grant university in the United States. On the platform's landing page (Figure 5.1), a search prompt is displayed: *"Discover Cornell courses and Explore Your Interests. Describe your ideal course in a few sentences: What do you want to learn more about? What skills do you want to master? What learning format do you like best?"* A large textbox is placed underneath the search prompt to provide students ample space to articulate their interests. Upon submitting their search query, they see the search result page (Figure 5.2), which shows a list of courses relevant to the search query. Courses are presented with the course title and description, course code, instructor names, grading basis, and any prior offerings. The list of courses is ranked by the cosine similarity between the search query and the course title and description, which is a standard algorithm used by many information retrieval platforms.

The online course catalog is a campus-wide resource that anyone at the university can have access to since its official launch in February 2020. Participants' log data was merged with student demographic data obtained from the university registrar using hashed student IDs. Most participants (91.3%; N = 4,032) are students for whom we have demographic records. The remaining participants are faculty and staff at the institution. The analysis was only conducted for student participants. Among them, most are undergraduates (84.2%), and some are graduate (7.8%) and professional students (8.0%). The demographic make-

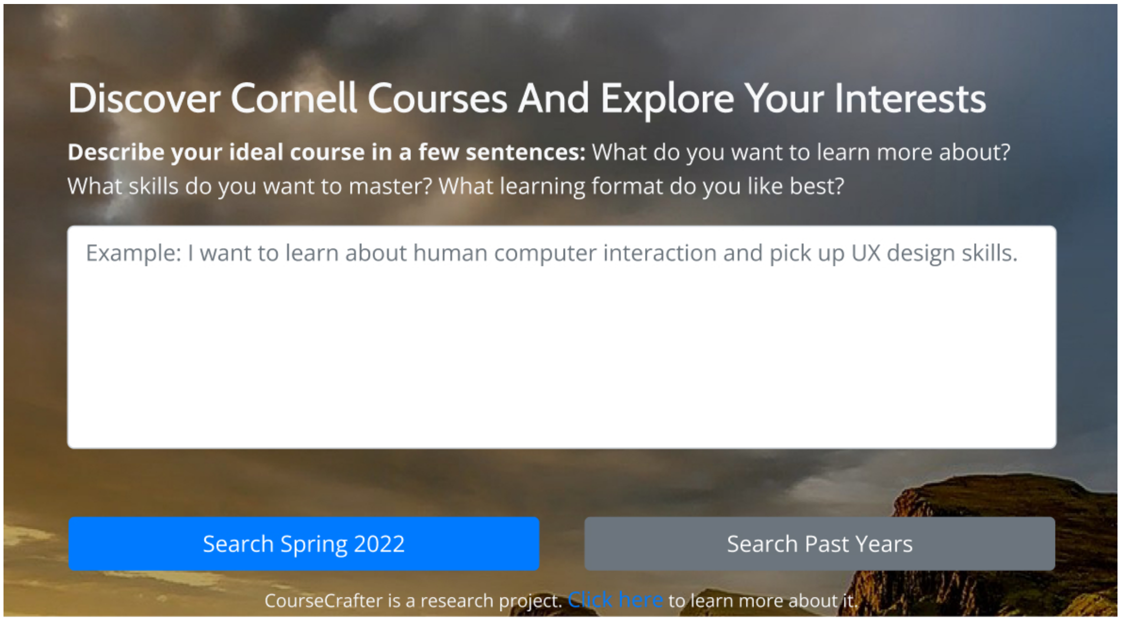

Figure 5.1: Screenshot of the landing page of the online course catalog in the control condition.

up is as follows: 55.3% female, 44.7% male; 31.0% White, 18.4% Asian, 12.7% Hispanic, 6.6% Black, 4.8% mixed-race, and 26.4% other or unknown race. The online course search tool is used especially 1-2 weeks leading up to the course enrollment deadline. The timeframe of the present study extended from the start of Fall '21 to the end of Spring '22. During this period students encountered multiple course pre-enrollment and add/drop periods. In total, the platform collected 7,500 search queries from participants.

5.4.2 Procedures

Upon first arrival at the landing page, participants were randomly assigned to one of three conditions with equal probability: the self-interest purpose intervention (N = 1,475), the self-transcendent purpose intervention (N = 1,460), and

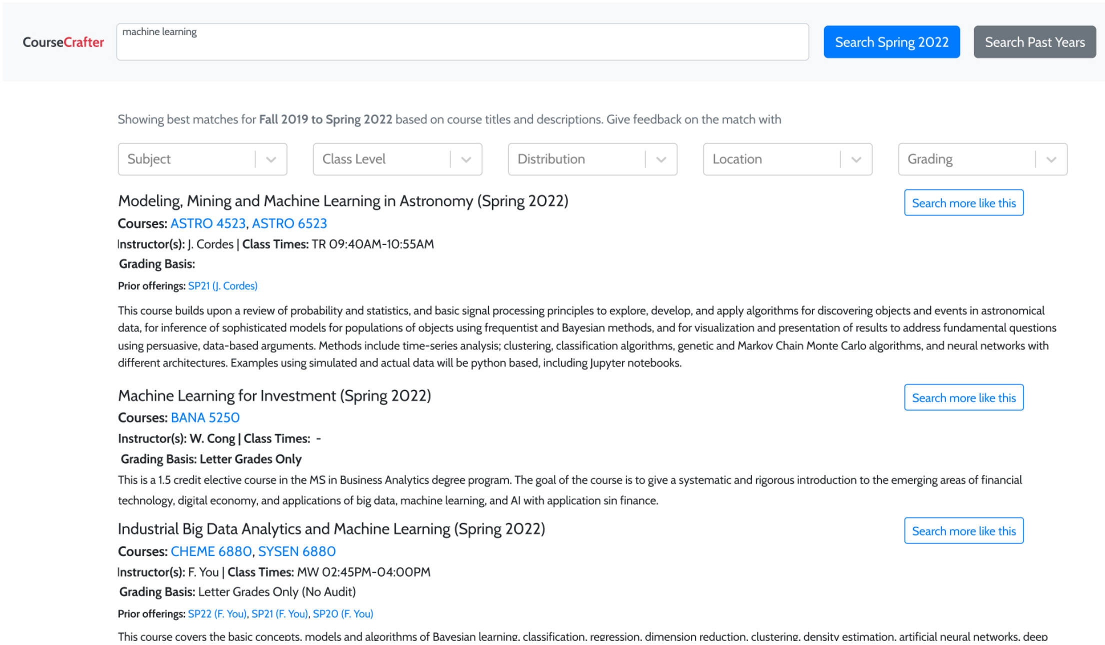

Figure 5.2: Screenshot of the search result page of the online course catalog.

the control condition (N = 1,483). Participants were unaware of their condition assignment and remained in the same condition throughout the study period. Based on the condition, we manipulated two static components of the landing page: the prompt above the search textbox and the example search query in the search textbox (see Table 5.1, for the exact text; Figure 5.1 shows the control condition). The manipulated text was shown for every search during the study period. We crafted the search prompt and search example texts based on prior research by Yeager and colleagues [316], who identify distinguishing features between a self-interest and a self-transcendent purpose. In each condition, one out of three example search queries was selected at random to be displayed on the search page. In the control condition, the example queries followed the format of "I want to learn about..." to describe an interest without describing a purpose. In the treatment conditions, the example queries followed the format of “I want to learn about...because...” to describe an interest with a purpose. Specifically, the example in the self-interest purpose condition focuses on purposes in relation to one’s skills or desires. The example in the self-transcendent purpose condition focuses on purposes in relation to making a positive impact to something larger than the self. The example search query was created as a worked example to help participants understand and follow the search prompt. Except for the search prompt and the example query, the interface and functionality are identical across all three conditions.

5.4.3 Measures

Engagement in Interest Exploration

We measured two dimensions of engagement in interest exploration: behavioral engagement and cognitive engagement. Behavioral engagement is measured by students’ search activities on the platform using two indicators. The first indicator is whether a student conducted at least one search on the platform during their initial use. The second indicator is whether a student returned to the platform another time after their initial use.

Cognitive engagement is measured based on how students engage in writing search queries. This measure is limited to students who conducted at least one search. We operationalized cognitive engagement using two indicators. The first indicator is the average number of words in a student’s search query. Prior work has shown that the number of written words can provide a valid measure of higher levels of cognitive processing [162, 290]. The second indicator is whether at least one search query from the participant showed evidence of causal thinking. Prior work suggests that purpose is often seen as addressing the "why" question behind an interest [315]. We used the causation index in the LIWC22 dictionary to identify if a search query contains words that indicate causal statements [41]. To reduce the number of false positives due to keywords related to causation (e.g., the search query "I'm interested in causal inference" has causal keywords but is not a causal statement), we coded all search queries with less than six words (73.2% of all queries) as not presenting causal thinking. We confirmed that there is no significant difference in the number of queries with less than six words across conditions ($F(2, 2090) = 2.33$, $p = 0.10$).

Areas of Interest

We measure areas of interest using a topic model fitted to all search queries and an individual-level probability distribution over the derived topics. We used search queries to derive areas of interest because their open-ended nature can provide an authentic representation of the areas that students are interested in, regardless of the performance of the search algorithm or whether the university offers courses in those areas. The topic model (details in Analytical Approach) identified five areas of interest: business, computer and data science, creative arts, social change, and all other topics. Based on all search queries a student submitted during the experiment period, we obtain a vector of probabilities over the five topics to characterize their areas of interest (e.g., for a student, their area of interest may be 70% business, 10% computer and data science, 3% creative arts, 2% social change, 15% other).

5.4.4 Analytical Approach

Regression Analysis

We used logistic regression models to analyze the intervention effect when the dependent variable is binary (e.g., whether a student returned to the site, or whether a student searched). We used linear regression models with robust (i.e. heteroskedasticity-consistent) standard errors to estimate treatment effects for the two continuous outcomes, which are the average query length and the topic probability of each area of interest in search queries derived from topic modeling results.

We separately analyzed outcomes for new and existing users of the search platform. New users are students who started using the platform after the experiment launched (61.6%), while existing users have used it at least once before the experiment (38.4%). This distinction is important because the text-based manipulation of our intervention is more likely to be overlooked by existing users who are familiar with the platform. We expect that the purpose intervention will have a stronger effect on new users than on existing users.

Topic Modeling

We employed topic modeling to find the areas of interest that participants indicated in their search queries (for this, we concatenate all of their queries into one text). Topic modeling is an unsupervised machine learning approach that identifies latent topics in documents based on the recurrence and co-occurrence of words. We used latent Dirichlet Allocation (LDA) [34] to perform topic modeling. LDA represents each document as a mixture of latent topics with topic probabilities and represents each topic as a mixture of words with word probabilities. We describe the pre-processing steps and topic identification process in more detail.

Pre-Processing To prepare the inputs for the LDA algorithm, we first concatenated search queries across all semesters during the experiment period to represent a "document" for each student. This is because short documents, such as Twitter posts, provide worse topic modeling results due to their limited information value [145]. Concatenating student queries results in longer documents that can substantially increase the quality of results [319]. Also, it is likely that a search query only represents one topic instead of a mixture of topics, threatening the basis of the LDA model [33]. Concatenating queries on the participant level allows us to understand the mixture of topics that a participant explored across all searches. Second, we tokenized each document into both unigrams and common bigrams. Third, we removed common stop words using the predefined list in the Natural Language Toolkit (NLTK) and additional ones unique to our research context (e.g. 'class', 'study'). These pre-processing steps improved the topic modeling results. For details of the pre-processing steps, see Appendix A.1.

Identifying Areas of Interest We used the tokenized documents as inputs to perform topic modeling using the Gensim package version 4.2 [246]. LDA requires the number of topics to be specified as an input. Determining the optimal number of topics is typically an iterative decision process that relies on the researchers' discretion based on the research purpose [61]. We systematically evaluated the topic modeling results across a range of topic numbers using the UMass metric to assess within-topic coherence [261]. We also used the most frequent tokens and most representative documents in each topic to evaluate the qualitative interpretability of the topic model results [153]. For details of the evaluation process, see Appendix A.2.

In the end, the topic model identified eight topics. We then combined several related topics into five areas of interest to arrive at a comparable level of granularity across areas. The five areas of interest are (1) business (combined 2 topics), (2) computer and data science, (3) creative arts (combined 2 topics), (4) social change, and (5) others (combined 2 topics). Table 5.2 summarizes the areas of interest with the average probability of each area across all conditions, examples of the most frequent terms related to the area, and example queries in each area.

Table 5.2: The Five Areas of Interest, the Average Probability of Each Area Across All Conditions, Examples of Most Frequent Terms Related to the Areas of Interest, and Example Queries

Areas of Interest	**Average Probability Across All Conditions**	**Examples of Most Frequent Terms**	**Example Query**
Business	22.0%	Business, law, management, marketing, consulting, finance, leadership	*"I want to learn about the business side of the biotechnology industry including venture capital and management"*
Computer and Data Science	18.2%	Data, science, learning, machine, machine learning, computer, data science, theory, intelligence, design	*"I want to learn about virtual reality machine learning and computer science"*
Creative Arts	22.9%	Art, arts, history, sciences, arts sciences, latin, design, research, writing, music, creative	*"I want to understand how to get talents to thinking creatively to give an organization a competitive advantage"*

(Table 5.2 continued from previous page)

Areas of Interest	Average Probability Across All Conditions	Examples of Most Frequent Terms	Example Query
Social Change	12.1%	Climate, animals, world, change, science, climate change, law, politics, philosophy, social	*"I want to learn about feminism and misogyny across the world and how gender roles have changed over time"*
Others	24.8%	Human, psychology, biology, health, art, engineering, science, medicine, quantum	–

5.5 Results

5.5.1 Effect on Engagement in Interest Exploration

First, we examined students' behavioral engagement in terms of whether they conducted a search and whether they returned to the platform. We found that the self-interest and self-transcendent purpose interventions resulted in behavioral disengagement in terms of students' likelihood to search, especially for new users, but not in terms of their likelihood to return. Specifically, new users were significantly less likely to search with the self-interest purpose intervention (43.0%; logOR = -0.38, z = -3.73, p < 0.01) and self-transcendent purpose intervention (42.8%; logOR = -0.37, z = -3.64, p < 0.01) compared to the control condition (52.1%). Existing users were less affected: They were less likely to search with the self-transcendent purpose intervention (54.8%; logOR = -0.32, z = -2.57, p = 0.01) compared to the control condition (62.5%), but remained similar with the self-interest purpose intervention (64.1%, logOR = 0.07, z = 0.58, p = 0.56). Neither intervention significantly affected whether students would return to the platform, no matter if they were new or existing users (self-interest purpose intervention: for new users, logOR = -0.06, z = -0.57, p = 0.57, for existing users, logOR = 0.04, z = 0.30, p = 0.77; self-transcendent purpose intervention: for new users, logOR = -0.03, z = -0.31, p = 0.75, for existing users, logOR = 0.10, z = 0.81, p = 0.42).

Second, we examined students' cognitive engagement based on how they wrote their search queries (analyzing data for the 2,092 students who conducted at least one search). We found significant intervention effects on cognitive engagement in query length (Figure 5.3) and causal thinking (Figure 5.4). Specifically, both the self-interest and self-transcendent purpose intervention encouraged students to write longer search queries (self-interest purpose intervention: for new users, mean diff. = 2.94, $t(1097)$ = 5.15, p < 0.01, for existing users, mean diff. in words = 2.14, $t(989)$ = 3.79, p < 0.01; self-transcendent purpose intervention: for new users, mean diff. = 2.50, $t(1097)$ = 4.24, p < 0.01, for existing users, mean diff. = 1.43, $t(989)$ = 2.61, p = 0.01).

Moreover, both the self-interest and self-transcendent purpose intervention

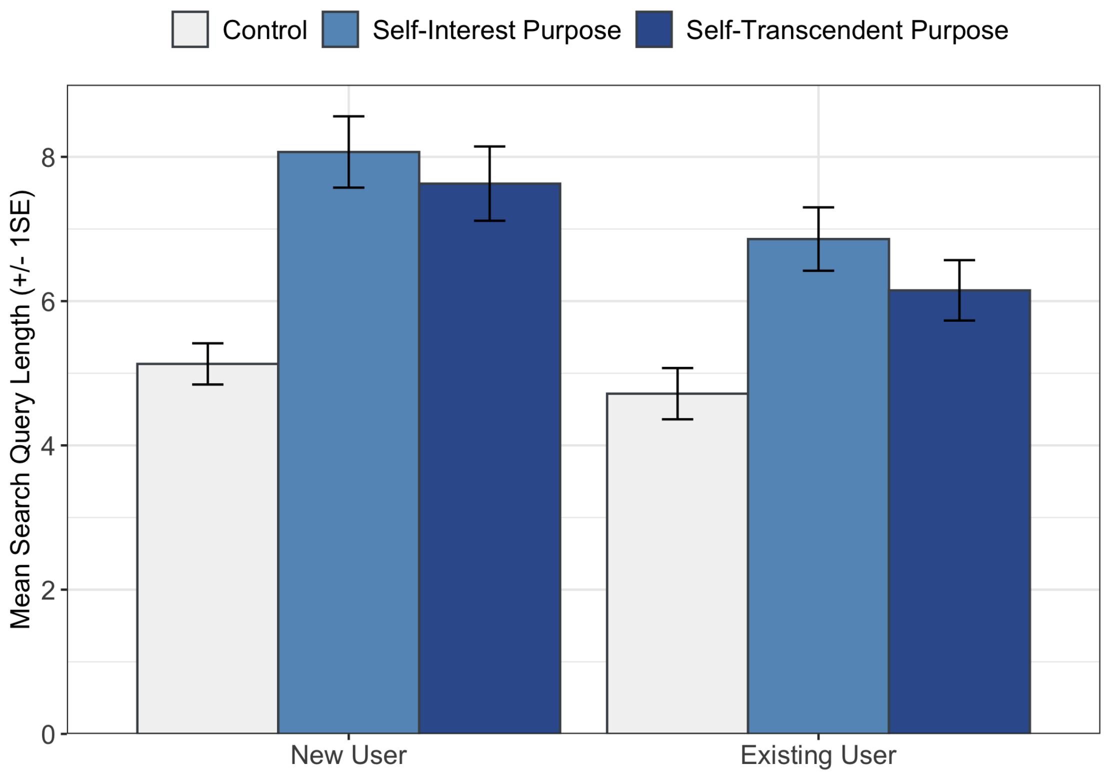

Figure 5.3: The Effect of Purpose Reflection Interventions on Search Query Length.

encouraged students to use more causal words in their search queries. In the self-interest purpose condition, the odds were 2.70 times greater for new users to write their search queries in a causal way and the odds for existing users were 1.86 times greater (logOR = 0.99, $z = 4.67$, $p < 0.01$; logOR = 0.62, $z = 2.78$, $p < 0.01$). In the self-transcendent purpose condition, the odds for new users were 2.29 times greater and the odds were 1.69 times greater for existing users to write their search queries in a causal way (logOR = 0.83, $z = 3.84$, $p < 0.01$; logOR = 0.53, $z = 2.23$, $p = 0.03$).

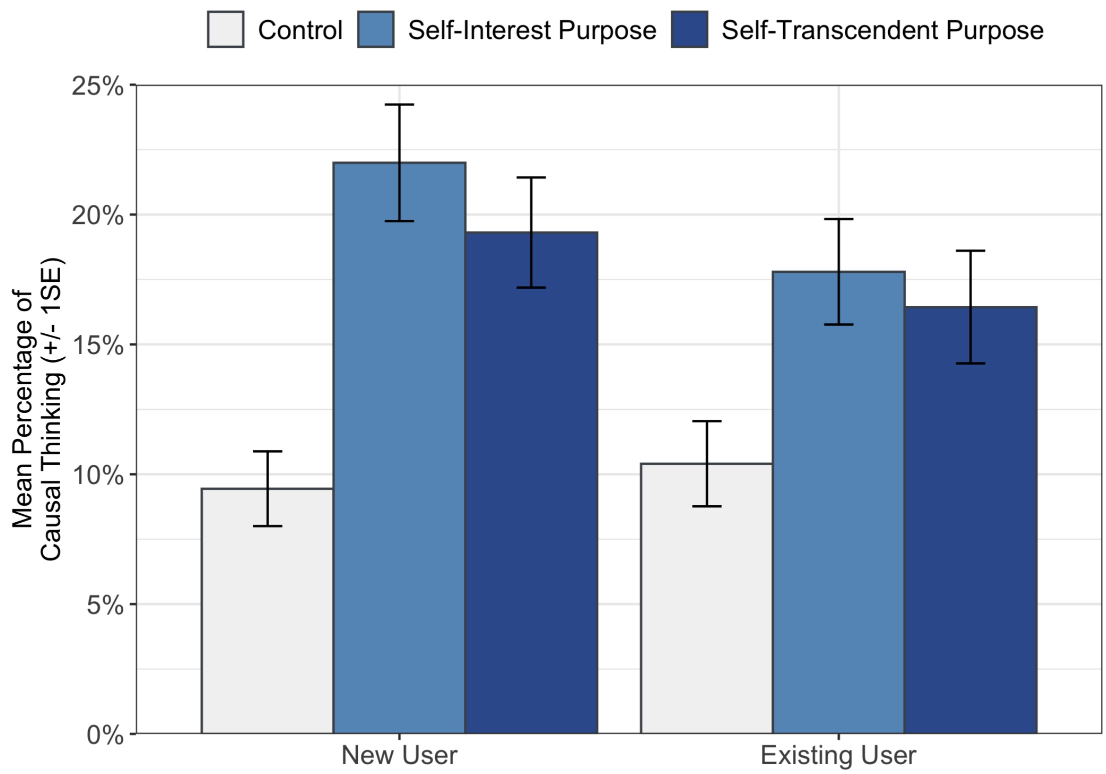

Figure 5.4: The effect of purpose reflection interventions on the percentage of causal thinking displayed in students' search queries.

5.5.2 Effect on Area of Interest

We hypothesized that the self-interest purpose intervention would increase students' interest in creative arts, the self-transcendent purpose intervention will increase interest in social change, and both interventions will decrease interest in business and computer and data science. Figure 5.5 illustrates the difference in students' areas of interest across the three conditions separately for new and existing users. We found that both the self-interest purpose intervention and the self-transcendent purpose intervention caused new users to be more interested in creative arts and social change, but less interested in computer and data

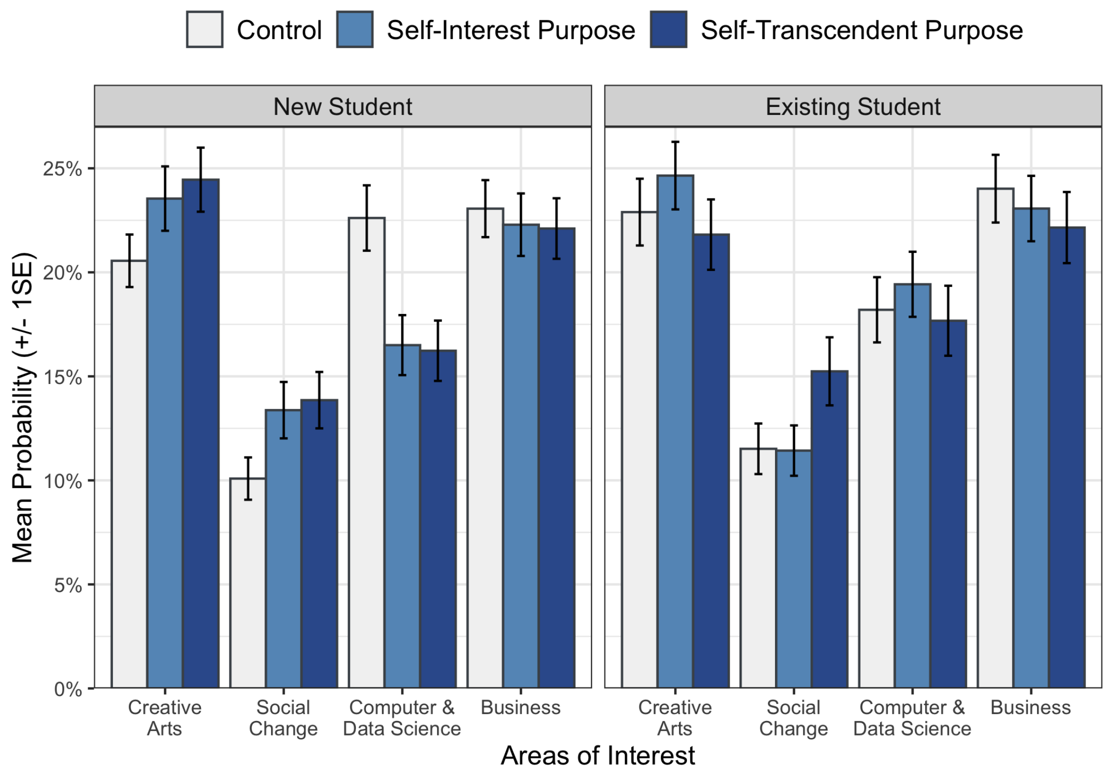

Figure 5.5: The effect of purpose reflection interventions on the percentage of causal thinking displayed in students' search queries.

science. The intervention did not affect their interest in business. For existing users, only the self-transcendent intervention affected students to be more interested in social change. We report the specific intervention effects for each area of interest.

For new users, the self-transcendent purpose intervention increased their interest significantly in creative arts from 20.1% to 24.8% ($t(1097) = 2.19$, $p = 0.03$) and in social change from 10.1% to 13.9% ($t(1097) = 2.23$, $p = 0.03$). In contrast, it led students to be significantly less interested in computer and data science from 22.6% to 16.2% ($t(1097) = -2.99$, p ¡ 0.01). It did not cause a significant change of interest in business (percentage point change = -0.8%, $t(1097) = -0.37$, $p = 0.71$).

The self-interest purpose intervention caused a similar shift of interest in these areas of interest (creative arts: pp change = 3.7%, $t(1097) = 1.75$, $p = 0.08$; social change: pp change = 3.3%, $t(1097) = 1.94$, $p = 0.05$; computer and data science: pp change = -6.1%, $t(1097) = -2.87$, p ¡ 0.01; business: pp change = -0.3%, $t(1097) = -0.15$, $p = 0.88$).

For existing users, the self-transcendent purpose intervention increased their interest in social change from 11.5% to 15.2% ($t(989) = 1.83$, $p = 0.07$), but it did not change their interest in other areas (creative arts: pp change = -1.6%, $t(989) = -0.68$, $p = 0.50$; computer and data science: pp change = -0.5%, $t(989) = -0.23$, $p = 0.82$; business: pp change = -1.8%, $t(989) = -0.73$, $p = 0.46$). The self-interest purpose intervention did not significantly change students' areas of interest (creative arts: pp change = 1.2%, $t(989) = 0.52$, $p = 0.60$; social change: pp change = 0.0%, $t(989) = 0.02$, $p = 0.96$; computer and data science: pp change = 1.2%, $t(989) = 0.55$, $p = 0.58$; business: pp change = -0.6%, $t(989) = -0.28$, $p = 0.78$).

5.6 Discussion

This study investigated the role of purpose in academic exploration by encouraging students to reflect on their purpose during course searches. Our findings show that a purpose reflection caused students to be less interested in computer and data science, and more interested in creative arts and social change. The self-interest and self-transcendent purpose interventions produced similar outcomes and primarily affected new users. The intervention encouraged students to be cognitively more engaged during course search but also discouraged students from engaging in search.

One of the main contributions of this study is establishing a causal relationship between purpose reflection and interest exploration. In line with our expectations, students are more interested in areas related to social change when they reflect on their purpose. This may be because making social change reflects an individual's "desire to make a difference in the world" [83], which is a prominent theme for having a purpose. Students are also more interested in creative arts as a result of purpose reflection. Previous research suggests that creativity can be an important pathway to meaning-making, especially in professional contexts [166]. When people have more freedom to be creative at work, they find their work more purposeful [198]. Our research provides further support for the importance of creativity in the pursuit of meaning by observing that purpose reflection leads individuals to gravitate toward creative courses. Future empirical research may examine the relationship between purpose and creativity.

We also found that the purpose intervention led to a substantial decrease in students' interest in computer and data science. We did not find a decrease in interest in business. This finding contributes valuable insights into students' motives for considering courses in computer and data science during enrollment. It suggests that students' choices in this area may be primarily driven by motives such as gaining high financial returns in the job market, which are commonly promised by fields of computer science and data science [298]. In contrast, purpose is associated with motives that are more profound, far-reaching, and high-order [83, 236]. Purpose reflection may have encouraged students to consider more abstract and long-term motives, and thus be less interested in computer and data science. This highlights the need for future research to investigate ways that can help students see more purpose in courses related to computer and data science, especially given the ubiquity of information technology in our daily lives and the potential for technological tools to create social good [296].

In contrast to our hypotheses, we did not find many significant differences between the self-interest purpose intervention and the self-transcendent purpose intervention in how they affect different areas of interest. Based on the distinction made by Yeager and colleagues [314], we initially hypothesized that the self-interest purpose intervention may affect students to explore interests that are more self-fulfilling and the self-transcendent purpose intervention may affect them to explore interests that are more related to benefiting others. However, our results showed that both interventions led to similar outcomes, suggesting that students in our sample may not distinguish between the two kinds of purpose. This is consistent with prior research showing that altruistic motives often coexist with egoistic motives [26, 103]. Interview research also shows that when students talk about their purpose, they commonly describe their purpose with mixed self-interest and self-transcendent motives [316, 315].

5.6.1 Theoretical Implications

This research makes theoretical contributions to the literature on purpose. We demonstrate that purpose reflection can be induced through a subtle intervention embedded in a digital tool. Prior research on purpose primarily uses qualitative methods and correlational survey studies (e.g., [44, 52, 207]), which has limitations in understanding causal relationships between purpose and other psychological or behavioral outcomes [137]. In recent years, studies have used interventions to experimentally investigate the psychological effects of purpose in educational settings. For example, two studies tested a 20-minute writing assignment to promote purpose during learning among middle school students [244, 314]. Our study contributes to this research effort by advancing purpose research through randomized field experiments. We demonstrated how a purpose reflection intervention affected course searches among college students. Although we did not measure if students' sense of purpose was raised by the intervention, we observed students being more reflective about their purpose when writing their search query. Compared to previous purpose intervention studies, our intervention is seamlessly integrated into an existing tool and requires no separate activity. We hope this intervention approach may inspire future research to investigate the effect of purpose reflection on various outcomes.

This research also contributes to the literature on interest and motivation. In recent decades, significant accomplishments have been made in understanding and supporting interest development [136, 148]. However, empirical studies have primarily focused on supporting interest in a single subject area (e.g., math interest in math classrooms [178]). While this kind of research is insightful for developing targeted approaches to facilitate interest in learning, it falls short of capturing the multiplicity of interests that an individual may have. How an individual reconciles their various interests, especially ones that compete for attention, may affect subsequent interest development. Recent work has called for and attempted to understand interest development under a multiple-interest perspective (e.g., interest across courses and domains [5, 300]). The idea of a broader perspective on interest development is also reflected in recent movements to study students' academic progress in higher education, which call for studying shifts in academic interests and academic choices across subject domains to understand how students develop their academic pathways as active agents as opposed to inert entities [175]. However, empirical and especially experimental studies that investigate multiple interests in authentic academic contexts are rare due to methodological challenges to documenting students' interests across multiple courses [5, 25]. Our study suggests that the course selection process is a valuable context to empirically investigate interest development with a multiple-interest perspective. Future research may further investigate how and why certain interests are prioritized and what other factors may influence engagement across interests.

5.6.2 Practical Implications

This research has practical implications for institutional leaders and for online course catalog design. We demonstrated a simple and scalable approach that institutions can adopt to help students reflect on their purpose during college experience. Having a sense of purpose is beneficial to students' academic motivation and achievement, subjective well-being, and future orientations [82, 108, 285], but reflection on purpose is seldom a part of the curriculum except for a few developmental programs offered at some universities. For most students, the closest experience they have with purpose reflection is writing a purpose statement for their college application. However, these purpose statements are rarely brought up again after students arrive on campus. Our study demonstrates that a purpose reflection prompt can influence students' interests. Compared to developmental programs, an online purpose intervention during course search holds two benefits. First, it is a low-cost approach that is integrated into an existing digital platform and can be equitably accessed and scaled to thousands of students at the university. This is substantially less labor-intensive compared to developing and running entire programs. Second, this approach is well integrated with students' authentic learning experiences. By integrating purpose reflection into the course selection process, students can connect their purpose with their course considerations and instantly receive relevant information about course options. This can be considered a constructivist learning experience because it emphasizes learning through contextual, personal experience and active reflection [21, 93]. This approach also aligns with prior work emphasizing the significance of the environment and access to timely opportunities for adolescent purpose development [209]. In summary, integrating purpose reflection into course search provides students with the opportunity to actively engage in their own learning and connect their personal experiences with their academic pursuits.

This research also suggests several cautionary considerations with the design of a purpose reflection intervention in online course catalogs. First, we found that the purpose reflection intervention only engaged students once they started writing a search query, but may cause students to opt out of searching in the first place. This may be because the process of purpose reflection, while beneficial, can be unpleasant [169, 270]. Generating a purpose requires insight, introspection, and planning [56], which is more cognitively demanding than simply describing one's interest alone. To reduce the cognitive load of purpose reflection, researchers may use common instructional techniques such as scaffolding. In our research, we used worked examples, a kind of scaffolding technique, to facilitate query writing. Many students (40.2%) wrote their search queries according to the example format. Other scaffolding techniques can be tested in the future, such as breaking the purpose reflection prompt down into several smaller questions.

Second, we found that the purpose reflection intervention primarily influenced the interests of new users of the online course catalog, not existing users. One explanation is that existing users have already formed a mental model of the platform and how to use it, which makes it harder to evoke behavioral change even if they notice the new search prompt. This explanation is partially evidenced by our findings on user engagement. We observed that existing users did write more and displayed more causal thinking in the intervention conditions, suggesting that they noticed the search prompt, but their level of cognitive engagement was still lower than new users. Another explanation is that new users pay more attention to the search prompt than existing users. Therefore, future intervention design can consider adding visual cues that can make the changes in the search prompt salient to existing users.

5.6.3 Limitations

We discuss five limitations of this study. First, outcomes in this study are limited to observations on an online course catalog. Future research could analyze subsequent course enrollments to examine the downstream impacts of purpose reflection and interest exploration. Second, causal estimates of the relationship between purpose reflection and interest may be biased given the differential disengagement in query writing across conditions. We cannot observe queries written by students who did not search and this selection effect could correlate with students' openness to changing their interests. Higher rates of disengagement are commonly found in opt-in intervention treatments [172, 174, 173].

Future work could examine patterns in who tends to disengage as a result of adding a purpose reflection intervention to account for the variation in disengagement during analysis and to design tailored interventions that better engage certain subpopulations.

Third, we did not measure whether the purpose reflection intervention induced a stronger sense of purpose, due to its authentic implementation during course selection. Nevertheless, our results suggest an increased sense of purpose based on students' increased cognitive engagement in query writing. We explicitly avoided using the word "purpose" in the intervention to not create a demand effect. Future studies could include pre- and post-surveys to the intervention to measure psychological constructs and gain better understanding of student experiences that are not directly observable. For example, the intervention may cause an increased sense of purpose along with other psychological constructs, such as meaningfulness. In fact, distinguishing purpose from these constructs has been empirically challenging [137].

Fourth, the topic model is limited in capturing the full range of topics in search queries due to its reliance on term co-occurrence. In our context, some terms with low co-occurrence may still belong to the same topic regarding areas of interest. For example, chemistry and physics both belong to the natural sciences but may not be often mentioned together in search queries. Thus, the topic model may categorize them into different topics even though they belong to the same area of interest. While topic models have been used in past intervention research to examine subgroup effects [172], future studies can complement this approach by using supervised learning techniques. For example, researchers can develop topic categories and dictionaries that label terms in each category in a training dataset of search queries. Prediction models can then be used to assign search queries to topic categories in a full dataset.

Fifth, the consequences of a purpose reflection intervention may be undesirable in contexts that prioritize academic progress on linear pathways to achieve timely graduation for a population of students who are at risk of dropping out of college [155]. In these contexts, a purpose reflection at the beginning of a student's academic pathway may be most appropriate and beneficial to encourage deliberate academic choices aligned with the student's purpose. Future work should evaluate the impact of this type of intervention in institutional contexts with more structured curricula and lower graduation rates.

5.7 Conclusion

Online course catalogs play an important role in college students' interest exploration and course consideration. In this study, we examined a subtle purpose reflection intervention in an online course catalog across over 4,000 college students through one whole academic year. Our findings show that the intervention caused students to be more engaged in search query writing, but less engaged in search activities. The intervention also led students to explore the areas of social change and creative arts over computer and data science. Overall, this study makes novel contributions to understanding how interest exploration can be influenced during course consideration. The study also has practical implications that demonstrate a scalable approach for purpose reflection using an online course catalog as a digital medium.

Table 5.1: Search Prompt and Example Search Query in Each Condition

Manipulations	**Self-Interest Purpose Condition**	**Self-Transcendent Purpose Condition**	**Control Condition**
Search Prompt	Discover Cornell Courses and Pursue Your Dreams. Describe your ideal courses in a few sentences: What do you want to learn more about and why? What skills do you want to master and why is it important to you?	Discover Cornell courses and make the world a better place. Describe your ideal courses in a few sentences: What do you want to learn more about and why? What skills do you want to master and why is it important to you?	Discover Cornell courses and explore your interests. Describe your ideal course in a few sentences: What do you want to learn more about? What skills do you want to master? What learning format do you like most?
Search Example (one is displayed at random)	Example: I want to learn about digital art because it can help me be an artist and work in the creative industry. Example: I want to learn about artificial intelligence because it will help me find jobs that pay well. Example: I want to learn about quantum physics because I think it advances our knowledge of the universe.	Example: I want to learn about sustainability because I think it addresses a lot of environmental concerns. Example: I want to learn about artificial intelligence because I believe it can have a positive impact on people's lives. Example: I want to learn about public health because I want to find better ways to respond to a global crisis like covid.	Example: I want to learn about human-computer interaction and pick up UX design skills. Example: I want to learn about how artificial intelligence is used in real estate. Example: I want to learn about the theory of dreams, Freud, and psychoanalysis.

CHAPTER 6
GENERAL DISCUSSION

In the last four chapters, I have provided a broad overview of research in academic decision making under the elective model in U.S. higher education with a special emphasis on the role of course information platforms, and introduced a new lens of viewing this process as a learning process for interests, purpose, and more (Chapter 2). I investigated how course information platforms can be used to support such learning processes by showing students accurate, diverse, and holistic information of academic pathways taken by prior students (Chapter 3 and Chapter 4) and embedding brief, psychologically-precise interventions for purpose reflection (Chapter 5). In this chapter, I synthesize the key takeaways from my research, discuss the challenges and implications behind them, as well as offer recommendations for education technology practitioners, researchers and institutional administrators.

6.1 The Challenge of Designing Course Information Platforms for Learning

Many academic decision support tools are designed to improve convenience. These systems aim to reduce the cognitive or logistical effort that students must undergo when navigating academic options. Some tools focus on logistical planning, such as helping students identify prerequisite chains in courses or avoid delays in degree completion [218, 311]. Other tools focus on course and major recommendations, which help students find matching options that students are most likely to be interested and succeed in [301, 302, 104]. The implicit assumption behind these tools is that students' interests and abilities are stable, or at least predictable based on past patterns. These tools can be extremely helpful and necessary, especially for students with limited advising access, but they predominantly target what I term *convenience outcomes*, which aims to increase the ease of academic decision making by "prescribing" students with an answer. In contrast, the tools and interventions developed and studied in this dissertation are designed to support *learning outcomes*. That is, the goal is not just to help students get better decision outcomes, but to help them *learn* through the decision process, and specifically, to reflect, articulate, and explore their developing interests and goals. In Chapters 3 and 4, the *Pathways* platform aims to support students in exploring their developing interests by surfacing diverse course trajectories as opposed to prescribing an answer. In Chapter 5, the purpose reflection prompt embedded in *CourseCrafter* encouraged students to engage with reflections on their purpose and how their purpose relates to their course interests. These tools and interventions are built on the assumption that students' interests and goals are not static, but actively constructed, and that academic decision making is a place for such learning. Under this view, changing one's interests and switching majors may sometimes not be indicative of a failure in academic progress because the goal of the tool is not to optimize for efficiency or outcome stability.

Designing tools to support learning presents a unique set of challenges. Tools that target convenience outcomes can improve students' ease of academic decision making by offering direct, prescriptive suggestions, such as which courses to take or which majors to choose. They promise efficiency and reduce cognitive effort. Thus, these tools are likely to see high uptake from students. In contrast, tools that target learning outcomes often encounter initial resistance in using the tools, even though they are proved to benefit students. This is revealed in the study findings in this work. In Chapter 3, many students using *Pathways* were initially resistant to exploring their interests and often struggled to articulate their interests without falling back on predefined terms like majors. However, after engaging with the platform, many students reported gaining new insights into their interests and academic identities. Similarly, in Chapter 5, adding a purpose reflection prompt to *CourseCrafter* led to reduced usage of the tool. Fewer students used the tool for course searching compared to the control group with a plain search prompt. However, those who complied with the intervention were more cognitively engaged, which indicated deeper reflection. These findings echo broader insights in formal learning contexts: productive learning often involves effort, struggle, and emotions such as confusion and frustration [84, 200]. Moreover, these states are even beneficial to student learning, as long as they are resolved [98]. Thus, from a learning perspective, certain negative experiences in student-tool interaction are unavoidable, and even beneficial, when using academic decision support tools. The challenge is to get students past the initial response of resistance. Today, the advancement of AI technologies, especially generative AI, creates more opportunities for advanced algorithms to be embedded in academic decision support tools to ”help” students. However, we must ask: are the tools helping students learn and grow, or simply helping them for convenience and to avoid difficulty? If students are shielded from the trial-and-error of exploration, we risk stripping away not just their agency but also the developmental process through which interest and purpose are formed.

To help students get pass the initial stage of resistance during academic decision making, one promising direction is to integrate non-intrusive, psychologically precise interventions that nudge students toward productive exploration, as opposed to interventions that requirement heavy mental investments. The purpose reflection prompt used in Chapter 5 offers one example: it was a brief, light-touch intervention embedded seamlessly within the interface. Even though we still see a reduction in students' behavioral engagement compared to not adding the purpose intervention, the reduced engagement is likely to be lower than interventions that require heavy mental investments, such as writing a long essay about their purpose. Future research could explore other light-touch interventions for student guidance, such as value alignment activities, and examine both the mediators (e.g., engagement) and outcomes. However, tool design alone is not enough. Institutional support structures can also reinforce the developmental value of exploration. In formal learning contexts, students are largely motivated by clear external incentives structures, such as course grades and degree attainment. By contrast, because the academic decision-making context has never been characterized as a formal learning context, it leaves students with abundant choice but light incentive structures. This could be especially unfavorable for students from disadvantaged backgrounds: Without institutional incentives, underrepresented students are more likely to steer away from effort-demanding fields like STEM even when they show early interest [23, 81]. Motivational structures can be established by the institution to pair with course information platforms for the learning support of these tools to sustain.

6.2 The Challenge of Outcome Definition in Academic Exploration

Although the work presented in this dissertation draws its conceptual inspiration from formal learning contexts, there are fundamental differences between learning in classrooms and learning through academic exploration, especially when it comes to outcomes. In structured learning environments, outcomes are often tied to measurable gains in knowledge or skills. In contrast, the learning that we hope to support in academic decision-making contexts, such as sense-making in one's interest and purpose, is far more ambiguous and less easily assessed. This creates a central tension: we value exploration for its developmental potential in learning, but we struggle to define and measure what a "successful" outcome is.

There are several reasons why outcome definition in academic exploration is a challenge. First, the learning outcomes in this context are difficult to see as clear and objective learning goals measured by conventional assessment approaches. For example, in Chapter 3, the qualitative interviews of students using *Pathways* show that students gained new insights that helped them question their initial assumptions when exploring others' academic pathways. Yet it is difficult to translate this into a measurable "gain". Second, the "gain" in academic exploration is deeply individualized. Through exploration, one student may reaffirm their interest while another student may discover a surprising new interest. There is no universal "correct" pathway and the benefit of these paths cannot be easily ranked or compared. This is also where the tension between a "pipeline" metaphor and a "pathways" metaphor for academic progression is revealed. The pipeline framework allows for straightforward, standardized outcomes that can be measured. Prior work has used the pipeline framework to support women staying in STEM majors by not ”leaking” out of the intended pipeline [257]. The pathways framework, while more inclusive of diverse academic trajectories, inherently lacks a single benchmark for success.

Third, the benefit of academic exploration is often non-linear and thus its beneficial outcomes may not be shown in the short term. Students typically go through iterative cycles of exploration, reflection, and gaining new insights. In Chapter 4, our randomized controlled experiment on *Pathways* did not reveal significant main effects on career self-efficacy and behavioral intentions. One explanation is that the outcomes were measured only immediately after a one-time exploration, which did not create enough time and dosage for the intervention on academic exploration. Fourth, the outcomes may not appear positive on the surface level. For example, in Chapter 5, students who reflected on their purpose during course exploration became more interested in courses related to social impact but less interested in courses related to computer science. From a humanistic perspective, this shift reflects deeper alignment between academic decisions and personal values. However, from an economic perspective, it may be interpreted as moving away from a field with high financial return.

These challenges have broader implications for the elective model. While the model is rooted in liberal arts ideals, it resists simple definition. Unlike specialized training programs with clearly defined outcomes (e.g., earning credentials, gaining employable skills), the benefits of learning through academic exploration are more ambiguous and long-term. The liberal arts ideals aim to facilitate academic exploration and self-discovery among students so that they can become holistic thinkers with an awareness of civic responsibilities. However, this educational idea is inherently difficult to define and assess. This problem becomes increasingly consequential as today's labor market presents more uncertainty. On the one hand, specialized trainings are criticized for failing to offer students meaningful opportunities for authentic self-discovery in an increasingly secular world [91]. On the other hand, the liberal arts ideal is criticized for being outdated and failing to keep up with a rapidly evolving job market. Ironically, this second critique persists even as employers consistently cite soft skills, such as communication and teamwork, as the most under-supplied skills in the workforce [40]. This mismatch ties back to the issue of defining and measuring learning outcomes of academic exploration at scale, which leaves the deeper human capacities championed by the liberal arts under-supported and under-recognized instead of becoming more relevant.

To investigate the likely benefits or to realize the educational pursuit of the elective model and the pathways paradigm, a central step is to move beyond the secular outcomes and test the outcomes of academic exploration that the elective model values in the first place. For example, in the conventional view, assessing engagement in course information platforms is seen as a mediator to important decision outcomes with secular significance, which is how engagement is defined in this research. However, as pointed out in the previous paragraphs, the engagement outcome is important in itself. Engagement behaviors on course information platforms can serve as indicators of productive exploration. For example, if a student begins by searching only within one department and later starts branching out into unfamiliar fields, this shift itself may reflect an exploratory gain. These signals may not replace long-term learning assessments, but they offer a more honest and developmentally appropriate way to gauge impact in an elective system.

6.3 Course Information Platforms as Part of the Institutional Infrastructure

Academic decisions are shaped by both personal development and institutional structures, such as degree requirements and curricular policies. As such, this final section shifts the focus from the individual to the institutional level. I discuss how course information platforms must be situated within broader ecosystems of support and how institutions bear the responsibility in shaping the conditions for course information platforms to provide support for academic exploration.

A key institutional responsibility is to ensure the development and sustainability of course information platforms that go beyond static catalogs and offer informed decision support. These tools rely fundamentally on access to institutional data. In the case of *CourseCrafter* and *Pathways*, development was made possible by institutional data including historical course enrollment data, course offerings and descriptions, as well as career survey data by graduating students. Additionally, the sustainability of such tools depends on long-term institutional investment. Many promising academic decision support tools remain confined to in-lab research projects that never reach broader student populations (for exceptions, see [297, 29, 226]). This gap not only limits the potential impact of the tools but also restricts research studying authentic student behaviors in real-world environments. In my research, large-scale field experiments (such as in Chapter 5) were made possible through institutional support from the Vice Provost's Office of Undergraduate Education and the Registrar's Office, which enabled us to reach students at the university at scale. Another example is the Digital Innovation Greenhouse (DIG) initiated by the University of Michigan, which supports the scaling of researcher-developed tools to the entire university community through multidisciplinary professional teams and IT infrastructure [90, 225]. Together, these examples underscore that the success of course information platforms depends not only on their design, but on the institution's support to develop and sustain.

Institutional integration should also include the platform's integration with existing curricular policy and advising practices. While course information platforms can provide comprehensive and diverse information on courses, majors, and academic trajectories, they lack the ability to provide the context and mentorship that students need to interpret or further make use of the information. In Chapter 3, we found that while students appreciated the descriptive value of *Pathways*, the tool could not answer deeper questions such as why certain academic paths were taken, or what challenges a student might face along a chosen path. This is where advising can provide essential narrative and relational support. In Chapter 4, our exploratory analysis on *Pathways* suggested that the tool benefited students at a later career decision stage, but not those at an earlier career decision stage. One explanation is that students in their earlier decision stage may lack the expertise to make use of the patterns shown in the academic trajectories, which shows the importance of expert guidance. Similarly, curricular policies can play a crucial role in either enabling or restricting students' ability to act on the insights they gain from the course information platforms. A student may discover a better-fitting major but be deterred by policies that make switching difficult, or may encounter rigid requirements that limit the room for exploration. Chapter 3 provides evidence that even though students have a lot of flexibility for academic decisions under the elective model, their choices are still largely bounded, especially in the freshman and sophomore years. Therefore, institutions should not only provide tools but also examine the structural incentives and constraints that affect students' academic agency.

Finally, institutions and course information platforms should align not only in functions but also in values. Course information tools can shape decision-making norms, signal priorities, and build cultures. For example, in Chapter 5, we used a beyond-the-self purpose reflection prompt to encourage students to consider how their course choices connect with what they could contribute to the community. This intervention shifted students' interests towards courses with topics related to social impact, but at the expense of less interest in computer science and data science courses. While this shift may be seen as a positive outcome in institutions that emphasize civic engagement, it may be interpreted differently in settings that focus on workforce readiness. This underscores the importance of designing platforms that reflect and reinforce the institution's fundamental educational mission, which could center on equity and inclusion, interdisciplinary exploration, civic responsibility, and many other values. When course information platforms are designed with a clear purpose and aligned with institutional values, they do more than support academic decisions on the individual level; they become important vehicles to help shape the culture of the institution.

CHAPTER 7

CONCLUSION

In this dissertation, I have demonstrated how course information platforms can be designed and studied to better understand and support academic decisions in U.S. higher education under the elective curricular model. The elective model is a unique feature of the U.S. higher education in which students can explore a wide range of courses before committing to a major. It is often credited with fostering student agency, critical thinking, and innovation through broad choices and multidisciplinary learning. However, the academic decision process in reality is often in the absence of structured guidance and characterized as overwhelming, confusing, and highly consequential. This gap between the ideal of academic exploration and the reality of student experience has been understudied, largely due to a lack of tools that can observe and intervene in students' decision processes at scale. The rise of digital tools and AI presents a new opportunity to not only observe how students navigate complex academic processes, but also to guide exploration in a more effective and inclusive way.

I developed two course information platforms, *CourseCrafter* and *Pathways*, to support students' academic exploration and used them as research tools to investigate students' academic exploration processes. *CourseCrafter* is a course search tool that encourages students to articulate their interests through intentional reflection and discover courses across departmental boundaries. *Pathways* is an academic trajectory discovery tool that allows students to explore how prior students who share similar interests made their decisions on courses, majors, and careers. *CourseCrafter* provides evidence on how search prompts can be used as brief interventions to effectively shape students' interests during course consideration. *Pathways* offers exploratory evidence that students can gain new insights through exploring others' academic journeys and enhance their career exploration self-efficacy and behavioral intentions among those at a later career stage. My research presents a feasible and scalable approach for course information platforms to become engines that support the elective model's mission.

Looking ahead, universities in general face renewed scrutiny amid growing pressure to justify the return on investment in higher education [30, 243]. Technological advancements have disrupted the labor market and introduced new demands. The flexibility of the elective model offers both opportunities and risks in this changing landscape. On the one hand, it gives students the freedom to pursue emerging interests that align with evolving societal needs. On the other hand, this broad range of choices creates barriers for students, especially those from disadvantaged backgrounds, to find the right path for academic success. This tension underscores the need for course information platforms, together with institutional reforms, to offer suitable guidance to students. Additionally, the advancement of generative AI, fuels a wave of new tools aimed at simplifying academic decisions and providing students with direct answers to their academic paths instead of the need to explore themselves. However, we must take caution when providing these tools as they may deprive students of their agency and valuable experiences of trials and errors essential to self-discovery and growth. Ultimately, the real challenge is not just about building smarter tools, but about building them to serve the purpose of education.

APPENDIX A

PRE-PROCESSING FOR TOPIC MODELING AND EVALUATING THE TOPIC MODELING RESULTS

A.1 Bigram Tokenization

In search queries, bigrams often can be more indicative of topics than unigrams. For example, although "learning sciences" and "machine learning" both include the word "learning", they refer to completely different disciplinary areas in which a bigram tokenization can differentiate but a unigram tokenization cannot. The addition of bigrams is especially useful for topic modeling given that search queries are "short documents". Bigrams can provide more information to infer topics in documents. The ten most frequent bigrams that we obtained from students' search queries are: "machine learning" (2.0% of all searches), "computer science" (1.5%), "data science" (1.4%), "artificial intelligence" (1.0%), "arts sciences" (1.0%), "real estate" (0.8%), "climate change" (0.7%), "information science" (0.5%), "data analytics" (0.5%), "classics class" (0.5%). We added bigrams to the list of tokens together with their unigrams as opposed to replacing the corresponding unigrams. For example, we added the bigram 'machine learning' together with the unigrams 'machine' and 'learning' to the document they belong to. We opted for this decision for two reasons. First, we want to remain agnostic as to whether it is the bigrams or the unigrams that contributed to the meaning of the words, given the low proportion of even the most frequent bigrams. Replacing bigrams with their corresponding unigrams assumes that the unigrams are a false interpretation of the real meaning of the words. Adding bigrams with their corresponding unigrams assumes that both unigrams and bigrams contribute equally to the real meaning of the words. Second, previous work suggested that replacing bigrams in documents to account for them in the topic model only mildly improves or does not impact the performance of the topic model [184]. In our study, we found that the interpretability of the topic modeling results became better when we added bigrams instead of replacing unigrams with bigrams.

A.2 Determining the Optimal Number of Topics in Topic Modeling

To determine the optimal number of topics in topic modeling, we first set the range of topic numbers to be 2 to 10. Thus, the granularity of topics would satisfy our research goal, which is to find broad subject areas, such as engineering, humanities, natural science, and business. Then, we used the UMass metric to evaluate within-topic coherence [261]. The closer the UMass score is to zero, the more coherent the topics are. We systematically examined the topic modeling results across 2 to 10 topics and across 5 to 15 minimum bigram frequencies. For every combination of parameters (i.e., topics and minimum bigram frequencies), we ran the model 20 times to obtain a robust evaluation of the coherence score. For every topic modeling result, we carefully discussed the interpretability of the results based on the most frequent tokens in the topics and the 20 most representative students in each topic based on the topic probabilities. Specifically, each author first independently evaluated and ranked the results based on interpretability. Then, we compared and discussed the ranking together. We found that changing the minimum bigram frequency did not affect the interpretability of the topic modeling results much once the value was above 10. We also found that when the number of topics is below 5, there are always topics that are mixed with terms from several distinctive subject areas that make it difficult to come up with a topic label. When comparing the number of topics from 6 to 10, all authors ranked eight topics as the most optimal number of topics in terms of within-topic coherence, interpretability, and meaningfulness for the research purpose. In the end, we decided on using eight topics with a minimum bigram frequency of ten as the topic modeling results for further analysis. The authors together labeled the topics based on the most frequent terms (i.e., unigrams and bigrams) in each topic and the search queries with the highest scores in each topic (Table A.1). We relied more heavily on representative search queries because some frequent terms appear commonly across more than one topic and the most representative search queries provide important contextual information on the topic.

Table A.1: The eight topics produced by the topic model.

Topic	**Average Probability**	**Most Frequent Terms**	**Example Query**	**Topic Label**
1	18.2%	Data, science, learning, machine, machine_learning, computer, data_science, theory, intelligence, design, real	*"I want to learn about virtual reality machine learning and computer science"*	Computer and Data Science
2	14.5%	Art, design, history, writing, music, creative, science, food, business, sustainability, wine	*"I want to understand how to get talents to thinking creatively to give an organization a competitive advantage"*	Creative Arts

(Table A.1 continued from previous page)

Topic	Average Probability	Most Frequent Terms	Example Query	Topic Label
3	14.4%	Health, psychology, science, liberal, studies, quantum, physics, social, human, mental, astronomy	*"I want to learn about applied physics and atmospheric physics"*	Humans and the Universe
4	13.0%	Business, law, management, marketing, consulting, design, environmental, human, development, social, technology	*"I want to learn about the business side of the biotechnology industry including venture capital and management"*	Business

(Table A.1 continued from previous page)

Topic	Average Probability	Most Frequent Terms	Example Query	Topic Label
5	24.8%	Climate, animals, world, change, science, climate_change, law, politics, philosophy, social, music	*"I want to learn about feminism and misogyny across the world and how gender roles have changed over time"*	Social Change
6	9.6%	Biology, medicine, human, art, neuroscience, engineering, biomg[1], psychology, anatomy, cooking, chemistry	*"I want to learn about cellular immunology and genetics for research purposes"*	Biology

(Table A.1 continued from previous page)

Topic	Average Probability	Most Frequent Terms	Example Query	Topic Label
7	8.4%	Arts, history, sciences, arts_sciences, latin, design, natural, research, field, writing, birds	*"I want to engage in interdisciplinary research on the relationship between people landscapes and histories"*	Creative arts
8	9.0%	Finance, leadership, analytics, business, technology, writing, data, data_analytics, financial, management, tech	*"I want to learn about finance and banking because I want to go into banking"*	Finance

After topic labeling, we merged the eight topics into five areas of interest to fit for our research purpose. First, we found that not all topics were on the same level of granularity. Specifically, Topic 8 "Finance" is a subset of Topic 4 "Business". Therefore, we combined Topic 8 "Finance" and Topic 4 "Business"

[1] *biomg* stands for Molecular Biology and Genetics, an acronym of a subject code at the present university.

into "Business". Second, we found that some topics are closely related. Specifically, Topic 2 and Topic 7 are both related to creative arts, and thus we merged them. Third, we found that Topic 3 "Human and the Universe" is too broad to be defined as a coherent area, and Topic 6 "Biology" may be too specific to be counted as an area for our study. In the end, we obtained five areas of interest (Table A.2).

Table A.2: The Five Areas of Interest Derived from the Eight Topics.

Topics Combined	**Average Probability**	**Label for Areas of Interest**
Topic 4, Topic 8	22.0%	Business
Topic 1	18.2%	Computer and Data Science
Topic 2, Topic 7	22.9%	Creative Arts
Topic 5	12.1%	Social Change
Topic 3, Topic 6	24.0%	Others

APPENDIX B

TREATING THE CAREER DECISION STAGES AS A CONTINUOUS VARIABLE

We investigated how the career decision stage moderates the impact of the information support tool on career exploration. Students responded to a survey item that categorized them into four stages: broad exploration, narrowing down, close comparison, and decided. In the main text, we combined the four stages into two broader stages for analysis. As a robustness check, we also repeated our analysis treating students' career decision stage as a continuous variable. This approach codes the four stages of career decision making (i.e., broad exploration, narrowing down, close comparison, and decided) as consecutive integers (i.e., 1, 2, 3, and 4). We found positive interaction effects, as in the binary specification, but the interaction was not statistically significant anymore for self-efficacy (self-efficacy: $t(210) = 1.13$, $p = 0.26$; behavioral intentions: $t(210) = 2.63$, $p = 0.01$). Figure B.1, Figure B.2 illustrate the intervention effect on students' self-efficacy and behavioral intentions, respectively, within each of the four career decision stages. The figures show exploratory evidence of a differential impact of the intervention. The direction of impact is more alike for students in the two early career decision stages and for those in the two later career decision stages. For self-efficacy in Figure B.1, we found that the intervention had a significant positive effect only among students who were in the "close comparison" career decision stage ($t(44) = 0.81$, $p = 0.01$). For behavioral intentions in Figure B.2, we found a significant intervention effect only for students in the "decided" career decision stage ($t(62) = 0.57$, $p = 0.01$).

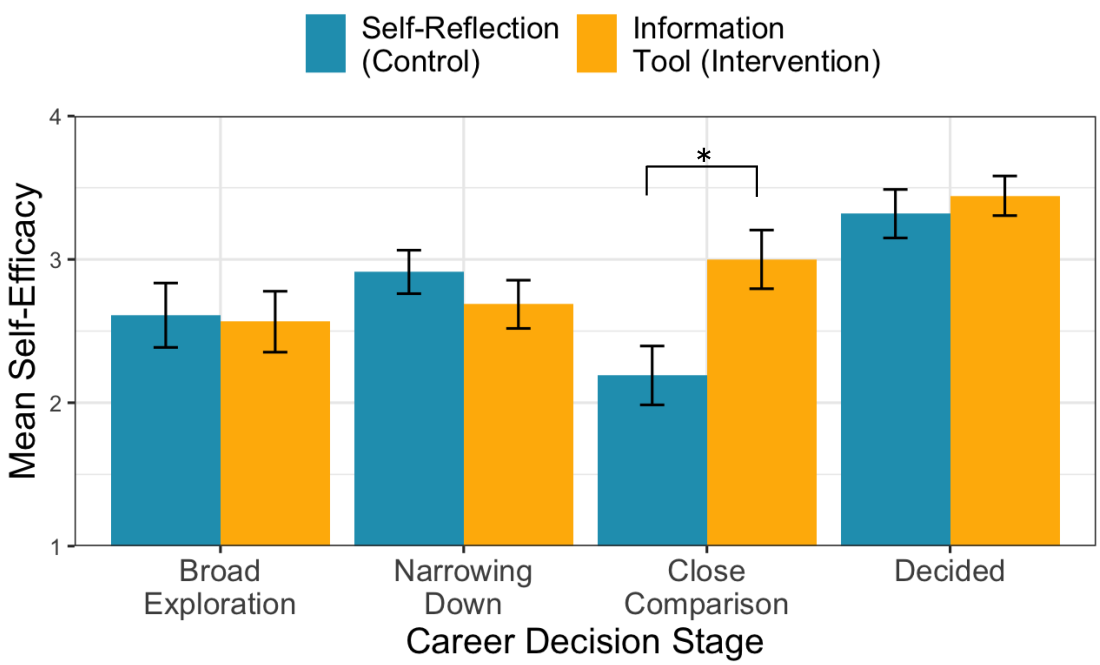

Figure B.1: Effect on self-efficacy in academic planning for career exploration across the four career decision stages. Error bars represent 1 standard error above and below the mean.

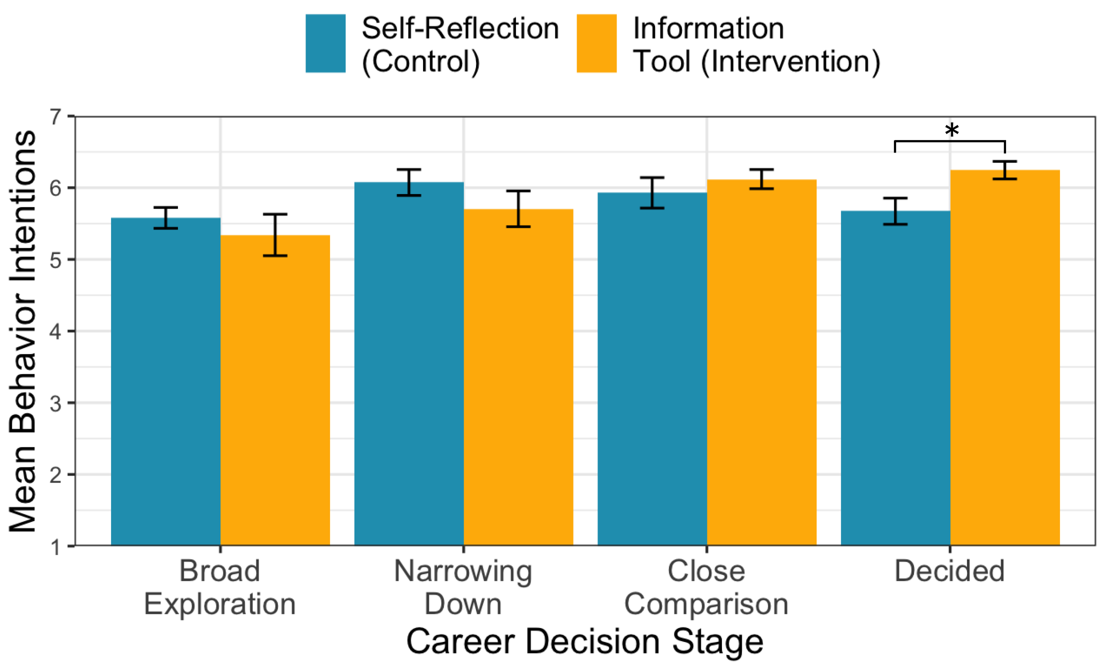

Figure B.2: Effect on behavioral intentions in career exploration across the four career decision stage. Error bars represent 1 standard error above and below the mean.

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