Seek and you shall find

Career exploration profiles in the transition to higher education

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Summary

Lien Demulder (2024). Seek and you shall find: Career exploration profiles in the transition to higher education.

Supervisors: Prof. dr. Karine Verschueren & Prof. dr. Vincent Donche

The transition from secondary to higher education can be challenging for many students. This PhD aimed to gain a deeper understanding of students’ study choice process during the transition to higher education. Utilizing the decisional tasks framework of Germeijs and Verschueren (2006) and data from the Columbus assessment tool, a large-scale exploration instrument to aid students in their study choice process, this dissertation provides a longitudinal, person-oriented perspective on this process.

First, this dissertation aimed to validate an instrument for assessing students’ engagement in different decision-making tasks within the study choice process. Chapter 1 (n = 11,559) presents the validation of the Shortened Study Choice Task Inventory (SSCTI), which assesses six decision-making tasks: orientation, self-exploration, broad exploration, in-depth exploration, decisional status, and commitment.

Second, it aimed to identify different career exploration profiles (Chapter 2, n = 5,660) and possible evolutions between these profiles (Chapter 3, n_{Fall} = 9,567, n_{Spring} = 7,254, n_{Longitudinal} = 672) during the final year of secondary education, utilizing a person-centered approach. Three career exploration profiles of students were identified through latent profile analyses on the orientation and exploration subscales of the SSCTI: passive, moderately active, and highly active explorers. Latent transition analysis showed the passive profile to be the most variable, while the moderately active profile was the most stable.

Third, it examined the associations between these profiles and various antecedents. The results showed that students with more effective learning strategies, a more positive academic self-concept, and higher levels of motivation were more likely to be initially categorized as highly active explorers rather than passive or moderately active explorers (Chapters 2 and 3). Additionally, motivation and test anxiety affected the transition probabilities (Chapter 3).

Finally, it examined the associations between these profiles and different outcomes related to the study choice process (Chapter 2) and academic success in the first year of higher education (Chapter 4, n = 5,358). The highly active explorers were more likely to have made a study choice decision, showed greater commitment to their chosen program, and possessed more knowledge about higher education. Furthermore, students’ knowledge about higher education had a positive direct effect on academic success. Additionally, a significant indirect effect of the exploration profiles on academic success through the amount of knowledge was observed.

This dissertation demonstrated the importance of the exploration process when choosing a study for higher education during the final year of secondary education. Three exploration profiles were identified, which were associated with different antecedents and outcomes relevant to the study choice process and academic success in higher education. For practice, tailored assistance can be developed based on these profiles. This dissertation also highlights the importance of the knowledge that students acquire about higher education, which is related to academic success in higher education.
Samenvatting

Lien Demulder (2024). Wie zoekt, die vindt: Exploratieprofielen in de keuze voor het hoger onderwijs.
Promotoren: Prof. dr. Karine Verschueren & Prof. dr. Vincent Donche


Ten eerste had dit proefschrift tot doel om een instrument te valideren om verschillende beslissingstaken binnen het studiekeuzeproces van leerlingen te meten. Hoofdstuk 1 (n = 11,559) presenteert de validatie van de Verkorte Vragenlijst Studiekeuzetaken (VVST), die zes beslissingstaken meet: oriëntatie, zelf-exploratie, exploratie in de breedte, exploratie in de diepte, beslissingsstatus en binding.

Een tweede doel was om verschillende exploratieprofielen van leerlingen te identificeren (Hoofdstuk 2, n = 5,660) en mogelijke evoluties tussen deze profielen te onderzoeken (Hoofdstuk 3, nLente = 9,567, nLente = 7,254, nLongitudinaal = 672) tijdens het laatste jaar van het secundair onderwijs, aan de hand van een persoonsgeoriënteerde aanpak. Drie exploratieprofielen van leerlingen werden geïdentificeerd door latente profielanalyses op de oriëntatie en drie exploratieschalen van de VVST: passieve, matig actieve en hoog actieve verkenners. Latente transitie analyse toonde dat het passieve profiel het meest stabiel was.

Ten derde werden de verbanden tussen deze exploratieprofielen en verschillende antecedenten onderzocht. De resultaten tonen aan dat studenten met effectievere leerstrategieën, een sterker academisch zelfconcept en hogere motivatie vaker werden gecategoriseerd als hoog actieve dan als passieve of matig actieve verkenners (Hoofdstukken 2 en 3). Bovendien waren motivatie en testangst van invloed op de kans om van profiel te veranderen (Hoofdstuk 3).

Tot slot werden de verbanden tussen deze profielen en verschillende uitkomsten met betrekking tot het keuzeproces (Hoofdstuk 2) en academisch succes in het eerste jaar van het hoger onderwijs (Hoofdstuk 4, n = 5,358) onderzocht. De hoog actieve verkenners hadden vaker reeds een keuze gemaakt, toonden meer binding aan hun voorlopige keuze en bezaten meer kennis over het hoger onderwijs. Bovendien had de hoeveelheid kennis een positief direct effect op succes. Verder werd een significant indirect effect van de profielen op academisch succes via de hoeveelheid kennis gevonden.

Dit proefschrift toont het belang aan van het exploratieproces bij het kiezen van een studie voor het hoger onderwijs tijdens het laatste jaar van het secundair onderwijs. Drie exploratieprofielen werden geïdentificeerd, die verband hielden met verschillende antecedenten en uitkomsten met betrekking tot het studiekeuzeproces en academisch succes in het hoger onderwijs. Op basis van deze profielen kan gepaste begeleiding worden ontwikkeld. Dit proefschrift toont ook het belang aan van de kennis die leerlingen bezitten over het hoger onderwijs, wat gerelateerd is aan succes in hoger onderwijs.
## Overview of Authorship

Published or accepted journal articles, and/or articles submitted for or worthy of publication

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<td>Original title</td>
<td>Het studiekeuzeproces voor hoger onderwijs in kaart: validering van de Verkorte Vragenlijst Studiekeuzetaken (VVST)</td>
<td>Identifying exploration profiles for higher education and their relationship with different student variables and outcomes</td>
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<td>Does the study choice process matter? An examination of the relationship between the study choice process and academic success among students entering higher education</td>
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<td>Motivation joint first authorship</td>
<td>Validation of the SSCTI; this required expertise on the study choice process (Demulder)</td>
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and the statistical techniques (Willems)

| Contribution         | Demulder, L.: lead on introduction and discussion
|                      | Willems, J.: statistical analyses and interpretation of results, lead on the associated sections of the manuscript

| Publication status   | Published in Pedagogische Studiën | Published in European Journal of Psychology of Education | Published in Frontiers in Psychology | Manuscript under revision for publication in Higher Education Research & Development


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Relationship between doctoral thesis and master's theses or other papers
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INTRODUCTION
The transition to higher education is a challenge for many students (OECD, 2022). International research has demonstrated the role of various predictors of academic success in higher education, examining a wide range of both cognitive and non-cognitive factors (Richardson et al., 2012; Robbins et al., 2004; van Rooij et al., 2018). However, the importance of the career decision-making process in the transition to higher education and its consequences for subsequent academic success have not been extensively explored in the literature. Choosing a higher education program is one of the most important decisions students face, with significant implications for both the individual and society at large (Gati & Asher, 2001b; Skorikov, 2007).

Previous research on the study choice process has mainly adopted a variable-centered approach, looking at (unique) associations between different study choice process variables, on the one hand, and predictors and outcomes, on the other. Up until now, a person-oriented perspective on study choice processes has rarely been adopted. This is unfortunate because identifying distinct career exploration profiles can help account for the heterogeneity in the career exploration process. As such, it may shed light on how different subgroups of students navigate the career decision-making process. Targeted interventions can be designed to meet the specific needs of each group (Hickendorff et al., 2018). Furthermore, the current body of research lacks a longitudinal perspective to examine the relationship between career exploration profiles and different outcomes.

The main goal of this PhD project is to investigate and gain a deeper understanding of students’ study choice process during the transition from secondary to higher education. Adding to existing research, our dissertation will provide a longitudinal and person-oriented perspective on this study choice process. Specifically, this dissertation first aims to validate an instrument for assessing students’ engagement in (different decisional tasks within) the study choice process. Secondly, our aim is to identify different career exploration
profiles and possible evolutions between these profiles during the final year of secondary school, using a person-centered approach. Thirdly, we will investigate the association between these profiles and different antecedents, such as academic self-efficacy, motivation, and learning strategies. Finally, we will examine whether these profiles are related to different outcomes concerning the study choice process and academic success in the first year of higher education.

In what follows, we will first define the main concepts and provide an overview of the major theoretical frameworks and empirical findings regarding the exploration process, its antecedents and outcomes. Finally, we will present the main aim and research questions and the corresponding chapters of this dissertation.

**Context**

In Flanders, Belgium, where this research was conducted, higher education is generally unconstrained, allowing students with a secondary education qualification to enroll freely in any higher education program, except for dentistry, medicine, veterinary medicine, and certain arts disciplines. Moreover, the tuition fees are intentionally kept very low to ensure accessibility for all students. While this open access increases accessibility to higher education for all students, it also results in low success rates and high drop-out rates. In Flanders, a significant 15% of students who started higher education in the 2020-2021 academic year dropped out after one year. Additionally, only 31% of students who started higher education during the 2019-2020 academic year finished their bachelor’s degree within the prescribed study period (Statistiek Vlaanderen, 2023a, 2023b). This particular context can make the choice of a major in higher education an important and difficult decision for students, due to the wide range of programs available to them. This can be overwhelming and make the study choice process more challenging.
When starting higher education, students have to decide between pursuing an academic or professional bachelor's program or, to a lesser extent, an associate’s degree program, and select a specific major. The distinctions between these programs are not always strict, but in general, academic bachelor’s programs emphasize abstract and theoretical knowledge and prepare students for a future master’s program, typically at university level. Professional bachelor’s programs, on the other hand, combine theory and practice and emphasize the development of competencies essential to professional practice. These programs are offered at university colleges (Onderwijs & Vorming Vlaanderen, 2023; Willems et al., 2021). Furthermore, associate’s degree programs are vocationally oriented programs and located between secondary education and professional bachelor’s programs, thereby preparing students for a particular occupation or a subsequent professional bachelor’s program. As of the 2019-2020 academic year, university colleges are responsible for their organization in Flanders (Onderwijs & Vorming Vlaanderen, 2023). Since the majority of students start either a professional (46.1%) or academic (42.9%) bachelor’s program (AHOVOKS, 2022), and we lack substantial data on the associate’s degree programs in our current datasets, also on their relationship with academic success in higher education, we will focus on these two types of programs in this dissertation.

Columbus

To support the decision-making process of students in their final years of secondary education, Columbus (www.onderwijskiezer.be/columbus) was implemented (Demulder et al., 2020). This online assessment tool was established at the request of the Ministry of Education and Training, which instructed the Flemish University and University Colleges Council (‘Vlaamse Universiteiten en Hogescholen Raad’, Vluhr) to develop the tool. A team of experts from Ghent University, KU Leuven, University of Antwerp, and
Artevelde University College in Flanders was then assembled. Therefore, Columbus is an institution-neutral tool, independent of any specific schools, universities, or university colleges. This large-scale online self-assessment tool includes validated and normed tests and questionnaires to help students explore their options, identify their strengths and areas for improvement, and gain insight into potential challenges associated with the transition to higher education. Columbus is freely available, provided to students by secondary schools and is preferably completed in class. Students complete online questionnaires on their study choice process, self-beliefs, motivation, learning strategies, and interests, as well as math, reasoning, and language tests. After completing the questionnaires and tests, students receive personalized and norm-referenced feedback on their scores relative to other students, as well as remediation tips for further improvement. Columbus is a valuable tool for guiding students in their study choice process (Demulder et al., 2020). Since its implementation in the 2016-2017 school year, Columbus has reached an increasing number of students, with up to 25,000 students annually. Over the past seven school years, it has reached more than 155,000 students. The present dissertation is based on data from several Columbus cohorts.

**Transition to Higher Education**

As mentioned above, the transition to higher education presents a difficult challenge for numerous students, with many students failing or dropping out (OECD, 2022). Research on the transition to higher education often focuses on predicting students’ academic achievement. Various factors have been identified as important predictors of academic success in higher education (Richardson et al., 2012; Robbins et al., 2004; van Rooij et al., 2018). Although cognitive abilities are generally the best predictors of academic success, a meta-analysis conducted by Credé and Kuncel (2008) shows that study motivation, attitudes, habits, and skills have incremental predictive value for academic
success, beyond the results on cognitive tests. A meta-analysis by Robbins and colleagues (2004) investigated the incremental value of psychosocial and study skill factors above traditional predictors such as high school grade point average (GPA) and socioeconomic status (SES), for both retention and GPA in higher education. Institutional commitment and academic goals were the strongest additional contributors to retention, while academic self-efficacy and achievement motivation were the strongest predictors for GPA. The meta-analysis conducted by Richardson and colleagues (2012) also shows academic self-efficacy to be one of the best incremental predictors of GPA, along with performance self-efficacy, grade goal, and effort regulation. Previous research indicates that there are also associations between the study choice process and higher education outcomes (De Clercq et al., 2013; Germeijs & Verschueren, 2007b; Negru-Subtirica & Pop, 2016). However, little attention has been given to the importance of the study choice process in the transition to higher education and its impact on academic success, especially when compared to research on other (non-)cognitive factors described above. Furthermore, most of the aforementioned predictors have been measured just before or after entering higher education, while Columbus measures variables during the last year of secondary education. Paying closer attention to the study choice process is important since it is malleable and can be influenced before transitioning to higher education.

**Study Choice Process**

Choosing a study for higher education is one of many important career choices that individuals have to make (Gati et al., 2019). Career choices can be viewed from different theoretical perspectives. One such perspective is the matching approach, which emphasizes the degree of fit or congruence between the person’s characteristics and the chosen work or educational environment, such as Holland’s RIASEC model (Nauta, 2020). Other theories take a more
developmental approach, such as Super’s life span, life space theory, which suggests that individuals go through different stages of development (Hartung, 2020). Lent’s Social Cognitive Career Theory takes a social-cognitive approach by focusing on the interplay between self-efficacy beliefs, outcome expectations, and goals in career-related choices (R. W. Lent et al., 1994; R. W. Lent, 2020). Savickas’ Career Construction Theory can be described as taking a narrative approach, since it describes the interpretive and interpersonal processes through which individuals construct their careers (Savickas, 2020).

This dissertation considers the study choice process from a decision-making approach that views the career decision-making process as a process consisting of different decisional tasks. Germeijs and Verschueren (2006b) identified six decision-making tasks in choosing a higher education program at the end of secondary education: orientation, self-exploration, broad exploration, in-depth exploration, decisional status, and commitment. These tasks are theoretically based on different taxonomies of problems in the study choice process (e.g., Campbell & Cellini, 1981; Gati et al., 1996), on theories that view the study choice process as a developmental process with various tasks (Gati & Asher, 2001b; Harren, 1979; Tiedeman & O’Hara, 1963), as well as literature focused on one or more career decisional tasks (Blustein et al., 1989; Stumpf et al., 1983).

Germeijs and Verschueren (2006b) developed the Study Choice Task Inventory (SCTI) which consists of six scales, each measuring students’ engagement in one of the six decision-making tasks. Orientation assesses students’ awareness of the need to make a decision and their motivation to make optimal career choices. Self-exploration measures the extent to which students gather information about themselves. Broad exploration assesses the acquisition of general information about higher education, while in-depth exploration evaluates the extent to which students seek detailed information about particular career options. Decisional status is another important task that
measures students' progress toward choosing a study. Finally, commitment assesses the degree to which students are confident in and committed to their chosen program of study (Germeijs & Verschueren, 2006b). These decision-making tasks are characterized by their dynamic and flexible nature; enabling individuals to skip or return to tasks as necessary (Germeijs & Verschueren, 2006b, 2010).

The SCTI is distinct from other questionnaires that aim to map students’ study choice process because it uses separate scales for each decision task. This allows for the examination of relationships between the different scales and between the scales and other variables (Germeijs & Verschueren, 2006b). The original SCTI is based on items from existing measures of career decisional tasks. The Orientation scale is based on the Attitude scale of the Career Maturity Inventory (Crites, 1973), supplemented with some new developed items. The Self-Exploration scale combines four domains of self-exploration with six relevant sources of information. The Broad and In-Depth Exploration scales are based on the behavioral checklist of career exploration activities (Athanasou, 1986) and an investigation of existing counseling materials in Flanders. Before completing the In-Depth Exploration scale, the students must name the studies for which they have already collected information. Decisional Status requires students to list the studies they are considering and to indicate their first choice, based on the Occupational Alternatives Question (Slaney, 1980). Finally, Commitment is based on the Commitment scale of the Groningen Identity Development Scale (Bosma, 1985). Research validating the SCTI in Flanders is quite outdated. Furthermore, considering the digitalization of information and the educational offer, some adjustments appear necessary.
Exploration

Within the decision-making process as conceptualized within the decisional tasks framework of Germeijs and Verschueren (2006b) and operationalized by the SCTI, exploration takes a central place. Stumpf and colleagues (1983) have defined career exploration as purposive behavior and cognitions related to vocational development, consisting of four components: “(1) where one explores, (2) how one explores, (3) how much one explores, and (4) what one explores (i.e., the focus of exploration).” (Stumpf et al., 1983, p. 192). Two major sources of information arise: the self and the environment. The concept of exploration originally derives from Erikson (1968). He states that late adolescence is marked by the psychosocial crisis of identity synthesis versus identity diffusion (Kroger & Marcia, 2011). Marcia, building on Erikson's theory, proposed two criteria for the presence of identity formation: exploration and commitment (Marcia, 1966). Based on Marcia, Luyckx and colleagues (2008) propose a process-oriented identity model, based on two commitment (commitment making and identification with commitment) and three exploration (in breadth, in-depth, and ruminative) processes. Exploration refers to actively exploring different identity alternatives, while commitment involves actively making choices and decisions about one’s identity. Based on these five identity processes they identified five identity types: troubled diffusion, carefree diffusion, moratorium, foreclosure, and achievement. For instance, individuals in the moratorium status are actively exploring but have not yet made firm commitments, while individuals in the foreclosure status have made commitments without much prior exploration (Luyckx et al., 2008).

In this dissertation, we focus on students’ career exploration process, specifically when choosing a study in higher education. The first four of the decision-making tasks outlined by Germeijs and Verschueren (2006b) are important in the context of career exploration. Firstly, students must be aware of the need and be motivated to make a decision and start the career
exploration process. The other three tasks each represent a dimension of exploration: exploration of the self, broad exploration of the environment, and in-depth exploration of the environment. Through career exploration, individuals explore themselves and their environment, thus enabling them to identify potential career options that correspond with their characteristics (Porfeli & Lee, 2012). There may be differences between individuals in the frequency of exploration. Both personal and environmental characteristics may influence the degree to which individuals engage in career exploration and subsequent outcomes (Jiang et al., 2019). These antecedents and outcomes will be described in further detail below.

**Person-centered Research**

Research on career exploration processes has primarily employed a variable-centered approach, focusing on the correlates of differences in variable scores related to career exploration tasks. However, an emerging trend in vocational research involves person-centered analysis techniques that cluster or group individuals based on common characteristics (Hickendorff et al., 2018; Woo et al., 2018). This approach allows to distinguish more homogeneous groups of individuals who share communalities regarding targeted research variables in a sample (Hofmans et al., 2020). In doing so, “person-centered analyses offer a useful compromise between the simplicity or parsimony of the variable-centered approach” (Woo et al., 2023, p. 7). Previous person-oriented studies on career decision-making have primarily used more general measures of career (in)decision (e.g., Argyropoulou et al., 2007; Cohen et al., 1995; Rojewski, 1994). Some studies have incorporated additional variables, such as personality measures, high school grades, and socio-economic status (SES), in their profile analyses (e.g., De Clercq et al., 2017; Germeijss et al., 2012; Porfeli et al., 2011; Sestito et al., 2015). However, the current body of research lacks a person-oriented view on exploration. This can help trace the heterogeneity in the
career exploration process back to a number of underlying homogeneous subgroups. By identifying distinct career exploration profiles, we can gain further insight into how students navigate the career decision-making process. In this way, targeted interventions can be designed to meet the specific needs of each group (Hickendorff et al., 2018). To date, there is also a lack of longitudinal research on the development of the career decision-making process in general, specifically on the exploration process. Longitudinal research by Germeijs and Verschueren (Germeijs & Verschueren, 2006a), using a variable-centered approach, demonstrated significant average improvement in all exploration tasks among students during their final year of secondary education as well as significant individual variation in growth. The current person-oriented research contributes to this literature by clarifying how the career exploration tasks combine into distinct career exploration profiles and how these profiles develop throughout students’ final year of secondary education. To examine the evolution of exploration profiles over time latent transition analysis will be used. This enables the combination of a cross-sectional measurement of categorical latent variables with a longitudinal description of change in the categories of the latent variable over time (Nylund, 2007; Woo et al., 2024). This addresses a current gap in the literature regarding the stability or variability of students’ exploration profiles over time, which has received limited research attention. Since research showed that students improve significantly in all exploration tasks during the last year of secondary education (Germeijs & Verschueren, 2006a), we expect that students will be able to transition to profiles with higher levels of exploration.

**Antecedents**

Jiang and colleagues (2019) present a framework of various personal and contextual antecedents that may influence adolescents’ career exploration. Their framework summarizes the existing evidence on the antecedents,
outcomes, and moderators of career exploration, revealing a mix of individual and contextual factors driving career exploration. Specific antecedents within this framework either foster or hinder study career exploration (Jiang et al., 2019). By studying these antecedents, we can gain more insight into why some students tend to engage more in exploration than others. For this project, we will examine these antecedents in relation to the exploration profiles and evolutions between profiles. We will focus on personal antecedents and broaden our scope beyond fixed characteristics to also encompass malleable characteristics, that can be influenced before entering higher education. The specific malleable antecedents from the framework examined in this dissertation include academic self-efficacy, academic self-concept, motivation, and test anxiety. The fixed background characteristics of gender, educational track, and socioeconomic status (SES) are also taken into account, both as predictors of the (transitions between) profiles and as control variables.

Self-efficacy has been identified as an important factor in career exploration. Self-efficacy reflects people's expectations and convictions about what they can achieve in given situations (Bandura, 1977; Bong & Skaalvik, 2002). Although career decision-making self-efficacy is most commonly assessed, one may also expect academic self-efficacy to relate with higher career exploration. Students with higher expectations of their academic abilities have a more well-defined sense of their interests and goals, which could lead them to more actively engaging in career exploration (Deng et al., 2022). While academic self-efficacy represents individuals’ convictions of what they can accomplish in given situations, academic self-concept refers to individuals’ perceptions of themselves in an academic situation (Bong & Skaalvik, 2002). Students’ perceptions about themselves in the academic domain could influence their awareness and motivation to engage in the decision-making process (van der Aar et al., 2019). Motivation measures the students' willingness to put up the effort required to successfully complete their
academic obligations (Weinstein et al., 2016). Decision-making tasks require persistence, so motivation is important to sustain the effort needed to engage in them. Highly motivated students are more aware of their needs which may drive them to engage more in exploration (Duchesne et al., 2012). Research on the relationship between anxiety and exploration is inconsistent. Findings indicate that various forms of anxiety (i.e. career anxiety, general anxiety) may affect exploration differently (Germeijss et al., 2006a; Vignoli et al., 2005; Vignoli, 2015). On one hand, anxiety can lead to a heightened focus on searching for threatening information. Since exploration is a complex task, it could cause anxious students to focus more on it. On the other hand, it may also incite the search for irrelevant information, which can hinder the search for vocational information (Vignoli, 2015; Vignoli et al., 2005). Further research is therefore needed.

In addition to these antecedents mentioned in the framework by Jiang and colleagues, we also consider students’ learning strategies (J. D. Vermunt, 1998). Learning strategies consist of processing and regulation strategies. Processing strategies are the cognitive learning activities that students use to process learning content, for instance memorizing or concrete processing. Regulation strategies refer to the learning activities that students use to regulate or steer their learning process. Examples are self-regulation or lack of regulation (J. D. Vermunt, 1998; J. D. Vermunt & Donche, 2017). Although the relationship between students’ learning strategies and career exploration profiles has not been empirically examined, we hypothesize that since the use of processing strategies facilitates the processing of learning content, and regulation strategies steer the learning process, these strategies may have benefits for information processing during the career exploration process.

Other important, but fixed, antecedents are students’ background characteristics. Research indicates that students’ background characteristics, including gender, prior educational track, and socio-economic status (SES), are
associated with the study choice process. Girls generally exhibit more engagement in school compared to boys, which is why we may also expect differences in their engagement in exploration. Research suggests girls tend to engage more in self-exploration (Lazarides et al., 2016; Seabi, 2012) and exhibit higher levels of environmental exploration (Gamboa et al., 2013). The general track of secondary education in Flanders specifically prepares students for higher education, while students opting for the technical track must make a more specific and definitive choice earlier on. Since students in the technical track are assumed to be more ready to make a decision, they obtain higher scores on decision-making tasks at specific moments. However, general track students demonstrate greater progress on decision-making tasks in their final year, leading to them even obtaining higher scores on the tasks at the end of secondary education (Germeijis & Verschueren, 2007a). Finally, previous research suggests that a higher socioeconomic status positively influences the decision-making process. Although the relation with exploration was not explicitly investigated, students who reported having a higher SES demonstrated more confidence in performing career decision-making tasks (Metheny & McWhirter, 2013; Thompson & Subich, 2006) and greater certainty in their career decisions (Thompson & Subich, 2006). These findings emphasize the importance of considering these background characteristics when examining the career exploration process in the transition to higher education.

Outcomes

This dissertation examines outcomes before and after the transition to higher education. The first focus is on outcomes of the study choice process, while the second involves a longitudinal perspective on subsequent academic success in higher education. In doing so, we try to provide a comprehensive understanding of possible outcomes of the exploration process, considering
both the impact on study choice process outcomes such as decisional status and commitment, as well as the long-term effects on academic success in higher education.

The way in which students engage in the decision-making tasks in secondary education can affect the outcomes of this process. There seems to be a positive association between engaging in career decision tasks and the amount of information students acquire about themselves, as well as general and specific career alternatives (Germeijs et al., 2006a). Career exploration tasks also appear to positively relate to decisional status, suggesting that career exploration might foster students’ readiness to decide on a particular career choice (Kleine et al., 2021). In particular, broad and in-depth exploration of study career alternatives are suggested to contribute positively to this, and both are also associated with higher levels of commitment (Germeijs et al., 2006a; Germeijs & Verschueren, 2007b). Similarly, in-depth exploration appears to be closely related to the process of career commitment, as indicated by research on vocational identity (Crocetti et al., 2008; Porfeli et al., 2011). Further research is needed to investigate the relationship between the career exploration profiles and the outcomes of the study choice process, i.e. the amount of information acquired about higher education, decisional status, and commitment. This will enable us to determine what leads to making more informed study choices.

Previous research suggests that the quality of the decision-making process regarding program choices for higher education can influence academic success, i.e., choice actualization, commitment to the chosen program, and academic adjustment in higher education (Germeijs & Verschueren, 2007b). Academic success can be defined as “inclusive of academic achievement, attainment of learning objectives, acquisition of desired skills and competencies, satisfaction, persistence, and postcollege performance” (Kuh et al., 2006, p. 5). Despite the importance of academic
success, few studies have examined the impact of the study choice process on academic success. For instance, research by Germeijs and Verschueren (2007b) demonstrated that students who exhibited more commitment to their study choice at the end of secondary education had a greater chance of actualizing their choice. Students who demonstrated higher levels of orientation, broad exploration, and in-depth exploration displayed greater commitment to their chosen higher education program, which subsequently reduced the likelihood of dropping out (Germeijs & Verschueren, 2007b). This complements research by Lacante and colleagues suggesting that the quality of coping with career decision tasks was associated with differences in drop-out rates (Lacante et al., 2001). De Clercq and colleagues (2013, 2021) also found that making an informed choice was positively related to academic achievement in higher education. Although some of the aforementioned studies did not directly assess decision-making tasks or questioned the decision-making process retrospectively in the first year of higher education, they do suggest that the quality of the study choice process is important for academic success. It is important to note that retrospective accounts of the study choice process can be affected by students’ academic adjustment and success. Due to the limited number of studies that have examined the relationship between the study choice process and academic success prospectively, further longitudinal research is necessary. This is particularly relevant in the context of an open admissions system like Flanders, where we assume the study choice process to play an important role in academic success, due to the wide range of programs available to students.

Main Aim and Research Questions

The overarching aim of this dissertation is to better understand students’ engagement in the career exploration process during the transition from secondary to higher education. The following theoretical model in Figure 1
(based on the literature described above) will be used and includes the exploration scales, the antecedents of the exploration process, the outcomes of exploration related to the study choice process, and the eventual outcomes in higher education. Specifically, this dissertation aims to identify exploration profiles, using a validated assessment for career exploration tasks and a person-centered approach. It investigates the development of these profiles throughout the final year of secondary education, their antecedents, and subsequent outcomes regarding the study choice process and in higher education. The main research questions guiding this dissertation are as follows:

- Is the Shortened Study Choice Task Inventory (SSCTI) a reliable and valid instrument for mapping students’ study choice process? (RQ1)

- Can different career exploration profiles of students be identified (RQ2A), and how do these profiles develop during the final year of secondary education (RQ2B)?

- What is the association between the identified exploration profiles and different antecedents? (RQ3)

- What is the association between the identified exploration profiles and different outcomes related to the study choice process and academic success in higher education? (RQ4)

The following section provides an outline of the four empirical chapters. Table 1 presents an overview of the chapters describing the four studies in the current dissertation, including their objectives, samples, main analysis techniques, and variables.
Introduction

Overview of Chapters

Chapter 1 provides the validation of a shortened and updated version of the Study Choice Task Inventory (SCTI), which is an instrument designed to measure students’ study choice process. The SCTI was originally developed in 2006. Recent developments, such as increased flexibility in higher education and digitization, necessitated an updated version of the questionnaire. Additionally, the large-scale assessment in the Columbus tool necessitated psychometrically sound and brief measures. We therefore updated and shortened the original SCTI, which we named the Shortened Study Choice Task Inventory (SSCTI). We assessed the reliability and validity of the SSCTI through exploratory and confirmatory factor analyses, as well as through measurement invariance analyses for gender and educational track (RQ1). The SSCTI was used during the 2016-2017 school year, the first large-scale implementation of the Columbus tool. We used data from 11,559 general, technical, and vocational track students from this cohort, selecting students who provided consent for their data to be linked to the databases of the Department of Education and Training, identifying them as authentic students in the second-to-last and final year of secondary education.

In Chapter 2, we aimed to identify different exploration profiles of students transitioning to higher education using person-centered analysis, specifically latent profile analysis (RQ2A). This study examined their
associations with different learner characteristics (learning strategies, gender, and educational track) (RQ3), along with different outcomes related to the study choice process, such as the amount of information acquired regarding higher education, decisional status, and commitment (RQ4). Data from the same cohort as Chapter 1 were used, but further selecting students in their final year who made the transition to higher education in the next academic year. In addition, students from both the general and technical tracks of secondary education were selected, as they are most likely to make the transition to higher education, leaving a dataset of 5,660 students.

Chapter 3 presents a longitudinal study that examines transitions between exploration profiles during the final year of secondary school, and the role of various antecedents in shaping the exploration process. A first aim was to identify distinct exploration profiles of students in the fall and spring of the final year of secondary school. Second, latent transition analysis was used to examine the transitions between these exploration profiles across the two timepoints (RQ2B). Finally, we examine how various antecedents (i.e., academic self-efficacy, academic self-concept, motivation, test anxiety, gender, educational track, and socioeconomic status) affected profile membership and transitions between profiles (RQ3). This study combined data from three cohorts (2017-2018, 2018-2019, and 2019-2020). Similar to the study in Chapter 2, it focused on final-year general and technical track students who enter higher education in the subsequent academic year. Since the 2017-2018 school year, students can fill out the SSCTI three times per school year. This study used three different samples; one cross-sectional sample composed of students who completed the SSCTI in the fall ($n = 9,567$), another composed of those who did so in the spring ($n = 7,254$), and a smaller longitudinal sample of students who completed the SSCTI at both timepoints ($n = 672$).

In Chapter 4, we describe a longitudinal study on the relationship between the career exploration profiles, acquired information about higher
education and study choice commitment in the final year of secondary education, and academic success in the first year of higher education. This study used Structural Equation Modeling to analyze how the exploration profiles relate to acquired information about higher education and study choice commitment in the final year of secondary education, and how these intervening factors, in turn, predicted academic success in the first year of higher education, controlling for the background characteristics of students (RQ4). Furthermore, this research investigated potential variations in these associations across academic and professional bachelor’s programs. The study used the spring dataset from Chapter 3, with additional restrictions on the intervening and outcome variables, resulting in a final sample of 5,358 students.

Finally, the concluding chapter of this dissertation presents a summary of the main findings from the four chapters, followed by critical reflections on these findings, the strengths and limitations of the dissertation as well as potential directions for future research, and implications for practice and policy.
### Table 1

**Overview of Chapters**

<table>
<thead>
<tr>
<th>Chapter</th>
<th>Aims</th>
<th>Sample</th>
<th>Main Analyses</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Validation SSCTI (RQ1)</td>
<td>Columbus cohort 2016-2017, ( n = 11,559 )</td>
<td>Exploratory and Confirmatory Factor Analyses</td>
<td>Orientation, Self-Exploration, Broad Exploration, In-Depth Exploration, Commitment, gender, educational track</td>
</tr>
<tr>
<td>2</td>
<td>Identification exploration profiles, association with learner characteristics and outcomes study choice process (RQ 2, 3 &amp; 4)</td>
<td>Columbus cohort 2017-2018, ( n = 5,660 )</td>
<td>Latent Profile Analysis</td>
<td>Orientation, Self-Exploration, Broad Exploration, In-Depth Exploration, Decisional status, Commitment, Amount of Information, gender, educational track, Self-Regulation, Lack of Regulation, Relating and Structuring, Concrete Processing, Memorizing</td>
</tr>
<tr>
<td>3</td>
<td>Transitions between exploration profiles, association with antecedents (RQ 2 &amp; 3)</td>
<td>Columbus cohorts 2017-2018, 2018-2019, and 2019-2020, ( n_{fall} = 9,567 ), ( n_{spring} = 7,254 ), ( n_{longitudinal} = 672 )</td>
<td>Latent Profile Analysis, Latent Transition Analysis</td>
<td>Orientation, Self-Exploration, Broad Exploration, In-Depth Exploration, Academic Self-Efficacy, Academic Self-Concept, Motivation, Anxiety, gender, educational track, SES</td>
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CHAPTER 1

The study choice process when choosing a study for higher education: Validation of the Shortened Study Choice Task Inventory (SSCTI)

Based on the following published manuscript (in Dutch):


1 Joint first authors
Abstract

The Study Choice Task Inventory (SCTI; Germeijs & Verschueren, 2006b) is a questionnaire designed to investigate the study choice process of students. Although the SCTI is a reliable and valid questionnaire, an updated version was necessary. When the SCTI was used in school year 2015-2016 in a representative sample of 2,482 students, it became clear that the construct validity of the SCTI could be improved. Based on this data from 2015-2016 a shortened and adapted version of the SCTI was developed, the Shortened Study Choice Task Inventory (SSCTI). This instrument then was used in school year 2016-2017. Based on the data of 11,559 students from this last cohort, the reliability and validity of the SSCTI were investigated. Based on the explorative and confirmatory factor analyses and measurement invariance analyses, the SSCTI appears to be a fitting instrument for exploring the study choice process for higher education.
Introduction

Making a study choice is one of the most important decisions students must make at the end of secondary education, impacting both the individual and society (Gati & Asher, 2001b). The way in which a student makes a study choice can have important consequences for the eventual outcome, such as commitment to the chosen study (Gati & Asher, 2001b; Germeijss & Verschueren, 2007b; Van Esbroeck et al., 2005), and can also influence dropout in higher education (Lacante et al., 2001). Research suggests that the more students figure out what they are good at and explore the different available options, the better the chosen study will align with their preferences (Hirschi et al., 2011; Stumpf et al., 1983) and the more commitment there will be to the final decision (Hirschi et al., 2011). Greater consistency between the student's preferences and the chosen study, in turn, results in increased satisfaction with the choice made (Stumpf et al., 1983).

Flemish education, unlike many other education systems in the world, has open access to higher education. This means that anyone who obtains a secondary education diploma can choose a program in higher education (except for medicine, dentistry, and certain arts programs for which passing an entrance test is required). Furthermore, the government provides partial financial assistance for higher education enrollment fees for certain (opportunity) groups, making it more financially accessible to students.

However, this open access is accompanied by low study success rates. According to the Department of Education (personal communication, March 13, 2019), only 42% of all generational students achieved a cumulative study efficiency (CSE) of 85% or higher during academic year 2016-2017, meaning they obtained 85% of the credits they take. Only 27% of these completed all of their credits. 35% even achieved a CSE of less than 50%.
This results in a high number of students experiencing study delays or drop-out. One possible explanation is that not all students go through the study choice process in an equally active manner. Insufficient exploration of study options can lead to a naïve study choice, resulting in less academic and social integration and less commitment to the chosen program, potentially resulting in drop-out (Germeijs et al., 2012). Therefore, reflecting on the activities involved in the process of making a study choice is crucial, and the use of a questionnaire can offer further valuable insights.

Germeijs and Verschueren developed the Study Choice Task Inventory (SCTI) in 2006 to map students' study choice process. The SCTI also provides feedback on answer scores to aid the decision-making process (Germeijs & Verschueren, 2006b). The SCTI has already been used in several studies, mainly in Flanders (e.g. Germeijs & Verschueren, 2006a, 2007b) but also internationally (Parks et al., 2017). While the SCTI has been demonstrated to be a reliable and valid instrument used extensively in both practice and research, research validating its use in Flanders is quite outdated (Germeijs & Verschueren, 2006b). Therefore, further research is needed. Several content-related and methodological considerations may be suggested.

In terms of content, the SCTI is an instrument reflective of its time and was developed before the implementation of the bachelor-master system (Decreet 4 April 2003 Betreffende de Herstructurering van Het Hoger Onderwijs in Vlaanderen, 2003). Since then, there have been various developments within secondary and higher education that have required modifications to some items. For example, there is the increased flexibilization of higher education and the digitalization of both information and the educational offer. Furthermore, there is increased responsibility for student guidance placed on the schools (Decreet Betreffende de Leerlingenbegeleiding in Het Basisonderwijs, Het Secundair Onderwijs En de Centra Voor Leerlingenbegeleiding, 2018), and the range of programs offered in higher
education has expanded (e.g., introduction of associate’s degree programs). As a result, more adolescents are now transitioning to higher education. Due to these recent evolutions, the update of several items was important.

From a methodological perspective, the SCTI is a rather lengthy questionnaire. A shorter version of the questionnaire could potentially lead to more efficient use in (longitudinal) research. Additionally, a shorter version would facilitate its use in large-scale online self-assessment and counseling tools designed to support adolescents in the study choice process. Furthermore, since the previous validation study, advanced statistical techniques have become more widely available and common. These techniques enable further investigation into the instrument’s construct validity. One such method is measurement invariance analysis, which can be employed to examine whether the interpretation of the questionnaire is not biased by different background characteristics of the students, such as gender or educational track. Finally, our preliminary research emphasizes the importance of conducting further validation research in the Flemish educational context. During the 2015-2016 school year, we administered the SCTI to a sample of 2,482 students in Flanders, which showed the need to improve the construct validity of the SCTI. For example, good construct validity for two scales, specifically Orientation (originally 12 items) and Commitment (originally 8 items) (see below), was impossible to reach without eliminating items. Based on the

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2 Item 1 in the Orientation scale, which states ‘I am not worried about my study choice yet’, had a low item-total correlation of .212. However, after removing this item and adding four error covariances, the fit indices of the modified scale still indicated an inferior fit to the data (CFI=.854; RMSEA=.141; SRMR=.097). Similarly, the original Commitment scale with 8 items also showed poor fit (CFI=.813; RMSEA=.197; SRMR=.076). Furthermore, items 5 (“What are you willing to do in terms of effort and problems to realize this study program?”) and 8 (“Do you defend this study program to others who disagree with it?”) had low corrected item-total correlations (.203 and .290, respectively). These items were removed, resulting in a good fit to the data (CFI=.986; RMSEA=.057; SRMR=.029).
analyses of these 2015-2016 data, a shortened and modified version of the SCTI was constructed (see Figure 1.1 for a visual representation of the different cohorts and developments).

**Figure 1.1**
*Overview cohorts and developments*

<table>
<thead>
<tr>
<th>Administration Original SCTI</th>
<th>Administration Initial SSCTI</th>
<th>Final SSCTI</th>
</tr>
</thead>
<tbody>
<tr>
<td>School year 2015-2016</td>
<td>School year 2016-2017</td>
<td>Present</td>
</tr>
<tr>
<td>55 items</td>
<td>33 items</td>
<td>28 items</td>
</tr>
</tbody>
</table>

The current study aims to further investigate the reliability and construct validity of the Shortened Study Choice Task Inventory (SSCTI) in a large sample from the 2016-2017 school year. Based on the data from this cohort, the reliability and validity of the SSCTI were examined (as shown by the last arrow in Figure 1.1). The following theoretical framework describes the importance of supporting the study choice process, the background and content of the SCTI, research using the SCTI, and the present study.

**Theoretical Framework**

**The Importance of Supporting the Study Choice Process**

As discussed above, not all students attain good study results in higher education, leading many students to drop out. Research from abroad (Richardson et al., 2012; Robbins et al., 2004) and in Flanders and the Netherlands (van Rooij et al., 2018) has investigated several factors associated with academic success in higher education. Both learner and environmental characteristics are important. Study results at the end of secondary education are one of the most important predictors of study success in higher education. Alongside this, non-cognitive characteristics such as motivation and self-
efficacy also play an important role. Regarding environmental factors, for example, the financial support offered by the institution plays a role.

A relation also exists with the quality of the study choice process. Students who dropped out of higher education decided later which study program to pursue in the first year of higher education and conducted a less thorough study choice process. They discussed their study choice less with others and engaged in fewer activities related to it, such as reading brochures (Lacante et al., 2001). Making an informed study choice is positively associated with academic success in the first year of higher education (De Clercq et al., 2013). The way students handle decision-making tasks at the end of their senior year contributes significantly to their commitment to the chosen study and academic adjustment during the first trimester of higher education. Less commitment to the chosen study in turn leads to an increased risk of drop-out, while academic adjustment is important for study success in the first year of higher education (Germeijs & Verschueren, 2007b; see also below).

The Study Choice Task Inventory (SCTI)

Germeijs and Verschueren (2006b) identify six decision-making tasks that are important in the decision-making process of secondary education students: Orientation, Self-Exploration, Broad Exploration, In-Depth Exploration, Decisional Status, and Commitment (see Figure 1.2). The theoretical background of the SCTI is based on various taxonomies of problems in the study choice process (e.g., Campbell & Cellini, 1981; Gati et al., 1996) as well as theories of the study choice process as a developmental process (Harren, 1979; Tiedeman & O’Hara, 1963). Compared to other questionnaires that attempt to map students’ study choice process and that, for example, focus only on certain tasks of the decision process or do not use different subscales

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3 See for aforementioned theories also Germeijs, 2006.
for the different decision tasks, the SCTI is unique in that it uses separate scales for each of the decision tasks.

**Figure 1.2**

*Tasks in the decision-making process*

The SCT measures students’ ability to handle these decisional tasks that are important when choosing a study for higher education. It comprises six separate scales that each measure one of these six decisional tasks. The original version (excluding the Decisional Status scale) consists of 55 items that students must self-rate (Germeijs & Verschueren, 2010).

'Orientation' measures students’ awareness of the fact that they need to make a study choice and their motivation to make the best decision possible. The original scale consists of twelve items. 'Exploration of the Self', 'Broad Exploration', and 'In-Depth Exploration' can be grouped under 'Exploration'. 'Exploration of the Self' evaluates the extent to which students reflect on their personal characteristics with themselves and with others. Originally, it contained 20 items. 'Broad Exploration' uses five items to evaluate the extent to which students have looked up general information about higher education, while 'In-Depth Exploration' measures the extent to which students have

looked up more detailed information about specific study programs. In-Depth Exploration originally consisted of ten items. ‘Decisional Status’ measures students’ progress in making a choice. ‘Commitment’ initially consisted of eight items and assesses the extent to which students are certain of and feel connected to the chosen study program (Germeijs & Verschueren, 2006b, 2010). These decision tasks are flexible; that is, they do not need to be addressed in a fixed order, and students may return to a previous task or skip a task if necessary (Germeijs & Verschueren, 2006b, 2010).

For each of these decisional tasks, Germeijs and Verschueren (2006b) developed several items, based on existing measurements of (career) decisional tasks. When the literature did not provide sufficient items, new ones were developed (Germeijs & Verschueren, 2006b). General items on making a career choice were tailored to the situation of making a study choice for the first year of higher education. After conducting thorough reliability and validity analyses in a sample of 946 students in general secondary education, a reliable and valid questionnaire emerged (Germeijs & Verschueren, 2006b). The SCTI is accessible both online and on paper to examine students' study choice process.

**Research with the SCTI**

The SCTI has been used for various types of research, mainly in Flanders but also internationally. For example, longitudinal research with the SCTI has indicated that adolescents make strong progress in the decision-making process during the final year of secondary education. Furthermore, latent growth curve analyses demonstrated that Orientation and Broad Exploration are important at the beginning of the study choice process while In-Depth Exploration and Decisional Status gain importance later (Germeijs & Verschueren, 2006a). Additional research using the SCTI found that how students handle decisional tasks at the end of their senior year significantly contributes to their commitment to the chosen program and academic adjustment during the first
trimester of higher education. Higher scores on Decisional Status and Commitment at the end of the senior year were found to increase the likelihood of actualizing the choice. Moreover, higher scores on In-Depth Exploration and Commitment resulted in more commitment to the chosen higher education program. Finally, higher scores on Self-Exploration and Commitment were also associated with better academic adjustment (see lower part of Figure 1.2). Less commitment to the chosen study in turn increases the likelihood of dropping out, while academic adjustment is important for academic success in the first year of higher education (Germeijs & Verschueren, 2007b).

Furthermore, it appears that the decision-making process differs between males and females and students from different educational tracks. Girls demonstrate higher scores than boys on Orientation and Broad Exploration. Moreover, students in technical and vocational tracks demonstrate a swifter readiness in decision-making compared to students from the general track and thus attain higher scores on decisional tasks than general track students at specific measurement times (Germeijs & Verschueren, 2007b).

The Present Study

The following research question is central to this study: to what extent is the Shortened Study Choice Task Inventory (SSCTI) a reliable and valid instrument for capturing students' study choice process? This research question was further specified into several sub-questions:

a) To what extent do the individual scales of the SSCTI have good internal consistency?

b) To what extent is the SSCTI construct valid?
c) To what extent do male and female students and students from different educational tracks (general, vocational, technical) interpret the questionnaire in the same way?

Method

Respondents
The SSCTI was administered to a total of 16,486 students in the last two years of secondary education during the 2016-2017 school year, using the online exploration tool Columbus. Columbus was commissioned by the Flemish Ministry of Education and Training to enhance the decision-making process for students in the last two years of secondary education (for more information, see www.onderwijskiezer.be/columbus). The online application was accessible from February 3 to June 12 in the 2016-2017 school year. During this period, students could fill out the SCTI once in a classroom setting. Of the students who participated in Columbus, 76% provided consent for their data to be linked to the databases of the Department of Education and Training. This connection of datasets enabled recognition of 11,559 students who completed the online exploration instrument Columbus during the 2016-2017 school year as officially enrolled in Flemish secondary education. The majority of students (94%) were in their final year of secondary education, while the remainder (6%) were in their second-to-last year. Of these students, 44% were male and 56% were female, with an average age of 18.34 years. The majority of students came from the general (54%) and technical (37%) tracks, with smaller numbers originating from vocational (7%) and arts (2%) tracks. Compared to the broader population of upper secondary education, the surveyed group used in this study shows an overrepresentation of students from general and an underrepresentation of students from vocational tracks. This may be explained by the fact that the questionnaire focuses on students who intend to make the transition to higher education.
Instrument

Based on reliability and validity analyses conducted on the data collected during the 2015-2016 school year with the original SCTI, the first version of the SSCTI was developed (33 items, Table 1.1), in which the original SCTI was shortened from 55 to 33 items as a first step. In a second step, based on the analyses during the 2016-2017 school year, the SSCTI was further shortened from 33 to 28 items. In doing so, the results of the statistical analyses were taken into consideration, and several items were updated. An example of an item that was updated is "I browsed brochures from different study programs" to "I viewed brochures or websites from different study programs". An example of reduction would be, for example, the merging of the items "I have talked to my parents about what I’m good at and not so good at," "I have talked to my friends about what I’m good at and not so good at," "I have talked to a teacher about what I’m good at and not so good at," and "I have talked to people other than those listed above about what I’m good at and not so good at (such as brothers, sisters...)’ into “I have had a conversation with others (such as parents, family, friends, teachers...) about what I’m good at and not so good at”. However, the general theoretical rationale and structure of the original instrument were retained.

For the Orientation scale, the answer to each of the seven items is given on a scale ranging from "Not at all applicable to me" (1) to "Very strongly applicable to me" (5). The Exploration of Self scale is composed of eight items classified into two groups, i.e., the extent to which a student has thought about characteristics of the self and the extent to which he/she has talked about them with others. To respond to these items, students use a four-point response scale ranging from "Not once" (1) to "Very often" (4). Broad Exploration consists of five items that are completed using the same response scale as Exploration of Self. Before filling out the Exploration in Depth scale, students should first write down the names of the programs about which they have
gathered information. If a student has yet to seek information, then this scale is not filled out. These seven items are again completed using the same response scale as the Exploration of Self and Broad Exploration scales. On the Decisional Status scale, students indicate the study programs they are currently considering and their preference for one of them by answering two items. Based on the responses, the student is assigned a score ranging from 1 to 4. Since this scale is not a Likert scale, it has not been included in the current validation study. Commitment is only filled out when a student has indicated a first choice on the Decision Status scale. This scale consists of six items, each completed on a six-point scale but with varying response categories. Items 1, 2, and 5 are completed on a scale from "Definitely not" (1) to "Yes, very much" (6). Item 5 is a reversed item such that 'Definitely not' is assigned score 6 and 'Yes, very much' is assigned score 1. Items 3 and 4 are both reversed items and are answered from 'Definitely not' (6) to 'Definitely yes' (1). Item 6 is answered on a scale from 'Not at all' (1) to 'Yes, completely' (6).
Table 1.1  
*Items Shortened Study Choice Task Inventory (SSCTI)*

<table>
<thead>
<tr>
<th>Orientation</th>
<th>Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>Or1</td>
<td>I often think about which study I will choose next year.</td>
</tr>
<tr>
<td>Or2</td>
<td>I want to do my best to make a good study choice for next year.</td>
</tr>
<tr>
<td>Or3</td>
<td>I am now willing to spend time looking for a study.</td>
</tr>
<tr>
<td>Or4</td>
<td><em>I often daydream about which study I will pursue.</em></td>
</tr>
<tr>
<td>Or5</td>
<td>I want to make an effort now so that I will make the right study choice.</td>
</tr>
<tr>
<td>Or6</td>
<td><em>I often think about the fact that I have to make a study choice.</em></td>
</tr>
<tr>
<td>Or7</td>
<td>I am already looking forward to thinking about which study I would choose.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Exploration of the Self</th>
<th>Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>ES1</td>
<td>I have thought on my own about what I am good at and not so good at.</td>
</tr>
<tr>
<td>ES2</td>
<td>I have thought on my own about what I like and dislike to do.</td>
</tr>
<tr>
<td>ES3</td>
<td>I have thought on my own about what I consider important and less important for my future.</td>
</tr>
<tr>
<td>ES4</td>
<td>I have thought on my own about my study approach.</td>
</tr>
<tr>
<td>ES5</td>
<td>I have had a conversation with others (such as parents, family, friends, teachers,…) about what I am good at and not so good at.</td>
</tr>
<tr>
<td>ES6</td>
<td>I have had a conversation with others (such as parents, family, friends, teachers,…) about what I like and dislike to do.</td>
</tr>
<tr>
<td>ES7</td>
<td>I have had a conversation with others (such as parents, family, friends, teachers,…) about what I consider important and less important for my future.</td>
</tr>
<tr>
<td>ES8</td>
<td>I have had a conversation with others (such as parents, family, friends, teachers,…) about my study approach.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Broad Exploration</th>
<th>Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>EB1</td>
<td>I went through an overview of what the structure of higher education looks like.</td>
</tr>
<tr>
<td>EB2</td>
<td>I have looked at brochures or websites of different study programs.</td>
</tr>
<tr>
<td>EB3</td>
<td>I have gone through overviews with the summaries of study programs.</td>
</tr>
<tr>
<td>EB4</td>
<td>I have read through overviews of program names.</td>
</tr>
<tr>
<td>EB5</td>
<td>I have gone through overviews of addresses of educational institutions.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>In-Depth Exploration</th>
<th>Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>ED1</td>
<td>I have thoroughly examined a brochure or website about a study program.</td>
</tr>
<tr>
<td>ED2</td>
<td>I have compared the brochures or websites of different study programs.</td>
</tr>
<tr>
<td>ED3</td>
<td>I went to an information day at an educational institution where one of the study programs is organized.</td>
</tr>
<tr>
<td>ED4</td>
<td>I have talked to students who are currently in higher education about one of the study programs.</td>
</tr>
<tr>
<td>ED5</td>
<td>I looked at a course book of one of the study programs.</td>
</tr>
<tr>
<td>ED6</td>
<td>I have talked to people with professional experience about their studies and/or profession.</td>
</tr>
<tr>
<td>ED7</td>
<td>I have talked to others (such as parents, friends, teachers,…) to learn more about a study program.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Commitment</th>
<th>Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>Co1</td>
<td>Are you sure about your choice for this study program?</td>
</tr>
<tr>
<td>Co2</td>
<td>Does choosing this study program make you feel confident and optimistic about your future?</td>
</tr>
<tr>
<td>Co3</td>
<td>Could you easily change the choice of this study program again?</td>
</tr>
<tr>
<td>Co4</td>
<td>Could you easily step away from your choice of this study program?</td>
</tr>
<tr>
<td>Co5</td>
<td>Are you uncertain about choosing this study program?</td>
</tr>
<tr>
<td>Co6</td>
<td><em>Is this study program entirely your own choice?</em></td>
</tr>
</tbody>
</table>

*Note.* Items in italics were later removed based on reliability and factor analysis of data from the 2016-2017 cohort.

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4 This chapter is based on a manuscript that was originally published in Dutch. Therefore, the original questionnaire was also formulated in Dutch (see Appendix 1.A for the original Dutch questionnaire).
Analyses

The SSCTI data from the most recent cohort (2016-2017) were evaluated for validity and reliability, using the software package lavaan in R (Rosseel, 2012) and the software program IBM SPSS Statistics 23. To cross-validate the formulated model, the total sample ($N = 11,559$) was split into multiple subgroups (MacCallum et al., 1992). First, a calibration sample ($n = 1,539$) and an independent validation sample ($n = 1,476$) were created based on random sampling. From the total sample, two subgroups were subsequently created based on gender, with one exclusively containing male ($n = 1,542$) and the other exclusively containing female ($n = 1,557$) respondents. Additionally, four subgroups were formed based on the educational tracks: general ($n = 1,565$), vocational ($n = 830$), technical ($n = 1,488$), and arts ($n = 190$) track students. The latter six subgroups may include respondents who were also included in the calibration and validation samples.5

The subgroup size was primarily chosen based on the guidelines for confirmatory factor analysis (CFA). Although Brown (2015) states that group size guidelines for CFA are not always uniform, the consensus seems to be at least 10 respondents per estimated parameter (Schreiber et al., 2006). Following the established consensus, for the full CFA model, as formulated by the theoretical framework (without modifications), a sample size of at least 1,090 respondents was determined. We therefore opted to keep the sample sufficiently large and selected a random sample of 1,500 respondents per subgroup (for all subgroups where the sample was large enough) for this purpose.

To answer the first research question regarding the factor structure of the questionnaire, we initially focused on the individual scales. For each scale,

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5 For instance, 182 (12%) respondents from the general track subgroup are also part of the calibration sample.
an exploratory factor analysis (EFA) with oblique rotation was first conducted on the calibration sample to determine whether the scale measures one or more components. Subsequently, a CFA for each scale was performed on the same sample to confirm the findings. Then the calibration sample was also subjected to an EFA and CFA, but this time on the full set of items (five scales).

During this phase of the analysis, changes to the structure of the CFA models (e.g., adding error covariances) were made and poorly performing items were removed. Several criteria were used to remove items: 1) the item loaded on a different factor than theoretically hypothesized in factor analysis; 2) the item had a (relatively) low factor loading; 3) removing an item increased the Cronbach's alpha index by at least .01; 4) the item had a corrected item-total correlation below .30 (Nunnally & Bernstein, 1994). In each decision to remove items, we considered both theoretical and content factors, as well as the goodness-of-fit indices of the CFA.

To compare the fit of different CFA models, the 'Akaike Information Criterion' (AIC) was used. A lower value on this index indicates a better model fit compared to a model with a higher AIC value (Kline, 2016). Additionally, we used other indices to determine model fit, including the 'comparative fit index' (CFI), 'root mean square error of approximation' (RMSEA), and 'standard root mean square residual' (SRMR) (Hu & Bentler, 1999; MacCallum et al., 1996).

In the next step, the resulting model was estimated on the remaining seven subgroups to ensure that the changes made did not rely too heavily on chance, as they were performed when fitting the model to one specific sample (MacCallum et al., 1992). First, we evaluated the model’s fit to the validation sample. Next, we examined whether the resulting factor structure also applied to groups consisting of only males, females, general track students, vocational track students, or technical track students. The group with arts track pupils was
too small to estimate the final model. Finally, Cronbach's alpha of the resulting scales was also calculated, thus providing an answer to research question 2.

Finally, we also conducted multigroup measurement invariance analyses (Meredith, 1993) on the validation sample and a new sample (see below under 'Results') to further test whether the factor structure of the final measurement model is equivalent across students' gender and educational tracks (Byrne, 2010), following research question 3. To test the equivalence of the factor structure, we estimated increasingly limited models in four hierarchical stages: (1) a configural invariance model, where only the number of factors and the factor loading pattern are equivalent across groups. Thus, at this stage, no equality constraints are imposed on the parameter estimates; (2) a metric invariance model requires only that the factor loadings be equal across groups; (3) a scalar invariance model, where intercepts are also kept equal across groups; and (4) a strict invariance model that additionally also places equality constraints on the error variances across groups (T. A. Brown, 2015; Gregorich, 2006). When metric invariance is achieved, it means that the different constructs measured in the measurement model have the same meaning across groups. Scalar invariance implies that averages of scales across groups can be compared (Bialosiewicz et al., 2013).

The invariance of the factor structure was evaluated by comparing the model fit of the more limited model with the fit of the less limited model (Byrne, 2010). Changes in CFI and RMSEA were used to verify this. A decrease in CFI by .01 or more (Cheung & Rensvold, 2002) and an increase in RMSEA by .015 or more (Chen, 2007) were considered evidence of significant deterioration in the more limited model, and thus no higher-level invariance.

**Results**

Several modifications were made at the scale level to obtain a sparse measurement model with good model fit, and good internal consistency. First,
taking into account the above criteria, items Or4 and Or6 were removed from
the Orientation scale (see also Table 1.1). After this modification, this scale
demonstrated acceptable to excellent fit (CFI=.977-.998, RMSEA=.030-.094,
SRMR=.014-.025; see Appendix 1.B) and very good internal consistency
($\alpha=.81-.93$) across all subgroups.

The results of the EFA indicate that the Exploration of Self scale
comprises two subcomponents: exploration of self through self-reflection
(items ES1, ES2, ES3, ES4) and exploration of self through communication
with others (items ES5, ES6, ES7, ES8). This was confirmed in the CFAs. As
the second-order latent variables are identified by only two first-order latent
variables, the factor loadings of the first order factors had to be fixed to one
(Morin, 2009; Schermelleh-Engel, 2015). In addition, four error covariances
were added to achieve a good model fit (see Figure 1.3). These can be
theoretically explained by the fact that the wordings of these items are similar;
e.g., items one and five both contain the text "...about what I am good at and
not so good at." After these modifications were made, the scale was found to
be construct valid (CFI=.929-.984, RMSEA=.049-.103, SRMR=.030-.055; see
Appendix 1.B) across subgroups. Moreover, the internal consistency of the
Exploration of Self scale was high ($\alpha=.79-.83$) within each subgroup. Finally,
the internal consistency of each of the two subscales was also assessed and
found to be adequate to high within each subgroup (exploration of self through
self-reflection: $\alpha=.66-.74$; exploration of self through communication with
others: $\alpha=.77-.84$).

No adjustments were necessary for the Broad Exploration scale, as it
appeared satisfactory as developed (CFI=.982-1.000, RMSEA=.000-.090,
SRMR=.009-.025; see Appendix 1.B, $\alpha=.86-.92$). However, upon studying the
EFA of the full set of items, we discovered that the first two items of the In-
Depth Exploration scale (ED1, ED2) loaded onto the Broad Exploration
component. It seems understandable that students perceive these items as
broad exploration. For example, the meaning of "thoroughly review" in item ED1 ("I have thoroughly examined a brochure or website about a study program.") may be unclear. As the addition of items ED1 and ED2 to the Broad Exploration scale did not make a significant theoretical contribution and even decreased the goodness-of-fit indices, they were removed. Finally, two error covariances were added (see Figure 1.3). These error covariances were introduced to account for the inherent interconnectedness of the three items, all pertaining to the same mode of exploration, namely, 'I have talked to...'. The resulting scale has an acceptable to excellent fit (CFI=.972-1.000, RMSEA=.000-.094, SRMR=.007-.024; see Appendix 1.B) and good internal consistency (\(\alpha=.73-.79\)) across all subgroups.

Finally, in the Commitment scale, item Co6 was removed and one error covariance was added (see Figure 1.3). This error covariance can be theoretically explained by the fact that items three and four are scored on a response scale with the same response categories. The other items of this scale are scored on different response scales. After making this adjustment, the scale demonstrated acceptable to excellent fit (CFI=.982-1.000, RMSEA=.000-.069, SRMR=.002-.035; see Appendix 1.B) and very good internal consistency (\(\alpha=.75-.87\)) across all subgroups.

The EFA and CFA of the full measurement model (five scales in one model) demonstrate good construct validity after implementing the aforementioned modifications. The goodness-of-fit indices of this measurement model, which indicate acceptable to excellent fit in the various subgroups, are shown in Table 1.2. The resulting factor structure with standardized parameter estimates (based on the validation sample) is depicted, for illustrative purposes, in Figure 1.3. In this CFA model, the latent factors were allowed to correlate with each other. These correlations were not included in Figure 1.3 for the sake of readability, but are shown in Table 1.3. The values of the correlations are similar to those found in previous research on the
original SCTI scales (Germeijs & Verschueren, 2006b). Descriptive statistics (mean and standard deviation) of the resulting scales by subgroup are presented in Appendix 1.C.

**Figure 1.3**

*Factor structure and associated standardized parameter estimates of final CFA model, fitted to validation sample*
Table 1.2
*Goodness-of-fit-indices CFA of the full model for different subgroups*

<table>
<thead>
<tr>
<th>Subgroup</th>
<th>CFI</th>
<th>RMSEA</th>
<th>SRMR</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>General – Calibration</td>
<td>.939</td>
<td>.045</td>
<td>.056</td>
<td>62760.195</td>
</tr>
<tr>
<td>General – Validation</td>
<td>.948</td>
<td>.042</td>
<td>.054</td>
<td>62654.893</td>
</tr>
<tr>
<td>Male</td>
<td>.934</td>
<td>.043</td>
<td>.054</td>
<td>62677.979</td>
</tr>
<tr>
<td>Female</td>
<td>.942</td>
<td>.044</td>
<td>.054</td>
<td>65082.364</td>
</tr>
<tr>
<td>General track</td>
<td>.946</td>
<td>.041</td>
<td>.049</td>
<td>72077.954</td>
</tr>
<tr>
<td>Vocational track</td>
<td>.937</td>
<td>.052</td>
<td>.068</td>
<td>26924.093</td>
</tr>
<tr>
<td>Technical track</td>
<td>.950</td>
<td>.042</td>
<td>.051</td>
<td>59176.801</td>
</tr>
</tbody>
</table>

*Note.* The arts track group was too small to estimate the full model.

Table 1.3
*Intercorrelations between latent variables*

<table>
<thead>
<tr>
<th></th>
<th>1.</th>
<th>2.</th>
<th>3.</th>
<th>4.</th>
<th>5.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Orientation</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Exploration of the Self</td>
<td>.67**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Broad Exploration</td>
<td>.65**</td>
<td>.62**</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. In-Depth Exploration</td>
<td>.49**</td>
<td>.63**</td>
<td>.64**</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>5. Commitment</td>
<td>.26**</td>
<td>.35**</td>
<td>.26**</td>
<td>.41**</td>
<td>1</td>
</tr>
</tbody>
</table>

** p < .001

In a final step, we also examined whether the factor structure found, as presented in Figure 1.3, is invariant across gender and educational forms by using measurement invariance analyses. Table 1.4 shows the fit indices of the different hierarchical multiple-group measurement variance analysis models for male and female students - as described in the analysis section. The ΔCFI does not decrease by more than .01 in each of the steps, and ΔRMSEA is below +.015 in each case, demonstrating that strict invariance is achieved. Strict invariance was also established when considering the educational track as a factor for the multiple-group analysis (see Table 1.5). The latter analysis excluded the arts track due to its small sample size, which prevented running the full model.
### Table 1.4

*Measurement invariance across gender of the full measurement model, fit on the validation sample*

<table>
<thead>
<tr>
<th>Model</th>
<th>CFI</th>
<th>RMSEA</th>
<th>Sig. Chi²</th>
<th>ΔCFI</th>
<th>ΔRMSEA</th>
</tr>
</thead>
<tbody>
<tr>
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<td>.043</td>
<td>/</td>
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<tr>
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</table>

### Table 1.5

*Measurement invariance across educational track (general-vocational-technical) of the full measurement mode, fit on the new sample*

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<th>Sig. Chi²</th>
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### Discussion

### Conclusion

This study examined the reliability and validity of the SSCTI, a modified and shortened version of the original SCTI (Germeijs & Verschueren, 2006b), in evaluating the quality of students' study choice process for higher education. The SSCTI was found to be a reliable and construct-valid instrument for mapping students' study choice process after removing some items, based on exploratory and confirmatory factor analyses and measurement invariance analyses on a large-scale study group. Moreover, updating the original SCTI to the current SSCTI has resolved the construct validity issues we encountered in the first cohort (2015-2016). The analyses indicate that items are interpreted similarly by both genders and across different educational tracks.

The SSCTI has been significantly updated and shortened compared to the original SCTI, resulting in increased efficiency in administration. The structure of the original SCTI, namely, the division of the questionnaire into six scales, each measuring one of the six choice tasks, was retained which keeps
the SSCTI consistent with taxonomies of decision-making problems (e.g., Campbell & Cellini, 1991; Gati, et al., 1996) and theories of the decision-making process as a developmental process (e.g., Harren, 1979; Tiedeman & O'Hara, 1963). Since the SSCTI still employs six distinct scales, each measuring one of the six decisional tasks, the questionnaire also continues to distinguish itself from other questionnaires that only focus on a limited set of tasks or that do not use separate scales for the different tasks. The confirmatory factor analysis also confirms the continued validity of this theoretical framework for study choice tasks.

**Future Research**

The SSCTI was found to be a reliable and valid instrument in the current study. However, there are some limitations to the study. Firstly, not all subgroups were large enough to test the full model, particularly the group of arts track students, which tends to be a smaller group of students transitioning to higher education. A second limitation relates to the fact that only quantitative data were collected. To further investigate the validity of the instrument, supplementing the quantitative data with qualitative data obtained from focus groups with students who completed the questionnaire could be useful.

Despite the study’s limitations, the SSCTI may be a valuable tool for future research in identifying the quality of the study choice process in different cohorts. In addition, it can be used to investigate the impact of students’ study choice process on their study paths. Follow-up research could focus on further validation of the SCTI, such as examining whether students from different socioeconomic backgrounds interpret the questionnaire in the same way. Further examination of the predictive validity of the SSCTI is necessary. One potential research avenue is to investigate the development of the decision-making tasks over time and whether feedback can influence them. Providing feedback may encourage students who initially exhibit limited exploratory behavior to improve. In addition, it may also be useful to relate this to further
quantitative data on higher education study efficiency, to assess the impact of using the tool on student achievement. It is expected that students who invest more effort in their study choice for higher education will show greater commitment and motivation towards their chosen field of study (see also Germeijs & Verschueren, 2007b for evidence). This, in turn, may lead to less reorientation and greater study efficiency throughout their higher education career.

Norming research is crucial for future use of the SSCTI. This will be possible based on the data that has been and will be collected over the past few school years as part of the Columbus platform, which includes the completion of the SCTI by students.

**Implications for Practice**

Since the SCTI can be used to examine students' choice process and to encourage reflection on the way the choice process was carried out and its significance (Germeijs et al., 2007), the questionnaire has been used in the past both by the CLBs in Flanders and by students individually through an online version of the questionnaire on the Onderwijskiezer (www.onderwijskiezer.be) and Luci (www.kuleuven.be/luci/) platforms.

The current study demonstrates that the SSCTI can map the six study choice tasks identified in the SCTI in a reliable and construct-valid manner. Furthermore, the instrument has been updated and shortened, allowing for more efficient use. This makes the SSCTI a promising tool for future platforms aimed at supporting students during their transition from secondary to higher education. For guidance to be valuable, it is important that students receive personalized feedback on their decision-making tasks based on their SSCTI scores. Additionally, further research should be conducted to examine the SSCTI's predictive validity, particularly by examining its relation to higher education careers and study efficiency in higher education.
The SSCTI was implemented in the Columbus instrument during the 2016-2017 school year. It is a non-binding exploration tool for all students transitioning to higher education. The platform encourages students to make a well-considered study choice by providing feedback and remediation tips based on their profile of decision-making tasks. The remediation tips encourage students to discuss their higher education program choices with other students to encourage broad exploration. To promote in-depth exploration, students are referred to the 'Onderwijskiezer' website, where they can compare different institutions and programs.

Study success in higher education depends on various factors, but making students aware of their study choice process in a timely manner can help them make a more well-informed decision for a study in higher education.
CHAPTER 2

Identifying exploration profiles for higher education and their relationship with different student variables and outcomes

Published manuscript:

Abstract

This study aims to better understand differences in the decision-making process behind study choices for higher education by investigating the presence of exploration profiles and then exploring the explanatory base. To achieve this, we first identified different exploration profiles of students transitioning to higher education \((n = 5,660)\), and then investigated whether they were predicted by different student variables (i.e., learning strategies, gender, and educational track) and linked with different outcomes of the decision-making process (i.e., the amount of information acquired regarding higher education, decisional status, and commitment). A latent profile analysis identified three exploration profiles based on the decisional tasks of orientation, self-, broad, and in-depth exploration: passive (35%), moderately active (52%), and highly active explorers (13%). Students’ learning strategies (regulation and processing strategies) were associated with these profiles. Students with more effective regulation and processing strategies were more likely to be highly active than passive or moderately active explorers. Female students and students from the technical track were more likely to be found in the highly active profile compared to the moderately active and the passive or moderately active profile, respectively. Finally, highly active explorers had the most favorable outcomes, measured by decisional status, commitment, and amount of information. Based on a substantial dataset, our findings contribute to a more comprehensive understanding of the explanatory base of important differences in the study choice making process of students opting for higher education. This may ultimately lead to more fitting support for students in less beneficial profiles.
Introduction

Choosing which program to study in higher education is one of the most important decisions students have to make, and the choice is hugely significant for both the individual and society (Gati & Asher, 2001b; Skorikov, 2007). The way in which this choice is made can have important consequences for the eventual outcome, such as commitment to the chosen study program (Gati & Asher, 2001b; Germeij & Verschueren, 2007b; Van Esbroeck et al., 2005) or adjustment to higher education (Skorikov, 2007). Research has suggested that adolescents who fully explore both themselves and their possible career options tend to experience a more suitable match between their preferences and their chosen program, as well as higher levels of commitment to the ultimate decision (Hirschi et al., 2011). In turn, greater congruence between the student’s career preferences and the chosen program tends to lead to a more satisfying career choice (Stumpf et al., 1983). Former research has indicated that the quality of the decision-making process regarding program choices for higher education can impact the choice actualization, commitment to the chosen program, and academic adjustment in higher education (Germeij & Verschueren, 2007b). Not only is the quality of the process significant, but it can also impact higher education drop-out rates (Lacante et al., 2001).

The present study aims to better understand differences in this decision-making process by first investigating the presence of exploration profiles based on four different decision-making tasks within the process (i.e., orientation, self-, broad, and in-depth exploration) and, secondly, by investigating whether different student variables and outcomes are related to these profiles. Regarding the student variables, first, we will investigate the relationship with different learning strategies. Learning strategies relate to metacognitive and cognitive processing strategies while studying learning content (J. D. Vermunt, 1998; J. D. Vermunt & Donche, 2017). Since the use
of processing strategies is conducive to processing learning content, and regulation strategies steer the learning process, it can be argued that these strategies may also be beneficial when processing information in the decision-making process. Processing information in the career decision-making process can be seen as a learning process in which the learning strategies could be of importance. Second, we will examine the relationship with gender and educational track and we will investigate if the learning strategies have unique explanatory value on top of these two variables. This could add to the literature by shedding additional light on why some students make more effective decisions. Finally, this study will also investigate the relationship between these profiles and different outcomes of the decision-making process (i.e., decisional status, commitment, and the amount of information acquired regarding higher education). In what follows, we will discuss the central concepts of this study.

**Study Choice Process and Profiles**

Germeijs and Verschueren (2006b) identified six decisional tasks in the process of deciding which program to study in higher education at the end of secondary education: orientation, self-exploration, broad exploration, in-depth exploration, decisional status, and commitment. These decision-making tasks are dynamic and flexible; there is no fixed order in which they should be tackled and tasks can be skipped or returned to as needed (Germeijs & Verschueren, 2006b, 2010). The decision-making process involves a substantial amount of career exploration (Gati & Asher, 2001a). Stumpf and colleagues (1983) defined career exploration as purposive behavior and cognitions that are associated with vocational development. In this process, people explore both themselves and the environment. There may be differences in the frequency of exploration and the amount of information people obtain (Jiang et al., 2019).

Person-centered perspectives have become increasingly common in vocational research. Person-centered analysis techniques cluster individuals
based on shared characteristics (Woo et al., 2018). These techniques allow one to examine how different characteristics combine into profiles (Hofmans et al., 2020). Several studies within the literature on career decision-profiles have adopted this perspective using samples of high school or college students. Multiple authors have used the concept of (in)decision to identify different profiles of (un)decided students (Argyropoulou et al., 2007; Cohen et al., 1995; Levin et al., 2022; Rojewski, 1994). Furthermore, these profiles have been found to relate to other student variables. For instance, Chartrand and colleagues (1994) identified profiles of indecisive students and related these profiles to cognitive and affective dimensions of career indecision, such as goal instability, self-esteem, and self-assessment confidence. Levin and colleagues (2022) showed that different career indecision profiles differed in career decision status and career decisional stress. Other researchers supplemented the measure of (un)decidedness with goal instability (Multon et al., 2007), or personality and ability measures (Kelly & Pulver, 2003).

Past research has also used alternative variables other than indecision to configure profiles. For example, both Porfeli and colleagues (2011) and Sestito and colleagues (2015) identified different vocational identity statuses. Germeijs and colleagues (2012) also identified different profiles of students’ decision-making process, based on six decisional tasks. They identified four profiles that paralleled Marcia’s identity statuses (Marcia, 1966), and found them to be associated with different personal (decision-making style, career choice anxiety, and career decision-making self-efficacy) and choice implementation variables (academic and social adjustment, and commitment to the chosen major) (Germeijs et al., 2012). De Clercq and colleagues (2017) based their profiles on high school grades, socio-economic status (SES), and self-efficacy beliefs in addition to study choice.

Most of these studies focused on career decision-making used more general measures of career (in)decision. Some of these studies used career
decisional, as well as personality, or other variables (e.g., personality measures, high school grades, SES) in their profile analyses. However, research suggests that using only career decisional variables in the profile analysis yields more accurate results as, in doing so, conclusions can be drawn without confounding influences from other related variables (Chartrand et al., 1994). Therefore, we will only include the career decisional variables in the profile analysis. Specifically, we will focus on different forms of exploration since career exploration forms a significant part of the career decision-making process. Additionally, while many researchers have attempted to identify different profiles of students, the explanatory base of these has been underexplored. It is nevertheless essential to understand if there are individual characteristics that could help explain this important study choice process. Accordingly, we seek to understand the explanatory base of these exploration profiles by investigating the unique contribution of a particular set of student variables (learning strategies, gender, and educational track) that are assumed to matter in the decision-making process. Next, we aim to relate these profiles to important outcomes of the study choice process (decisional status, commitment, and amount of information).

**Student Variables**

The literature suggests that gender and educational track may influence study choice processes. Research found gender differences on most—but not all—decisional tasks, with boys generally scoring lower than girls (Gamboa et al., 2013; Germeijs & Verschueren, 2006b). Other researchers also found these differences regarding exploratory behavior, in that girls tended to score higher on self-exploration (Lazarides et al., 2016; Seabi, 2012) or have more favorable exploration of the environment (Gamboa et al., 2013). Another study from Germeijs and Verschueren (2007a) revealed that girls scored higher on the subscales orientation and broad exploration at the beginning of their last year.
of secondary education. However, no significant differences were found at that timepoint for all other tasks. For in-depth exploration, girls showed greater progress than boys, meaning that they displayed higher levels of in-depth exploration at the end of secondary education (Germeijs & Verschueren, 2007a). This could be explained by the fact that, compared to boys, girls tend to show more engagement at school, meaning they, for instance, generally put more effort into school related tasks (Lietaert et al., 2015). This highlights a need for further research into the role of other student variables in the decision-making process. Regarding educational track, secondary education students from the technical track are generally assumed to be more ready to make a decision than those from the general track, which seems to be why they tend to score higher on the decision-making tasks at certain moments (Germeijs & Verschueren, 2007a). The general track of secondary education in Flanders specifically prepares students for higher education. Students who choose the technical track may already have to make a more specific and determining choice than those who opt for the general track. However, general track students tend to make greater progress during their final year of secondary education, which possibly explains their higher scores on some decisional tasks at the end of their schooling (Germeijs & Verschueren, 2007a).

As stated above, research into study choice processes has mainly focused on student variables such as gender and educational track. However, other interesting student variables that could be associated with the exploration profiles, are the learning strategies of students. In this study, we aim to explore whether learning strategies of students might be related to this exploration behavior regarding the study choice process. In contrast to background variables such as gender and educational track, these regulation and processing strategies can be changed and remedied. A multitude of studies have indicated individual differences in learning strategies in samples of students during their transition to higher education (Coertjens et al., 2017; J. D. Vermunt & Donche,
Regulation strategies are the learning activities used by students to regulate or steer their learning process. Processing strategies are the cognitive learning activities that students use to process learning content (J. D. Vermunt, 1998; J. D. Vermunt & Donche, 2017). To the best of our knowledge, the connection between students’ learning strategies and career exploration profiles has not been empirically investigated but can theoretically be assumed. Since the use of processing strategies is conducive to processing learning content, and regulation strategies steer the learning process, these strategies could be beneficial for processing information during the career exploration process (which in turn could also be associated with a better decisional outcomes). Research has shown, for instance, that a lack of self-regulatory skills is indicative of study choice uncertainty (Minnaert, 2000). Therefore, in addition to gender and educational track, we expect that students’ regulation and processing strategies might have additional value in explaining why the profiles differ regarding their exploration process.

Outcomes

Former research showed how the quality of the study choice process matters; a more informed choice was found to be positively related to study success in higher education (De Clercq et al., 2017). Students’ coping with career decisional tasks at the end of secondary education significantly contributed to their commitment to the chosen major during the first term of higher education (Germeijs & Verschueren, 2007b). Students with lower levels of decisional status and commitment at the end of secondary education had a decreased likelihood of actualizing their choice intention in higher education. Furthermore, students who displayed less in-depth exploratory behavior or showed less commitment to their choice at the end of secondary education were more likely to experience a weaker commitment to their chosen higher education program. Moreover, students who showed less commitment to their
choice had a higher risk of drop-out (Germeijs & Verschueren, 2007b). Research has also shown that lower levels of self-, broad and in-depth information acquired, decisional status, and commitment were positively related to career indecision (Germeijs et al., 2006a).

Based on previous research it can be expected that how students engage in exploration of study choices has an impact on the outcomes of this process. Three outcomes are of interest here: decisional status, commitment, and the amount of information acquired regarding higher education. Research has indicated positive associations between the career decision tasks and the amount of information students acquire about themselves, as well as about general and specific career alternatives (Germeijs et al., 2006a). Previous research has also suggested a positive relationship between career exploration tasks and decisional status. Career exploration enhances students’ readiness to decide on a particular career choice (Kleine et al., 2021). Indeed, broad and in-depth exploration of study career alternatives positively contribute to this in particular, and both are also associated with higher levels of commitment (Germeijs et al., 2006a; Germeijs & Verschueren, 2007b). Likewise, in vocational identity research, in-depth exploration has shown to be closely related to the process of committing to a career (Crocetti et al., 2008; Porfeli et al., 2011). Therefore, we expect that students who engage more in broad and in-depth exploration might be closer to making a decision and show higher levels of commitment compared to others showing less exploration of career alternatives.

The Present Study

This study aims to further understand individual differences in the decision-making process of students aiming to start a higher education program. Using a person-oriented research perspective, we want to identify different exploration profiles, to further unravel the explanatory base of student
variables, and to understand the relationship with crucial outcomes of the study choice process.

The research questions and expectations that guided this study are as follows. First, we are interested in unravelling which different exploration profiles can be identified, based on the four decisional tasks orientation, self-, broad, and in-depth exploration. Looking at prior research (see above), we expect to identify different profiles of students choosing a study for higher education which may indicate varying degrees of study choice quality. Since research has identified a range of different profiles (Argyropoulou et al., 2007; Chartrand et al., 1994; De Clercq et al., 2017; Germeijs et al., 2012; Kelly & Pulver, 2003; Sestito et al., 2015), we do not state explicit hypotheses regarding the specific nature of these profiles. In order to further understand the explanatory base of these profiles and the unique contribution of student variables, we will investigate the relationship with students’ regulation and processing strategies, gender, and educational track. We theoretically assume that more self-regulated students would also be more in control of their study choice process than their less-regulated peers. Likewise, using deeper processing strategies could be beneficial for processing information in the decision-making process (J. D. Vermunt & Donche, 2017). Since research indicates that female students score higher on most decisional tasks, we expect them to generally have more beneficial profiles than males (Gamboa et al., 2013; Germeijs & Verschueren, 2006b, 2007a; Lazarides et al., 2016; Seabi, 2012). Regarding educational track, research suggests that depending on the timepoint, general or technical track students could score higher on the decisional tasks (Germeijs & Verschueren, 2007a). As former studies have also highlighted the impact of the decision-making process on outcomes, we also investigate the associations with crucial outcomes of the process, such as decisional status, commitment, and amount of information. We expect students who undertake more active exploration to score higher on these
outcomes (Germeijs & Verschueren, 2006b, 2007b). Figure 2.1 shows the conceptual model used for this study.

**Figure 2.1**
The conceptual model for this study

**Methodology**

**Participants and Procedure**

Data used in this study are part of data collections taking place in the Columbus project — a large-scale research initiative funded by the Flemish Department of Education and Training. Columbus is also the name of the exploration instrument designed to improve the career decision-making processes of students nearing the end of secondary education (Demulder et al., 2020). The instrument consists of a set of validated questionnaires and tests, which by providing normed and personalized feedback, helps students explore their possibilities, explains their strengths and areas for improvement, informs them about possible risks when entering higher education, and provides them with suitable remediation tips for further development. The Columbus test results are non-binding; the purpose of the project is to inform students, the results do not influence their entrance to higher education.
Our (substantial) dataset consisted of 5,660 students who transitioned to the first year of higher education in the 2017-18 academic year. We selected students from the general track and technical track in secondary education because they most often make the transition to higher education. Since higher education in Flanders is largely unconstrained, students can freely choose from all study programs. Data regarding these students’ study choice processes and regulation and processing strategies were collected in February and March 2017 when students used the exploration instrument in their last year of secondary education. 40% of these students were identified as male and 60% as female. Their mean birth year was 1999, meaning that, on average, students were 18 years old when using the instrument. 66% were in the general track of secondary education and 34% in the technical track. Regarding higher education, no selection was made regarding the programs; all programs chosen by the students selected in the dataset were included. This resulted in a total of 135 different higher education programs. 51% of students were in an academic bachelor’s program and 49% in a professional bachelor, with most students choosing a program related to economics (18%), followed by engineering (10%), healthcare (10%), and education (9%).

Measures

**Exploration Profiles**

In the instrument, students are asked to self-report about their study choice process by filling out the previously validated shortened and updated version of the Study Choice Task Inventory (SCTI; Germeijs & Verschueren, 2006b). The shortened and updated version, the Study Choice Task Inventory (SSCTI), consists of six scales, each of which measures one of the six career-decisional tasks: Orientation, Self-Exploration, Broad Exploration, In-Depth Exploration, Decisional Status, and Commitment (Demulder et al., 2019). The
SSCTI has been validated in a former study on data stemming from the same project (Demulder et al., 2019).

For the latent profile analysis, the Orientation and Exploration subscales will be used. The subscale Orientation ($\alpha = .81$) assesses students’ awareness of the need to make a study career decision, as well as their motivation for making this decision. The students answer five items on a 5-point scale. The Self-Exploratory Behavior scale ($\alpha = .80$) measures the degree to which students gather information about themselves and consists of eight items answered on a 4-point scale. Broad Exploration ($\alpha = .84$) evaluates the extent to which students research general information about higher education, while In-Depth Exploration ($\alpha = .74$) measures the detailed information students gather about specific career alternatives. Both scales consist of five items answered on a 4-point scale. Before answering the In-Depth Exploration questions, the students have to list which majors they already explored. Those who have not collected information on programs do not have to fill out the In-Depth Exploration scale.

**Outcomes**

The central outcomes in this study are decisional status, commitment, and amount of information. The measurement of decisional status and commitment was based on the items and respective scales of the SSCTI. Decisional status, the first outcome, measures the progress of students in choosing a career option. This information is collected by two survey questions that ask the students to list the studies they are considering and to indicate whether they have a first choice. Their score is based on a combination of the answers to these two questions: (1) no first choice, no alternatives; (2) alternatives without first choice; (3) first choice with alternatives; and (4) first choice with no alternatives. The second outcome, commitment, was measured by the respective scale in the SSCTI ($\alpha = .85$) and evaluates how confident and
attached students are to their chosen career options. They answer five questions on a 6-point scale. Only students who indicate having a first choice in the question regarding decisional status (i.e., score 3 or 4) have to complete this scale. To measure the third outcome, amount of information, we used four items of the respective scale ($\alpha = .70$), based on research by Germeijs (2006). This scale evaluates students’ knowledge about the general structure of higher education and differences between different types of higher education. All items are answered on a five-point response scale.

**Student Variables**

We obtained information about students’ gender and educational track by linking the dataset to the database of the Flemish Department of Education and Training, which contains information about students’ secondary education careers.

We measured students’ learning strategies, and in particular students’ regulation and processing strategies by using the scales from the short version of the Inventory of Learning patterns of Students (ILS-SV; Coertjens et al., 2017; Donche & Van Petegem, 2008; J. D. Vermunt & Donche, 2017). To tap two distinct regulatory skills of students, we measured students’ self-regulation and lack of regulation. The scale ‘Self-regulation’ ($\alpha = .73$) assesses students’ ability to regulate and organize their own learning process, whereas the scale ‘lack of regulation’ ($\alpha = .70$) measures students’ difficulty with steering their own learning process. Students’ cognitive strategies were tapped by three distinct scales. The scale ‘Relating and structuring’ ($\alpha = .78$) measures students’ ability to seek and identify connections between their own knowledge and new learning content, and between different learning contents and distinct courses. The scale ‘Concrete processing’ ($\alpha = .71$) measures the degree to which they connect the learning content with their own experiences or tangible examples.
Finally, ‘Memorizing‘ ($\alpha = .67$) assesses students’ use of rote learning to remember facts, concepts, and features.

**Data Analysis**

To answer the first research question, unraveling which different exploration profiles can be identified, we standardized the scores of the four study choice tasks orientation, self-exploration, broad exploration, and in-depth exploration from the corresponding SSCTI scales before entering them into the analysis. Next, we performed a latent profile analysis on these scores using Latent Gold software (J. K. Vermunt & Magidson, 2016). A latent profile analysis is a model-based approach in which individuals are allocated into clusters based upon membership probabilities estimated directly from the model. This makes the choice of cluster criterion less arbitrary compared to standard cluster analysis techniques (Spurk et al., 2020; J. K. Vermunt & Magidson, 2002). With latent profile analysis, we can look into qualitatively different configurations of variables (Spurk et al., 2020). We used different parameters to evaluate distinct cluster solutions. We used the Bayesian Information Criterion (BIC) statistic to determine whether including additional classes would improve the model fit. The BIC for a solution with $k$ classes should be lower than for a solution with $k-1$ classes. Entropy (E) and the classification error (CE) were used to check the classification accuracy. The closer E is to 1 and CE is to 0, the more accurate the predictions (J. K. Vermunt & Magidson, 2005). Finally, it is important to determine the number of classes not only based on the fit indices, but also while considering theoretical justification, parsimony, and easiness of interpretation (Jung & Wickrama, 2008; J. K. Vermunt & Magidson, 2003).

To analyze the data in terms of the second research question—i.e., examining how gender, educational track, and regulation and processing strategies are associated with the exploration profiles—we used a multinomial logistic regression. To answer the third research question, searching for
associations between the exploration profiles and the three outcomes of the study choice process, we used 3-step analyses with correction methods to account for classification errors in the latent class/profile membership (Bakk et al., 2014; Gudicha & Vermunt, 2013). The Bolck-Croon-Hagenaars (BCH) correction method uses a weighted multiple-group analysis in the last step, whereas the ML method is a maximum likelihood method that takes the classification errors into account (Asparouhov & Muthen, 2021; Gudicha & Vermunt, 2013). The BCH method is the preferred method for continuous dependent variables, while the maximum likelihood (ML) method performs best with ordinal and nominal dependent variables (Bakk et al., 2013).

Results

Profiles

We inspected 1–8 cluster solutions so as to identify exploration profiles in the present dataset. All parameters are shown in Table 2.1. We used a combination of the BIC, classification error, and entropy (J. K. Vermunt & Magidson, 2005).

Table 2.1
Model fit statistics for the latent profile analysis

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<td>.20</td>
<td>.69</td>
</tr>
<tr>
<td>8</td>
<td>51,683.73</td>
<td>52,155.25</td>
<td>3594.49</td>
<td>.18</td>
<td>.76</td>
</tr>
</tbody>
</table>
With theory, parsimony, and interpretability in mind, and to ensure sufficient differentiation between the profiles, we chose the three-profile solution over other solutions indicating more profiles. The final three-profile solution is presented in Figure 2.2. The profiles are depicted using z-scores.

**Figure 2.2**
The three exploration profiles and corresponding z-scores for the four career-decisional tasks

A third of the students in our data belonged to profile 1 \((n = 1,985, 35\%)\), which consisted of students scoring relatively low on the four career decisional tasks. They were low to unengaged in orientation, self-, broad, and in-depth exploration. We labeled this profile the “passive explorers”. Over half of our sample belonged to profile 2 \((n = 2,933, 52\%)\), and scored moderately on all four career decisional tasks. They scored slightly above the mean for the study choice related activities regarding orientation and exploration, which is why we considered them to be moderately scoring. We labeled this profile the “moderately active explorers”. Profile 3 was a minority within the dataset \((n = 742, 13\%)\) that consisted of students scoring relatively high on all four career decisional tasks, meaning they undertook far more orientation and exploration.
activities compared to the other two profiles. Accordingly, we labeled this profile the “highly active explorers”. These results show that 87% of students are passive or moderately active explorers at the beginning of the final term of the last year of secondary education.

**Student Variables**

We used a multinomial logistic regression to investigate the associations between the profiles and student variables. Table 2.2 presents two sets of estimates: one for profile 1 (passive explorers) and one for profile 2 (moderately active explorers). Profile 3 (highly active explorers) serves as the reference group. We used two binary predictor variables: gender and educational track. Moreover, we also used five quantitative variables that measured self-regulation, lack of regulation, relating and structuring, concrete processing, and memorizing. For the multinomial logistic regression examining the effects of the predictor variables, the likelihood ratio test for the overall model revealed that the overall model was significantly more accurate than the intercept-only model $\chi^2 (14, N = 5,660) = 1,302.28, p < .001$. Indeed, Nagelkerke’s pseudo $R^2$ indicated that the model accounted for approximately 24% of the variance. In addition, the likelihood ratio test for individual effects revealed that all of the independent variables were significantly related to the categories of the dependent variable (self-regulation: $\chi^2 (2) = 155.90, p < .001$; lack of regulation: $\chi^2 (2) = 21.24, p < .001$; relating and structuring: $\chi^2 (2) = 53.99, p < .001$; concrete processing: $\chi^2 (2) = 56.49, p < .001$; memorizing: $\chi^2 (2) = 77.99, p < .001$; gender: $\chi^2 (2) = 273.36, p < .001$; educational track: $\chi^2 (2) = 8.78, p < .05$). The parameter estimates from the logistic regression model can be found in Table 2.2. According to these results, gender is significantly related to the distinction between the profiles, controlling for educational track and the regulation and processing strategies. Regarding gender, compared to the reference group (profile 3, the highly active explorers), male students were
more likely to be included in profiles 1 and 2 (passive or moderately active explorers) than female students. Examining educational track, there was only a significant difference between the moderately and highly active explorers: general track students were more likely to be placed in profile 2 than technical track students. Regarding the regulation and processing strategies, students scoring higher on self-regulation, relating and structuring, concrete processing, and memorizing were less likely to be included in profiles 1 and 2 (passive or moderately active explorers) than in profile 3 (highly active explorers), controlling for gender and educational track. In addition, the results also show that students reporting more lack of regulation in their own learning were more likely to be passive or moderately active explorers. Students who are more self-regulated and process learning contents in an active way were also found more present in the group of active explorers, even after controlling for gender and educational track. Finally, when examining the full multinomial logistic regression model, we could identify a risk profile of students (passive explorers, 35%) which tends to consist more of male students and students with lower scores for self-regulation, relating and structuring, concrete processing, and memorizing, while simultaneously having higher scores for lack of regulation.
Table 2.2
Multinomial logistic regression results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Passive versus Highly active</th>
<th></th>
<th></th>
<th>Moderately active versus Highly active</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β (SE)</td>
<td>95% CI for Odds Ratio</td>
<td>95% CI for Odds Ratio</td>
<td>β (SE)</td>
<td>95% CI for Odds Ratio</td>
<td>95% CI for Odds Ratio</td>
</tr>
<tr>
<td>Interception</td>
<td>6.88 (.37)</td>
<td>4.11 (.34)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Self-regulation</td>
<td>-.95** (.08)</td>
<td>.33 .39 .46</td>
<td></td>
<td>-.39** (.07)</td>
<td>.59 .68 .78</td>
<td></td>
</tr>
<tr>
<td>Lack of regulation</td>
<td>.31** (.07)</td>
<td>1.19 1.36 1.55</td>
<td></td>
<td>.18* (.06)</td>
<td>1.07 1.20 1.35</td>
<td></td>
</tr>
<tr>
<td>Relating and structuring</td>
<td>-.57** (.09)</td>
<td>.48 .57 .67</td>
<td></td>
<td>-.27* (.08)</td>
<td>.66 .77 .89</td>
<td></td>
</tr>
<tr>
<td>Concrete processing</td>
<td>-.49** (.08)</td>
<td>.53 .61 .72</td>
<td></td>
<td>-.15* (.07)</td>
<td>.75 .86 .99</td>
<td></td>
</tr>
<tr>
<td>Memorizing</td>
<td>-.56** (.07)</td>
<td>.51 .57 .65</td>
<td></td>
<td>-.34** (.06)</td>
<td>.64 .71 .80</td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>1.53** (.11)</td>
<td>3.71 4.60 5.71</td>
<td></td>
<td>.65** (.10)</td>
<td>1.57 1.91 2.33</td>
<td></td>
</tr>
<tr>
<td>Educational track</td>
<td>.18 (.10)</td>
<td>.98 1.19 1.46</td>
<td></td>
<td>.27* (.09)</td>
<td>1.09 1.30 1.56</td>
<td></td>
</tr>
</tbody>
</table>

Note. The reference category includes profile 3 students; females were the reference group for gender; technical track was the reference group for educational track.
* Significant at the <.05 level
** Significant at the <.001 level

For completeness, we also conducted analyses using the moderately active profile as a reference group. This table can be found in Appendix 2.A.
Outcomes

To answer the third research question (i.e., to investigate the relationship with different outcomes of the decision-making process) we used 3-step analyses with ML and BCH correction methods. We first ran a 3-step analysis with ML correction to detect differences in decisional status across the different profiles. Due to the fact that two cells contained fewer than five cases, we collapsed the data, meaning that scores 1 and 2 were combined to form an “undecided” category, and scores 3 and 4 were combined to form a “decided” category. The results indicated a significant association between the profiles and Decisional Status (Wald $\chi^2 (2) = 49.50, p < .001$). Decided students were more likely to be placed into profile 3 (highly active explorers; 92.5%) compared to profile 1 (passive explorers; 81.1%) and profile 2 (moderately active explorers; 86.9%). Profile 1 contained more undecided students (19%) than profile 2 (13.1%) and profile 3 (7.5%). The highly active explorers were thus more likely to have made their decision than the passive and moderately active explorers. The passive explorers were the most likely to fall into the undecided category.

We used 3-step analyses with BCH corrections to determine whether significant differences existed among the three profiles based on the scales for Amount of Information and Commitment (see Table 2.3). The overall models for both outcomes were significant (Commitment: Wald $\chi^2 (2) = 349.41, p < .001$; Amount of Information: Wald $\chi^2 (2) = 1493.93, p < .001$). For the commitment outcome, the highly active explorers ($M = 4.66, SE = .04$) demonstrated a significantly higher mean than the moderately active explorers ($M = 4.34, SE = .02$), who in turn scored significantly higher than the passive explorers ($M = 3.89, SE = .02$). For Amount of Information, the analysis indicated similar results, with profile 3 demonstrating a significantly higher mean ($M = 4.50, SE = .02$) than profile 2 ($M = 4.09, SE = .01$), who in turn scored significantly higher than profile 1 students ($M = 3.50, SE = .02$). In terms of the obtained outcomes of their study choice processes, profile 3
students thus showed higher levels of commitment and acquired a greater amount of information compared to profile 2 and 1 students, respectively. On the other hand, profile 1 students showed less commitment and acquired a smaller amount of information compared to profile 2 and 3 students.

Table 2.3
Means, Standard Errors, and Wald statistics for Commitment and Amount of Information

<table>
<thead>
<tr>
<th></th>
<th>Passive explorers</th>
<th>Moderately active explorers</th>
<th>Highly active explorers</th>
<th>Wald χ²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SE</td>
<td>M</td>
<td>SE</td>
</tr>
<tr>
<td>Commitment</td>
<td>3.89</td>
<td>.02</td>
<td>4.34</td>
<td>.02</td>
</tr>
<tr>
<td>Amount of Information</td>
<td>3.50</td>
<td>.02</td>
<td>4.09</td>
<td>.01</td>
</tr>
</tbody>
</table>

* \( p < .001 \)

Discussion

The present study aimed to further unravel the differences present within the decision-making process of last year students in secondary education making a study choice to transition to higher education. To that end, we examined students’ exploration profiles and the association with theoretically relevant student variables and study choice process outcomes.

The first objective was to identify different exploration profiles. We chose to adopt a person-centered approach in order to deepen the understanding of the decision-making process. Following recommendations by Chartrand and colleagues (1994), we only used decision-making variables to determine the profiles. We chose a latent profile analysis over standard cluster analysis techniques because the model-based approach makes the choice of cluster criterion less arbitrary (J. K. Vermunt & Magidson, 2002). The latent profile analysis on four decision-making tasks revealed the presence of three exploration profiles. A third of the sample fell into the passive explorers profile who we found to be relatively low to unengaged in terms of orientation or
exploration regarding their study choice. Over half of the students were slightly more aware of the need to decide and were in the process of exploring both themselves as well as information regarding higher education. Accordingly, we labeled them as moderately active explorers. The minority of students (13%) fell into the profile of students who were already invested in orientation as well as all three exploration tasks. We labeled them as highly active explorers. It may seem surprising that the majority of students fell into the low and moderate profile instead of the high profile. One possible explanation for this could be the time at which the students completed the SSCTI. The survey was administered in February and March, the beginning of the second term of the school year or about six months before the start of higher education. Results could have been different had we measured the variables in later stages of the decision-making process, i.e. the last two months of the school year (May or June); in that case, we would expect more students to have been highly active. In Flanders, students can freely choose any program at a university or college of their choice, a few exceptions (i.e., medicine, dentistry, and some art programs that do have admission tests) left alone. This means they have a lot of options to choose from, which could explain why their exploration and decision-making process takes a longer time. A second explanation could be the diversity in our dataset. The dataset consisted of a substantial number of students \(n = 5,660\) from both the general and technical educational tracks. At last, our findings suggest that at the start of the final term in secondary education, on the verge of transitioning to higher education, a majority of students are not quite actively involved in the study choice exploration process, which highlights the urgency of fostering this decision-making process within students at an earlier stage.

Second, we investigated the relationship between the profiles and different student variables. The results indicate significant associations between
the profiles and the student variables regulation and processing strategies, gender, and educational track.

As theoretically expected, different regulation and processing strategies were associated with the different exploration profiles. Students scoring higher on self-regulation, relating and structuring, concrete processing, and memorizing, and lower on lack of regulation were far more likely to be highly active than passive or moderately active. Conversely, students with poor regulatory skills and showing low processing strategies were more frequently classified as passive explorers, and thus at risk of suboptimal decision-making. This finding supports our hypothesis that, since the use of regulation and processing strategies is beneficial when processing learning content, these strategies are also important for processing information in the exploration process, which in turn could lead to better decision-making outcomes.

We found that male students were more likely to be passive or moderately active explorers than their female counterparts, who themselves were more frequently profiled as highly active explorers with high scores on all four decision-making tasks. These results are in line with Germeijs and Verschueren (2007a), who found that female students generally score higher on orientation and broad and in-depth exploration, and with research by Gamboa and colleagues (2013) who found that girls report higher levels of exploration of the environment. Other research by Seabi (2012) and Lazarides and colleagues (2016) also showed that girls achieved higher scores on self-exploration. We have now confirmed this finding in a larger dataset which also included technical track students.

We only found one significant difference when examining educational track. Compared to technical track students, those in the general track were more likely to be moderately active than highly active explorers. A possible explanation could be the quite early timepoint at which the students completed the questionnaire. Research from Flanders shows that technical track students
tend to be more ready to make their decisions than those in the general track, which is why they are more likely to have higher scores on the decision-making tasks at certain moments (Germeijs & Verschueren, 2007a). This might be explained by the fact that technical track students in Flanders had to make a more specific and determining study choice compared to those who opted for the general track. If the questionnaire had been administered at a later moment, the situation could have been different, since research indicates that general track students make greater progress during the last year of secondary education, and thus score higher on some decisional tasks at the end of secondary education (Germeijs & Verschueren, 2007a).

Finally, the different profiles were associated with decisional status, commitment, and the amount of information acquired regarding higher education. First, the highly active explorers scored significantly higher on Amount of information than the moderately active explorers who in turn had higher scores than the passive explorers. These results accord with research showing positive associations between exploratory behavior during the career decision process and the amount of information acquired (Germeijs et al., 2006a). Logically, and as evidenced in our data, students who are more engaged in the broad exploration of the higher education system and the in-depth exploration of specific career alternatives seem to gather more knowledge about the structure of higher education during this exploration process.

Second and as expected, the highly active explorers were the most likely to have already made a decision regarding their program choice. Moreover, this group also appeared more likely to already have a first choice compared to the other two profiles. These results are in line with research indicating a positive relationship between career exploration tasks and decisional status (Germeijs et al., 2006a; Germeijs & Verschueren, 2007b; Kleine et al., 2021). Students who displayed higher levels of broad and in-depth exploration were more likely to report being closer to making a decision.
Nevertheless, even among the passive and moderately active explorers, a large proportion of students (81.1% and 86.9%, respectively) indicated that they already had a first choice in mind. This suggests that students do not necessarily engage actively in an exploration process when deciding on a study choice, as some may foreclose (Germeijss et al., 2012). Also, given that the study choice process is conceived as a circular process (Germeijss & Verschueren, 2006b), making tentative choices may stimulate students to take further steps in the exploration process later on.

Finally, the highly active explorers scored significantly higher on commitment than the moderately active explorers who themselves outperformed the passive explorers. Research has shown that broad and in-depth exploration are associated with higher levels of commitment (Germeijss et al., 2006a; Germeijss & Verschueren, 2007b; Porfeli et al., 2011). Accordingly, since the highly active explorers displayed high levels of broad and in-depth exploration, they also obtained higher scores for commitment to their decision than their moderately active and passive counterparts who conducted less exploration. However, it is worth noting that not all students completed the commitment scale due to it being conditional; it was only completed by those who indicated having a first choice in the decisional status scale.

Limitations and Directions for Further Research

The present study has some limitations which, when addressed, may also provide suggestions for future research. First, although we used a large sample and looked at the two most important education tracks that prepare for higher education, it could be interesting to also examine the exploration profiles at a more fine-grained level by looking at the possible relationship with specific study programs within the two educational tracks. Second, we based the exploration profiles on self-report measures, which could have allowed for bias as students may have answered questions in a socially desirable way.
Nevertheless, we found quite a diversity of exploration profiles not just indicating so-called positive exploration profiles. A final limitation concerns the cross-sectional design used, which does not allow the examination of directionality. Students completed the questionnaire at only one timepoint in the year. Future research could opt for a longitudinal design in which the SSCTI is administered at multiple timepoints during a school year to check the stability and variability of the exploration profiles across time. Longitudinal research could also further explore the relationship between exploration profiles and learning outcomes such as student success in the chosen higher education program.

**Implications**

Through the identification of different exploration profiles, this study contributes to a more comprehensive understanding of the different ways that students decide upon what to study for higher education. Given the variety of exploration profiles found, these insights can lead to more tailored support for the different profiles throughout the decision-making process. Tailored assistance or intervention programs that more effectively match students’ exploration profiles could be developed. For instance, the passive explorers, who often might yet have to fully start the decision-making process, could be activated to invest more effort in the exploration process and supported in how to start gaining information about the self and career options. Indeed, given their low self-regulation when processing learning contents, they could possibly benefit from higher levels of externally regulated guidance. Being more guided and coached in this important decision-making process for their future study career could thus be important for them. Moreover, it seems crucial here that these regulation and processing strategies can be changed and remedied. In the study choice process guidance at school, it could be important to take into account that learning strategies are related to the exploration process. It may
be interesting to differentiate the counseling of this process based on the learning strategies. By training students in these important academic skills, they could also improve in processing the information in the exploration process, which in turn could lead to a more beneficial exploration profile, as well as associated beneficial outcomes of the decision-making process (Hattie et al., 1996). The moderately active explorers could benefit from support in identifying and organizing the different options open to them as they advance through the career decision-making process. The highly active explorers—who have already conducted a lot of exploration—could perhaps use some extra help to commit to their provisional decisions, such as assistance with identifying the necessary steps for turning a decision into a tangible and committed-to reality. However, since self-regulation and deep processing of information are important assets to process a wealth of information when making a study choice, it seems that these active exploration students also might be more successful in this process. This is indeed supported by their higher scores for decisional status and commitment as found in the current study.

Finally, we have also identified that not all students are highly engaged at this crucial time for making a choice for future higher education; indeed, many students may even be described as ‘at risk’. This is clearly the case for the passive explorers who are far away from making decisions, seem less knowledgeable about higher education, and, in the case they already have a study choice in mind, show far less commitment. This illustrates the importance of the identification of these exploration profiles. By raising greater awareness among students about their engagement in the study choice process, important feedback could be provided to them. Offering these students the necessary support could possibly prevent future failure in higher education caused by making an underexplored study choice.
CHAPTER 3

Understanding transitions in exploration profiles of students opting for higher education

Published manuscript:

Abstract

Since previous research on educational career exploration has mainly been cross-sectional and has therefore been unsuccessful in explaining how this process can change during the final year in secondary education before students make the transition to higher education, this study aimed to examine changes over time in the exploration process. A person-centered research perspective was taken to further deepen the understanding of how different exploration tasks jointly combine into meaningful profiles. In this way, this study tried to gain more insight into why some students go through this process successfully and others do not. Three goals guided this study: identifying exploration profiles of students in Fall and Spring of the final year in secondary school based on four decisional tasks (orientation, self-, broad, and in-depth exploration), investigating transitions between exploration profiles across these two timepoints, and examining the role which different antecedents (i.e., academic self-efficacy, academic self-concept, motivation, test anxiety, gender, educational track, socio-economic status) play in explaining both profile membership and transitions between profiles. Using self-report questionnaires to measure the exploration tasks and the antecedents in final year students, two cross-sectional samples collected in Fall ($n = 9,567$) and Spring ($n = 7,254$), and one longitudinal sample ($n = 672$) were examined. Latent profile analyses identified three exploration profiles at both timepoints: passive, moderately active, and highly active explorers. Latent transition analysis showed the moderately active explorers profile to be the most stable profile, while the passive profile was the most variable. Academic self-concept, motivation, test anxiety, and gender had an effect on the initial states, while motivation and test anxiety affected the transition probabilities. For both academic self-concept and motivation, students scoring higher were found to be less present in the passive or the moderately active than in the highly active profile. Furthermore,
compared to students who remained in the passive profile, higher levels of motivation were associated with a higher probability of transitioning to the moderately active profile. Furthermore, compared to students who remained in the highly active profile, higher levels of motivation were associated with a lower probability of transitioning to the moderately active profile. Results on anxiety were inconclusive. Based on substantial cross-sectional as well as longitudinal data, our findings contribute to a more comprehensive understanding of the explanatory base of important differences in the study choice making process of students opting for higher education. This may ultimately lead to more timely and fitting support for students with different exploration profiles.
Introduction

The process of choosing a program in the transition to higher education is very important. The quality of this decision-making process can have an impact on choice actualization, commitment to the chosen program, and academic adjustment in higher education (Gati & Asher, 2001b; Germeijs & Verschueren, 2007b; Skorikov, 2007; Van Esbroeck et al., 2005). Career exploration is a key component of study choice processes and, accordingly, of higher education adjustment and success.

In Flanders, Belgium, the higher education system is open access, with no centralized exams at the end of secondary education and no entrance exams at the start of higher education (a few exceptions such as medicine, dentistry, and some art programs left alone). Unfortunately, Flemish higher education is also characterized by high levels of study delay and drop-out, implying high potential costs for individuals and society at large (OECD, 2022). In Flanders, of the students who started higher education in 2018-2019, only 30% obtained their bachelor’s degree within the predetermined study duration (Statistiek Vlaanderen, 2022b). In the academic year 2019-2020, 14% of students dropped out after one year of higher education (Statistiek Vlaanderen, 2022a). The quality of the study choice is diverse in this context and can have an important impact on higher education success and drop-out rates (Germeijs & Verschueren, 2007b; Lacante et al., 2001). This research context is therefore interesting, in order to gain more insight into individual differences in the career exploration process of students opting for higher education in the last year of secondary education and understanding the role of antecedents. It can contribute to more evidence on the explanatory base of important differences in the career exploration process of students opting for higher education.
Theoretical framework

Study Choice Process, Profiles and Transitions

The decision-making process involves a substantial amount of career exploration (Gati & Asher, 2001a). Stumpf and colleagues (1983) defined career exploration as purposive behavior and cognitions that are associated with vocational development. In this process, people explore both the self and the environment to better understand their characteristics and to uncover potential career options (Porfeli & Lee, 2012). Germeijs and Verschueren (2006b) identified six decisional tasks within the higher education decision-making process: orientation, self-exploration, broad exploration of the environment, in-depth exploration of the environment, decisional status, and commitment. These decision-making tasks are dynamic and flexible; there is no fixed order in which they should be tackled and tasks can be skipped or returned to as necessary (Germeijs & Verschueren, 2006b, 2010). Four of these are important regarding career exploration. Orientation assesses students’ awareness of the need to decide and their motivation to make the best possible career choice. Self-exploratory behavior measures the extent to which students learn about their interests and abilities, and to what extent they discuss their attributes with significant sources of information (e.g., parents, friends, teachers). Broad exploration evaluates how much general information about higher education students research, while in-depth exploration measures the extent to which students acquire detailed information about specific career perspectives (Germeijs & Verschueren, 2006b).

Most studies examining career exploration processes have used a variable-centered approach, investigating correlates of differences in variable scores for career exploration tasks. Demulder and colleagues (2022) complemented previous research by adopting a person-centered approach. Person-centered analysis techniques cluster or group individuals based on
shared characteristics (Hickendorff et al., 2018; Woo et al., 2018) and have become increasingly common in vocational research. These analyses allow us to distinguish more homogeneous groups of individuals who share more communalities with regard to the targeted research variables in a sample, in this study, their ways of engaging with the different study choice tasks for higher education. Based on students’ scores on four decisional tasks (i.e. orientation, self-, broad, and in-depth exploration), Demulder and colleagues (2022) identified three exploration profiles using latent profile analysis: passive, moderately active, and highly active explorers. However, a longitudinal design could offer supplementary insight into the variability of the exploration profiles over time. Up until now, longitudinal research addressing the development of the career decision-making process in general, and the exploration process in particular, is very scant. As one of the exceptions, Germeijs and Verschueren (2006a), using a variable-centered approach, showed that, on average, students progressed a lot during the last year in secondary education and showed significant improvement in all exploration tasks. The present study aims to add to this literature by clarifying how the career exploration process of students deciding for higher education, changes during the final year of secondary education, using a person-centered approach. Particularly, latent transition analysis is useful for combining the cross-sectional measurement of categorical latent variables and the longitudinal description of change in the categories of the latent variable over time (Nylund, 2007). This allows us to further understand if and why students’ exploration profiles are variable or stable across time.

Antecedents

Jiang and colleagues (2019) present a framework of different individual and contextual antecedents that may influence career exploration in adolescence. This framework summarizes the existing evidence regarding the antecedents,
outcomes, and moderators of career exploration. It shows that career exploration is powered by a combination of personal and contextual factors. Some antecedents foster exploration while others hinder it (Jiang et al., 2019). Several of these antecedents, both fostering and hindering, will be jointly examined in the present study to unravel the explanatory base of important differences in the study choice making process of students opting for higher education. In the present study, the antecedents will be jointly investigated in contrast with previous research focusing more often on separate antecedents. In addition to characteristics that are fixed, we choose to also focus on malleable characteristics since the students can take action on these themselves. The antecedents that will be further focused on in the present study are the following: academic self-efficacy, academic self-concept, motivation, test anxiety, gender, educational track, and socioeconomic status (SES).

Self-efficacy has been identified as a crucial factor in career exploration. Self-efficacy reflects people's expectations and convictions about what they can achieve in given situations (Bong & Skaalvik, 2002). Research has shown self-efficacy to be positively related to exploration as well as career planning, with more confident students reporting more career exploration (Creed et al., 2007; Rogers et al., 2008; Rogers & Creed, 2011). Self-efficacy also showed to be positively related to career exploration over time (Creed et al., 2007). An intervention study by Chiesa and colleagues confirmed that an increase in self-efficacy is positively associated with an increase in career exploration; improvement of self-efficacy was effective in increasing career exploration (Chiesa et al., 2016). Usually, career decision-making self-efficacy is assessed, also in the previously mentioned studies. Deng and colleagues (2022), however, used a measure of academic self-efficacy and investigated how this was related to different career development profiles. Their results demonstrated that the profile with the highest level of career exploration also
showed a higher level of academic self-efficacy compared to profiles showing less career exploration (Deng et al., 2022).

While academic self-efficacy portrays individuals’ convictions of what they can accomplish in given situations, academic self-concept refers to individuals’ perceptions about themselves in an academic situation (Bong & Skaalvik, 2002). Academic self-concept has been shown to be an important predictor for the awareness to start the career choice process for a future study (i.e., orientation) and demonstrates to be negatively associated with problems with orientation. How adolescents judge their academic abilities is related to how they think about engaging in orientation for a career in the future (van der Aar et al., 2019). Relatedly, vocational self-concept crystallization (i.e., “the degree of clarity and certainty of self-perception with respect to vocationally relevant attitudes, values, interests, needs and abilities” (Tokar et al., 2003, p. 5)) demonstrates a negative relationship with career indecision (Landine, 2016; Tokar et al., 2003), so a positive vocational self-concept can prevent career indecision and facilitate the decision-making process (Landine, 2016).

In addition, student motivation plays a part in career exploration. Motivational factors have been established as important predictors of broad and in-depth exploration, both at the between-person and within-person level (B. Lee et al., 2016). Research by Deng and colleagues (2022) showed that a career development profile highest in career exploration also showed higher levels of academic motivation compared to other profiles showing less exploration. Paixão and colleagues (2017) argued that the type of motivation might play a role. For instance, self-determined students exhibited the most positive vocational behavior. More specifically, they showed higher levels of exploration and lower levels of career indecision (Paixão & Gamboa, 2017). In line with these findings, research by Duchesne and colleagues (2012) demonstrated that students who actively explored showed higher levels of self-determined academic motivation. In comparison, non-self-determined
students exhibited the most negative vocational behavior and showed low levels of career exploration and high levels of indecision (Duchesne et al., 2012).

Anxiety can also be linked to exploration, but results on this relationship are inconsistent. According to research, different types of anxiety may influence exploration in various ways. Career anxiety is demonstrated to be positively related to environmental exploratory behavior (Germeijs et al., 2006b; Vignoli et al., 2005). Career anxiety seems to decrease the processing of all non-vocational information while increasing the processing of vocational information (Vignoli et al., 2005). On the other hand, general anxiety is shown to limit exploration, possibly because it is not targeted toward the academic and vocational future. General anxiety is shown to incite the search for irrelevant information, which may hinder the search for academic and vocational information (Vignoli et al., 2005). However, other research by Vignoli (2015) unexpectedly showed a positive relationship between general anxiety and career exploration. Their research also showed that the fear of failing in school played a greater, positive, role than general anxiety in career exploration (Vignoli, 2015). These inconsistent results show that different types of anxiety may influence exploration differently and that even the same types of anxiety can demonstrate different relations with exploration.

Research suggests gender may also influence the decision-making process. Boys tend to make their final decision more quickly, whereas girls tend to put more effort into the decision-making process and consult others more (Gati et al., 2010). According to Germeijs and Verschueren (2006b), boys often score worse than girls on the majority of decision-making tasks. Girls generally scored better on self-exploration (Lazarides et al., 2016; Seabi, 2012) or had higher levels of exploration of the environment (Gamboa et al., 2013). Another study from Germeijs and Verschueren revealed that girls scored better on the subscales orientation and broad exploration at the start of their senior year of
high school. For all other tasks, there were no significant differences found at that timepoint. However, girls made more progress than boys in in-depth exploration, demonstrating higher levels of in-depth exploration at the end of secondary school (Germeijs & Verschueren, 2007a). Research from Demulder and colleagues (2022) associated gender with different exploration profiles and confirmed the aforementioned findings and showed that girls were more likely to be found in the highly active explorers profile compared to a moderately active or passive explorers profile. These results regarding gender could be explained by the fact that girls exhibit greater levels of engagement in school than boys do, meaning they, for instance, generally put more effort into school-related tasks (Lietaert et al., 2015).

The general track of secondary education in Flanders specifically prepares students for higher education. Students who choose the technical track may already have to make a more specific and determining choice than those who opt for the general track. Therefore, students from the technical track are generally assumed to be more ready to decide than students from the general track, which seems to be why they tend to score higher on the decision-making tasks at certain moments (Germeijs & Verschueren, 2007a). However, general track students tend to make greater progress during their final year of secondary education, which possibly explains their higher scores on some decisional tasks at the end of their schooling (Germeijs & Verschueren, 2007a). Research by Demulder and colleagues (2022) demonstrated inconclusive results regarding the relationship between educational track and different exploration profiles. Compared to technical track students, those in the general track were more likely to be moderately active than highly active explorers, but no significant difference between the passive and highly active explorers profile was found.

Finally, a higher socioeconomic status was demonstrated to be positively related to the decision-making process. Students who indicated
having greater economic resources, social power, and social prestige, expressed greater confidence in their capacity to carry out career decision-making tasks (Metheny & McWhirter, 2013; Thompson & Subich, 2006) and reported more certainty in their career decision (Thompson & Subich, 2006).

**The Present Study**

The present study aimed to examine the exploration process using a person-centered approach to better understand differences in the higher education decision-making process. We first investigated the presence of exploration profiles based on four different decision-making tasks within the process (i.e., orientation, self-, broad, and in-depth exploration) cross-sectionally at two timepoints (Fall and Spring of the senior year in secondary education). Secondly, we examined in which way students transition between exploration profiles across the two timepoints. Finally, we investigated different antecedents of both profile membership and transitions between profiles. Four research questions guided this study. The first research question is as follows: “Which exploration profiles of students can be identified in Fall and Spring of the final year in secondary school?” We expected to find three exploration profiles at both timepoints: passive, moderately active, and active explorers, based on previous research with a similar sample (Demulder et al., 2022). The second research question of this study was “To what extent do students transition between exploration profiles across these two timepoints?” Since research showed that students improve significantly in all exploration tasks during the last year of secondary education (Germeijs & Verschueren, 2006b), we expected that if students transition between profiles they will primarily move to profiles with higher levels of exploration between Fall and Spring. The third and fourth research questions both looked further into the role that different antecedents play: “Can different antecedents (i.e., academic self-efficacy, academic self-concept, motivation, test anxiety, gender, educational
track, socio-economic status) explain profile membership?” and “Can these different antecedents explain who transitions between profiles?”. Based on previous research, we expected academic self-efficacy, academic self-concept, and motivation to have a positive effect on exploration. Research on the relationship between exploration and anxiety has been inconsistent and has not yet focused much on test anxiety, but we expect it to also have a positive effect based on the research by Vignoli and colleagues (2015). So, we expected students with higher average scores for academic self-concept, academic self-efficacy, motivation, and test anxiety to have more active profiles and to be able to transition to a more active exploration profile. Since research indicates that female students score higher on both self- and environmental exploration (Gamboa et al., 2013; Germeijs & Verschueren, 2006b, 2007a; Lazarides et al., 2016; Seabi, 2012) and are more likely to be in a highly active profile (Demulder et al., 2022), we expect girls to have more active profiles and to be better able to transition to a more active exploration profile. Regarding educational track, research suggests that technical track students are generally more ready to make a decision than those from the general track, but that general track students tend to make greater progress during their final year of secondary education (Germeijs & Verschueren, 2007a). We thus expect the technical track students to have more active initial profiles but the general track students to be more capable of transitioning to a more active exploration profile. SES has shown to be positively related to the decision-making process. Therefore we expect students with higher SES to have more active profiles and to be able to transition more easily to a more active exploration profile. Figure 3.1, based on the framework proposed by Jiang et al. (2019), shows the conceptual model used for this study.
Figure 3.1
The conceptual model for this study

<table>
<thead>
<tr>
<th>Individual antecedents</th>
<th>Career exploration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personal beliefs: Academic self-efficacy, Academic self-concept</td>
<td></td>
</tr>
<tr>
<td>Motivation</td>
<td></td>
</tr>
<tr>
<td>Psychological states: Test anxiety</td>
<td></td>
</tr>
<tr>
<td>Demographics: Gender, Educational track, SES</td>
<td></td>
</tr>
</tbody>
</table>

Methodology

Participants and Procedure

Data used in this study are part of data collections taking place in the Columbus project — a large-scale research initiative of the Flemish Department of Education and Training. Columbus is also the name of the exploration instrument designed to improve the career decision-making processes of students nearing the end of secondary education (Demulder et al., 2020). The instrument consists of a set of validated questionnaires and tests, which, by providing normed and personalized feedback, helps students to explore their possibilities, explains their strengths and areas for improvement, informs them about possible risks when entering higher education, and provides them with suitable remediation tips for further development.

Data from three cohorts (school years 2017-2018, 2018-2019, 2019-2020) were merged to ensure sufficient data were present for the analyses. We selected students from the general and technical tracks because they most often make the transition to higher education. Since higher education in Flanders is largely unconstrained, students can freely choose from all study programs. Furthermore, we selected those students who filled out the Shortened Study Choice Task Inventory (SSCTI) a first time in Fall and a second time in Spring and who actually started higher education in the following academic year. These two timepoints were chosen since previous research showed an increase
in all exploration tasks between the first and second trimester of the senior year (Germeijs & Verschueren, 2006b). For Fall the months of October and November were selected, and for Spring the months of February, March, and April. This resulted in three datasets for further analysis: a cross-sectional dataset for Fall (sample A), a cross-sectional dataset for Spring (sample B), and a longitudinal dataset (sample C). For the longitudinal dataset, an extra selection was made in that students should have completed the scales regarding the antecedents in Fall. The data were standardized and examined for outliers, defined as students who scored higher than three SDs above or below the mean on the scales under investigation.

After deleting 299 students because they were outliers \( (n = 150) \) or answered one or both of the bogus items incorrectly \( (n = 153) \), sample A (cross-sectional Fall dataset) consisted of 9,567 students. Of these students, 36.6% were identified as male and 63.4% as female. On average, students were 18 years old when using the instrument. 68.5% were in the general track of secondary education and 32.5% were in the technical track. Regarding higher education, no selection was made regarding the programs; all programs chosen by the students selected in the dataset were included. This resulted in a total of 160 different higher education programs being present in the final dataset for sample A. 53.4% of students were in an academic bachelor’s program, 45.6% in a professional bachelor’s program, and 1% in an associate’s degree program with most students choosing a program related to economics (16.5%), healthcare (9.4%), social work (8.8%), or engineering (8.6%).

After deleting 184 students because they were outliers \( (n = 49) \) or answered one or both of the bogus items incorrectly \( (n = 138) \), sample B (the cross-sectional Spring dataset) consisted of 7,254 students for timepoint 2 (Spring). Of these students, 40.9% were identified as male and 59.1% as female. They were 18 years old when using the instrument. 59.8% were in the general track of secondary education and 40.2% were in the technical track.
Regarding higher education, no selection was made regarding the programs; all programs chosen by the students selected in the dataset were included. This resulted in a total of 159 different higher education programs in the final dataset for sample B. 48.2% of students were in an academic bachelor’s program, 50.6% in a professional bachelor’s program, and 1.2% in an associate’s degree program with most students choosing a program related to economics (16.6%), engineering (11.7%), healthcare (9.8%), or social work (8.9%).

After deleting 39 students because they were outliers ($n = 6$) or answered one or both of the bogus items incorrectly ($n = 33$), sample C (the longitudinal dataset) consisted of 672 unique cases. Of these students, 31.7% were identified as male and 68.3% as female. 60.1% were in the general track of secondary education and 39.9% in the technical track. Again, all programs chosen by the students selected in the dataset were included. This resulted in 102 different higher education programs being present in the data. 49.9% of students were in an academic bachelor’s program, 48.2% in a professional bachelor’s program, and 1.9% in an associate’s degree program. Most students chose a program related to economics (15%), healthcare (10%), social work (9.7%), engineering (9.5%), or education (8.8%).

**Measures**

*Exploration Profiles*

Students completed the validated shortened and updated version of the Study Choice Task Inventory (SSCTI; Demulder et al., 2019). The Study Choice Task Inventory (SCTI) has six scales, each of which measures one of six career-decisional tasks: Orientation, Self-Exploration, Broad Exploration, In-Depth Exploration, Decisional Status, and Commitment (Germeijs & Verschueren, 2006b).
In the current study, the Orientation and Exploration subscales were used. The subscale Orientation ($\alpha_{\text{range sample A, B, C}} = .79-.82$) measures students’ awareness of the need to make a study career decision, as well as their motivation for making this decision. On a 5-point scale, the students respond to five items. The Self-Exploratory Behavior scale ($\alpha_{\text{range sample A, B, C}} = .78-.84$), which consists of eight items scored on a 4-point scale, assesses the degree to which students gather information about themselves. Broad Exploration ($\alpha_{\text{range sample A, B, C}} = .84-.85$) assesses the extent to which students investigate general information about higher education, while In-Depth Exploration ($\alpha_{\text{range sample A, B, C}} = .66-.77$) measures the level of detailed information students gather about specific career options. Both scales consist of five items answered on a 4-point scale. Before answering the In-Depth Exploration questions, the students had to list what majors they already explored. The In-Depth Exploration scale was not required for those who had not gathered information on programs.

**Antecedents**

All antecedents were measured using a combination of scales from different validated instruments. Academic self-efficacy ($\alpha_{\text{range sample A, B, C}} = .88$) is part of the short version of the Inventory of Learning patterns of Students (ILS-SV; Donche and Van Petegem, 2008; Vermunt and Donche, 2017) and measures the students’ confidence in their capabilities and in their way of studying. Self-efficacy consists of four items that students answer on a 5-point scale. Academic self-concept ($\alpha_{\text{range sample A, B, C}} = .85$) was measured by using an adjusted version of the academic subscale of the Self-Concept Scale (Wouters et al., 2011). Students answered seven items on a 5-point scale. Motivation ($\alpha_{\text{range sample A, B, C}} = .71-.75$) and Anxiety ($\alpha_{\text{range sample A, B, C}} = .82$) are two scales from the Learning and Study Strategies Inventory (LASSI; Weinstein et al., 2016). Both scales consist of six items that are answered on a 5-point scale.
Motivation measures the students' willingness to put up the effort required to successfully complete their academic obligations. Test anxiety assesses the degree to which students worry about school and their academic performance.

Information about students’ gender, educational track, and SES was obtained by linking the datasets to the administrative database of the Flemish Department of Education and Training, which contains information about students’ secondary education careers. Socio-economic status was operationalized as the educational level of the mother, with students with a mother without a higher secondary education degree considered as low SES.

**Data Analysis**

To answer the first research question, unravelling which different exploration profiles can be identified cross-sectionally, we applied latent profile analysis (J. K. Vermunt & Magidson, 2016). A latent profile analysis (LPA) is a model-based approach in which individuals are allocated into clusters based on membership probabilities estimated directly from the model. This makes the choice of cluster criterion less arbitrary in comparison with standard cluster analysis techniques (Spurk et al., 2020; J. K. Vermunt & Magidson, 2002). With LPA, we can look into qualitatively different configurations of variables (Spurk et al., 2020).

To answer the second research question, exploring if and in which way students transition between exploration profiles at the two timepoints, latent transition analysis was used. Latent transition analysis (LTA) is a longitudinal version of latent profile analysis. It combines the cross-sectional measurement of categorical latent variables and the longitudinal description of change in the categories of the latent variable over time. LTA is a type of autoregressive model to examine time-to-time change in latent categorical variables (Nylund, 2007). LTA describes how students move between groups by providing transition probabilities that describe the probability of transitioning from a
particular latent class to another latent class between measurement points (Sorgente et al., 2019).

For all LPA’s and LTA, the scores of the four study choice tasks orientation, self-exploration, broad exploration, and in-depth exploration from the corresponding SSCTI scales were standardized using z-scores before entering them into the analyses. We used different parameters to evaluate fit. We used the Bayesian Information Criterion (BIC) statistic to determine whether including additional classes would improve the model fit. The BIC for a solution with k classes should be lower than for a solution with k-1 classes. Entropy (E) and the classification error (CE) were used to check the classification accuracy. The closer E is to 1 and CE is to 0, the more accurate the predictions (J. K. Vermunt & Magidson, 2005). Finally, it is important to determine the number of classes not only based on the fit indices, but also by considering theoretical justification, parsimony, and easiness of interpretation (Jung & Wickrama, 2008; J. K. Vermunt & Magidson, 2003). After identifying the profiles, we checked whether there were significant differences among the profiles for each of the scales included in the latent profile analysis. In Appendix 3.A and 3.B, two tables containing means, standard deviations, and ANOVA’s are included to examine differences between the profiles for the four exploration tasks at both timepoints. For both timepoints, the ANOVA’s showed significant profile differences. Post hoc tests showed significant differences between all profiles on all exploration tasks at both timepoints, with students in the highly active profile scoring higher than students in the moderately active profile, who, in turn, scored higher than students in the passive profile, except for in-depth exploration where no significant difference was found between the moderately active and highly active profiles in Fall.

Following the LPA’s and LTA, we investigated the effect of the antecedents on the initial states and the transition probabilities. The log odds ratios in Latent Gold were transformed into log odds to ease interpretation.
For the effect of the antecedents on the transitions, the odds ratios describe the probability of transitioning to another profile compared to the probability of remaining in the same profile. All analyses were performed in Latent Gold.

**Results**

**Latent Profile Analyses**

We inspected 1–6 profile solutions to identify exploration profiles in both datasets. Since the best loglikelihood value was not replicated for all profile solutions, we decided to increase the random sets and the iterations to be sure to avoid local maxima. However, after adjusting the start values multiple times, at both timepoints, not all profile solutions appeared stable. For sample A (Fall), only the profile solutions up to three were found to be stable. For sample B (Spring), the profile solutions were stable up to four. All parameters are shown in Tables 3.1 and 3.2.

**Table 3.1**

*Model fit statistics for the latent profile analysis for sample A (Fall)*

<table>
<thead>
<tr>
<th>Number of profiles</th>
<th>AIC</th>
<th>BIC</th>
<th>ΔBIC</th>
<th>CE</th>
<th>Entropy R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>108611.88</td>
<td>108669.21</td>
<td>/</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>102120.33</td>
<td>102242.15</td>
<td>6427.06</td>
<td>.10</td>
<td>.66</td>
</tr>
<tr>
<td>3</td>
<td>97137.22</td>
<td>97323.54</td>
<td>4918.61</td>
<td>.11</td>
<td>.74</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
We used a combination of the BIC, classification error, and entropy to compare which models fit the data best. In addition, it is important to take into account the interpretability of the profiles. The statistical indices might suggest a solution that is not a useful model for capturing the population's heterogeneity. So, when choosing the number of profiles, it is important to take into account both statistical and practical considerations (Nylund, 2007). Hence, with theory, parsimony, interpretability, and stability in mind, and to ensure sufficient differentiation between the profiles, at both timepoints, we chose the three-profile solution over other solutions indicating more profiles. The final three-profile solutions are presented in Figure 3.2. The profiles are depicted using z-scores. The profile with students scoring relatively low on the four decisional tasks was labeled as the ‘passive explorers’. This profile was most present in our data for sample A (48%) and the second largest for sample B (44%). Students scoring moderately on all four decisional tasks were named the ‘moderately active explorers’. This was the second-largest profile in sample A (41%) and the largest profile in sample B (45%). At both timepoints, the ‘highly active explorers’ were least present in the data (respectively 10% and 11%) and scored relatively high on all four decisional tasks.

### Table 3.2

Model fit statistics for the latent profile analysis for sample B (Spring)

<table>
<thead>
<tr>
<th>Number of profiles</th>
<th>AIC</th>
<th>BIC</th>
<th>ΔBIC</th>
<th>CE</th>
<th>Entropy R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>82355.84</td>
<td>82410.96</td>
<td>/</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>76300.10</td>
<td>76417.21</td>
<td>5993.74</td>
<td>.09</td>
<td>.70</td>
</tr>
<tr>
<td>3</td>
<td>72057.12</td>
<td>72236.24</td>
<td>4180.97</td>
<td>.10</td>
<td>.77</td>
</tr>
<tr>
<td>4</td>
<td>70897.16</td>
<td>71138.29</td>
<td>1097.95</td>
<td>.15</td>
<td>.71</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>
Latent Transition Analysis

For the LTA, we first checked the longitudinal sample cross-sectionally using the same procedure and parameters as in the earlier stage to determine the number of profiles, or states, as they are called in LTA. As in samples A and B, the parameters showed the three-profile solution to be most suitable at both timepoints in sample C. At both timepoints, the ‘moderately active explorers’ were the largest profile, representing respectively 46% and 49% of students.
The ‘passive explorers profile’ made up 43% and 35% of students, respectively. At both timepoints, the ‘highly active explorers’ were the smallest group within the dataset (11% and 16%, respectively). Based on these cross-sectional results, we proceeded with the LTA of the longitudinal data with three latent statuses. The pattern of transition between groups is presented in Table 3.3.

**Table 3.3**

*Latent transition probabilities between profiles across Fall and Spring*

<table>
<thead>
<tr>
<th></th>
<th>Fall</th>
<th>Spring</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Moderately active</td>
<td>Passive</td>
</tr>
<tr>
<td>Moderately active</td>
<td>.779</td>
<td>.001</td>
</tr>
<tr>
<td>Passive</td>
<td>.440</td>
<td>.519</td>
</tr>
<tr>
<td>Highly active</td>
<td>.418</td>
<td>.005</td>
</tr>
</tbody>
</table>

The ‘moderately active explorers’ proved to be the most stable profile, with 78% staying in the same profile between Fall and Spring. Of the students who were in the ‘moderately active explorers’ profile in Fall, 22% transitioned to the ‘highly active’ profile in Spring. For the ‘passive’ profile, 52% remained in the same profile across time. 44% of them transitioned to the ‘moderately active’ profile, while 4% transitioned to the ‘highly active’ profile. Of the ‘highly active explorers’, 58% stayed in the same profile. However, 42% of them transitioned to the ‘moderately active’ profile.

**Antecedents**

Following the LTA, we tried to further unravel the effect of different antecedents. First, we checked the association of the antecedents with the initial states. The results showed that test anxiety (Wald $\chi^2 (2) = 17.94, p < .001$), academic self-concept (Wald $\chi^2 (2) = 20.58, p < .001$), motivation (Wald $\chi^2 (2) = 21.13, p < .001$) and gender (Wald $\chi^2 (2) = 6.34, p < .05$) had a significant relation with profile membership. Students scoring higher on test anxiety were less likely to be included in the ‘passive’ profile than in the ‘highly active’ profile ($OR = .44, p < .001$). For academic self-concept students scoring higher were
found to be less present in the ‘passive’ (OR = .16, p < .001) or the ‘moderately active’ profile (OR = .35, p < .05) than in the ‘highly active’ profile. Also for motivation students scoring higher were less likely to be included in the ‘passive’ (OR = .21, p < .001) or the ‘moderately active’ profile (OR = .46, p < .05) than in the ‘highly active’ profile. Regarding gender, only the overall effect was significant. For academic self-efficacy, educational track, and SES no significant associations with the initial states were found.

In a final step, we measured the effect of the antecedents on the transitions between profiles. Males were the reference group for gender, technical track was the reference group for educational track, and having a mother without a higher secondary education degree was the reference group for SES. The results showed that both motivation (Wald $\chi^2 (6) = 25.30, p < .001$) and test anxiety (Wald $\chi^2 (6) = 13.14, p < .05$) had an overall significant effect on transition probabilities between profiles. Compared to students who remained in the ‘passive’ profile, higher levels of motivation were associated with a higher probability of transitioning from the ‘passive’ to the ‘moderately active’ profile (OR = 4.74, p < .001). Furthermore, compared to students who remained in the ‘highly active’ profile, higher levels of motivation were associated with a lower probability of transitioning from the ‘highly active’ to the ‘moderately active’ profile (OR = .09, p < .05). For motivation, no significant effect was found for the transitions from and to the other profiles. Regarding test anxiety, compared to students who remained in the ‘moderately active’ profile, higher levels of test anxiety were associated with a higher probability of transitioning from the ‘moderately active’ to the ‘highly active’ profile (OR = 2.02, p < .05). In addition, compared to students who remained in the ‘passive’ profile, higher levels of test anxiety were associated with a lower probability of transitioning from the ‘passive’ to the ‘highly active’ profile (OR = .07, p < .05). No significant effect was found for the transitions from or to the other profiles. For gender, there was no overall significant effect, but
compared to students who remained in the ‘passive’ profile, girls had a higher probability than boys to transition from the ‘passive’ to the ‘moderately active’ profile ($OR = 2.21, p < .05$). For academic self-concept, academic self-efficacy, educational track, and SES no significant effects on the transition probabilities were found.

**Discussion**

The present study aimed to further unravel individual differences present within the decision-making process of last year students in secondary education making a study choice for higher education. To that end, we examined students’ exploration profiles during Fall and Spring of the final year before they entered higher education, both cross-sectionally and longitudinally, and examined if different antecedents (i.e., academic self-efficacy, academic self-concept, motivation, test anxiety, gender, educational track, socio-economic status) could explain the initial states and transitions between profiles.

Our first objective was to identify different exploration profiles cross-sectionally at two timepoints, Fall and Spring of the last year before transitioning to higher education. We chose to adopt a person-centered approach to deepen the understanding of how different exploration tasks jointly combine into meaningful profiles. We chose a LPA over standard cluster analysis techniques because the model-based approach makes the choice of the cluster criterion less arbitrary (J. K. Vermunt & Magidson, 2002). The LPA on four decision-making tasks revealed the presence of three exploration profiles at both timepoints. The passive explorer profile, which we found to be relatively low to unengaged in terms of orientation and exploration regarding their study choice, consisted of 48% of students in Fall and 44% of students in Spring. Other students, more specifically 41% of students in Fall and 45% of students in Spring, were slightly more aware of the need to decide and were in the process of exploring both themselves as well as the higher
education environment. Accordingly, they were labeled moderately active explorers. At both timepoints, a minority of students (respectively 10% and 11%) were part of the profile of students that were already engaged in orientation and all three exploration tasks (i.e., self-exploration, broad and in-depth exploration of the study environment). They were labeled the highly active explorers. These findings attest to the robustness of the three-profile solution across timepoints and samples. The same three distinct profiles as in previous research with a similar, but only one, sample and at only one timepoint emerged (Demulder et al., 2022). Given the variety of exploration profiles that were revealed cross-sectionally as well as longitudinally, our findings underline the various ways that students engage with the transition from secondary to higher education and show the possibility of detecting at-risk students in terms of the exploration activities they show or do not show over time. Student counselors should embrace this diversity and not use the same guidance for all students. Tailored counseling could be developed to more effectively match students’ exploration profiles. For example, the passive explorers, who often have not yet fully started the decision-making process, could be more activated to invest effort into the exploration process and given guidance on how to start gaining information about the self and career alternatives (see also Demulder et al., 2022). Also, students who remain in the passive profile over time may need more intense guidance and counseling than students whose lack of exploration is only temporary.

Our second objective was to investigate the within-person transition probabilities between profiles across the two timepoints. Our results showed that the passive profile was the most variable profile, with only 52% of students staying in this profile. So, almost half of them are able to make a ‘positive’ transition, moving mostly to the moderately active profile (44%) and rarely to the highly active profile (4%). In addition, 22% of students are able to transition from the moderately active to the highly active profile, even though it is the
most stable profile with 78% of students staying in this profile between Fall and Spring. Most students being able to make a positive transition is in line with previous variable-centered research showing general increases during the last year in the degree of exploration (Germeijs & Verschueren, 2006b). Students seem to be making progress in both orientation and exploration during their last year of secondary education, which could be why they are most often able to move out of the passive profile to the two other profiles demonstrating more exploration. Rather unexpectedly, students from the highly active profile also transitioned quite commonly to the moderately active profile (42%). However, the highly active profile was the smallest in the data so in absolute numbers it concerns only a small fraction of students. It could be that after a period of high exploration behavior, a subsequent period with less exploration occurs since the students may have already gone through the most important phase of their decision-making process. Transitions from the highly active or the moderately active to the passive profile were almost absent. These results show that moving to the moderately active profile is the most common while transitioning to the passive profile is the least common. Transitioning from the passive exploration profile is more common than transitioning from the other two exploration profiles. However, 52% of students stayed in the passive profile between Fall and Spring. A possible explanation for this could be that a number of "stayers" do not see the need to change and thus do not undertake any action. It could also be that they started their exploration process between Fall and Spring but gave up in the meantime. The research on transitions between profiles adds to the understanding of the timing of interventions to help students in their decision-making process. Early tracking of students who have a passive exploration profile in Fall may help to take targeted actions to prevent them from remaining in this profile over time. Effective interventions might have a beneficial impact on this group of
students, of whom more than half seem to remain more passive in their study choice making process.

Our final objective was to further unravel the association with different antecedents. The current study was able to test multiple antecedents from the framework by Jiang et al. (2019) to unravel the explanatory base of differences in the career exploration process of students opting for higher education. In addition to characteristics that are fixed, we also chose to focus on malleable characteristics, as students can take action on these themselves and they can be put in motion by interventions and counseling. First, we checked the associations of the antecedents with the initial states. Subsequently, we examined the effect of different antecedents on the latent transitions between profiles. Results only partially confirmed our hypotheses. Academic self-concept was only associated with the initial states. Students scoring higher were less likely to be in the passive or moderately active profile than in the highly active profile for the initial states. Variable-centered research findings showed how academic self-concept is important for the awareness to start the orientation process, and this relationship also seems important to understand differences in students’ exploration profiles (van der Aar et al., 2019). Since students with a lower self-concept have less clear perceptions about themselves, they could experience problems with the integration of self- and environmental information. It may be more difficult for them to match new incoming information with their existing knowledge about themselves since this knowledge is still unclear. A clear and certain self-concept could thus facilitate the exploration process.

Motivation proved to be associated with the initial states as well as with the transition probabilities. Students scoring higher were less likely to be in the passive or moderately active profile compared to the highly active profile for the initial states. Moreover, high levels of motivation were associated with a higher probability of remaining in the highly active profile compared to
transitioning from the highly active to the moderately active profile, and were associated with a higher probability of transitioning from the passive to the moderately active profile compared to remaining in the passive profile. Variable-centered research confirmed the importance of and the positive relationship between motivation and exploration (Deng et al., 2022; Duchesne et al., 2012; Paixão & Gamboa, 2017). The current study demonstrates that motivation is important to understand differences in students’ exploration profiles, hence explaining why students scoring higher on motivation can more often be found in the highly active profile compared to the moderately active or passive profile. Moreover, motivation seems to protect students in the highly active profile from moving to the moderately active profile, and it supports students in transitioning from the passive to the moderately active profile. Since students with higher motivation are more willing to invest effort in academic requirements, these motivations may also play a role in students’ engagement in career planning activities. Students willing to invest more effort in academic tasks may also be more willing to invest more effort in dealing with the different tasks in the decision-making process.

Test anxiety was also associated with both the initial states and the transition probabilities. Students scoring higher were less likely to be included in the passive profile than in the highly active profile, so highly active students do not seem to show well-adjusted behavior regarding all antecedents. As mentioned above, results on the relationship between anxiety and exploration are inconsistent, depending on the type of anxiety that is measured. Both career (Germeijs et al., 2006b; Vignoli et al., 2005) and test (Vignoli, 2015) anxiety proved to be positively related to exploration, while general anxiety shows confusing results, with some studies showing a negative relationship (Vignoli et al., 2005) and others a positive relationship with exploration (Vignoli, 2015). The measure of anxiety used in the current study assessed the degree to which students worry about school and their academic performance. Highly active
explorers show higher test anxiety than their passive counterparts, which could explain why they also show more exploration. Regarding the transition probabilities, high levels of test anxiety were associated with a higher probability of transitioning to the highly active profile compared to staying in the moderately active profile, and associated with a higher probability of staying in the passive profile compared to transitioning to the highly active profile. On the one hand, our results show that among students who do explore, higher test anxiety may lead to increased engagement in exploration over time. On the other hand, test anxiety may hinder passive explorers from becoming more highly engaged in exploration. So, depending on the individual, test anxiety may have different consequences, either hindering growth in exploration or fostering it. Being aware of the differential impact of anxiety for different individuals may be useful for guiding them in the decision-making process. It would be interesting for future research to investigate if the group of highly active explorers with high test anxiety encounter more difficulties deciding on and committing to a study choice. It should be noted, however, that anxiety only influenced the transition from the moderately active to the highly active profile and from the passive to the highly active profile. There was no significant influence on the transition probabilities to and from the other profiles.

Finally, girls had a higher probability than boys of transitioning to the moderately active profile compared to staying in the passive profile. Previous variable-centered research on gender has shown that girls report higher levels of exploration of the environment (Gamboa et al., 2013) and self-exploration (Lazarides et al., 2016; Seabi, 2012) and that girls make more progress than boys in in-depth exploration, showing higher levels at the end of secondary school (Germeijs & Verschueren, 2007a).

For the other antecedents (i.e. academic self-efficacy, educational track, and SES) no significant associations with the initial states or the
transition probabilities were found. A possible explanation for this could be that the variance is already explained by other variables in the model. For self-efficacy, another explanation could be the form of self-efficacy used in the present study. Results could have been different if, for instance, career decision-making self-efficacy had been used. Most research on self-efficacy used career decision-making self-efficacy (Creed et al., 2007; Rogers et al., 2008; Rogers & Creed, 2011), while the current study used a measure of academic self-efficacy that measures students’ confidence in their capabilities and in their way of studying.

Since this study showed that academic self-concept, motivation, and test anxiety are associated with the initial exploration profiles and that motivation and test anxiety can have an effect on the transition probabilities, interventions and counseling taking into account these antecedents could be beneficial in helping students to better cope with the challenges of the decision-making process. For instance, students with a more positive academic self-concept are more often highly active explorers. Working on a more positive self-concept could indirectly also improve their exploration process or profile. In addition, since motivation appears to be positively related to transitioning from the passive to the moderately active profile, interventions aimed at increasing motivation could be beneficial. Research by Chiesa and colleagues (2016) has already shown that improving self-efficacy through an intervention can also increase career exploration. In the current study, test anxiety was associated with both the initial exploration profiles and the transition probabilities but showed confounding results. It could thus be useful for counselors to be aware of the different types of anxiety to help students manage their anxiety and assist them in the decision-making process.
Limitations and Directions for Future Research

The current study has some limitations which, if addressed, might also offer suggestions for future research. First, the LPA’s and LTA were based on self-report measures, which may have allowed for bias as students may have answered questions in a socially desirable way. However, based on substantial samples investigated in this study, both in the LPA’s and LTA quite a diversity of exploration profiles and transitions between profiles were found, not only indicating so-called positive exploration profiles. A second limitation of the current study is the fact that only two timepoints were taken into account. Taking into account three or more timepoints would be interesting to better understand the linear trend of the exploration process. For instance, an extra timepoint at the very end of the academic year, before leaving secondary education, could possibly bring useful insights. It would also be interesting to measure the antecedents at multiple points in time so changes in antecedents over time can be associated with transitions between profiles. Third, this study was able to test several, but not all, antecedents from the framework by Jiang and colleagues (2019). Future research could build on the present study by further examining the other antecedents from the framework in a person-centered way. Their review study has shown how different antecedents are related to career exploration. However, less is known about how these relations occur when using a person-centered approach. For instance, the role of career interests, or especially different contextual antecedents such as school or parental support in study choice guidance could be further investigated as predictors of profile membership or transition probabilities.
CHAPTER 4

Does the study choice process matter? An examination of the relationship between the study choice process and academic success among students entering higher education

Abstract

The process of choosing a study in higher education has been suggested to impact academic success. This longitudinal study examined how career exploration profiles (i.e., highly active, moderately active, passive explorers), the amount of information acquired about higher education, and study choice commitment in the final year of secondary school interrelate to explain academic success in the first year of higher education (n = 5,358). Second, differences in relationships across academic and professional bachelor’s programs were tested. Structural Equation Modeling (SEM) revealed that the exploration profiles significantly influenced the amount of information and commitment. Moderately active and highly active explorers displayed higher levels of commitment and more information about higher education than passive explorers. Amount of information had a positive direct effect on academic success. Also, an indirect effect of the exploration profiles on academic success through amount of information was observed. Multiple-group SEM analysis revealed no differences in the structural paths between academic and professional bachelor’s programs, indicating the generalizability of the model across program types. This study provided valuable insights into the relationship between the study choice process and academic success in a large and diverse sample of students, with a meaningful role for the amount of information about higher education.
Introduction

The transition to higher education presents a challenge for many students. Only 39% of students complete their bachelor’s program within the theoretical length of the program, and 12% drop out after one year (OECD, 2022). Extensive research has been conducted to identify predictors of success in higher education, examining an extensive array of both cognitive and non-cognitive factors (e.g., Richardson et al., 2012; Robbins et al., 2004; van Rooij et al., 2018). In addition, several theoretical models on career decision-making suggest that, beyond these factors, the process of choosing a study in higher education may impact subsequent chances of success, such as choice actualization and commitment to the chosen program in higher education (Gati & Asher, 2001b; Germeijs & Verschueren, 2007b; Van Esbroeck et al., 2005). To date, however, there has been little empirical research on the relationship between the study choice process and academic success in higher education. Consequently, this study aims to investigate the impact of the study choice process on students’ academic success in their first year of higher education.

Research Context

In Flanders, Belgium, where this study was conducted, higher education is largely unconstrained, allowing students with a secondary education qualification to freely enter any higher education program, with only a few exceptions, such as dentistry, medicine, veterinary sciences, and some art disciplines. The present study focused on students from the general and technical tracks in high school, as they best prepare for continuing higher education. Additionally, tuition fees are intentionally very low to allow all students to participate in higher education. However, this open entrance leads to low success rates and high drop-out rates. Merely 31% of the students who started higher education during the 2019-2020 academic year managed to complete their bachelor’s degree within the prescribed study period, and
additionally, a significant 15% of students who started higher education in the academic year 2020-2021, dropped out after one year (Statistiek Vlaanderen, 2023a, 2023b). This particular context makes the study choice for higher education an important career decision for most of these students. In these contexts, the study choice process is expected to play a crucial role in academic success due to the wide range of programs available to students. This can be overwhelming and make the study choice process more challenging.

When entering higher education, students have to decide between an academic or professional bachelor's program, as well as a specific major. Academic bachelor’s programs are characterized by an orientation towards more abstract and theoretical knowledge, focus on research competencies, prepare students for a future academic master’s program, and are usually pursued at the university level. In contrast, in professional bachelor’s programs theory and practice are combined, focusing more on developing competencies that are essential for professional practice. They are offered at university colleges (Onderwijs & Vorming Vlaanderen, 2023; Willems et al., 2021). An underexplored topic relates to the differences between these academic and professional bachelor’s programs in how the study choice process predicts academic success. Hence, this study also seeks to investigate whether the associations between the study choice process and academic success differ across various programs, encompassing both academic and professional bachelor’s programs. These findings may be relevant to the field of study choice guidance. If no discernible differences exist, the study choice processes are generalizable across the two program types, eliminating the need for

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As of the 2019-2020 academic year, a third type of program has been introduced in Flemish higher education: associate’s degree programs. Since the majority of students start either a professional (46.1%) or academic (42.9%) bachelor’s program (AHOVOKS, 2022), and we do not have sufficient data on the associate’s degree group, we will focus only on these two types of programs in the current study.
differentiation in study choice guidance between the two. However, if differences do emerge, tailored counseling may be necessary.

**Study Choice Process**

Germeij and Verschueren (2006b) identified six decisional tasks within the higher education decision-making process: orientation, self-exploration, broad exploration of the environment, in-depth exploration of the environment, decisional status, and commitment. These tasks are theoretically based on different taxonomies of problems in the study choice process (e.g., Campbell & Cellini, 1981; Gati et al., 1996), as well as theories that view the study choice process as a developmental process with various tasks (Harren, 1979; Tiedeman & O’Hara, 1963). These decision-making tasks are characterized by their dynamic and flexible nature, allowing individuals to skip or return to tasks as necessary (Germeij & Verschueren, 2006b, 2010). The first four of these tasks are important regarding career exploration. Career exploration plays a pivotal role in the decision-making process (Gati & Asher, 2001a) and involves purposeful behavior and cognitions related to vocational development (Stumpf et al., 1983). By engaging in this process, individuals explore themselves and the environment, enabling them to identify potential career options that align with their characteristics (Porfeli & Lee, 2012). Orientation measures students’ awareness of the need to make a decision and their motivation to make optimal career choices. Self-exploration assesses how much information students gather about themselves. Broad exploration assesses the acquisition of general information about higher education, while in-depth exploration evaluates the extent to which students seek detailed information about specific career alternatives (Germeij & Verschueren, 2006b). Decisional status is another crucial task, measuring students' progress toward choosing a study. Finally, commitment assesses the degree to which students are confident in and committed to their chosen study program (Germeij & Verschueren, 2006b).
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Existing research has demonstrated a positive relationship between broad and in-depth exploration of career alternatives and the level of commitment (Germeij & Verschueren, 2007). Similarly, research on career identity has shown a positive relationship between in-depth exploration and the process of career commitment (Crocetti et al., 2008; Porfeli et al., 2011). Moreover, research has shown that engaging in career decision tasks is positively associated with the amount of information acquired about oneself and career alternatives (Germeij & Verschueren, 2007). Consequently, exploration appears to play a crucial role in acquiring career-relevant knowledge about the self and possible study options and fostering commitment to the chosen study for higher education. In turn, more knowledge about higher education and commitment to a chosen study have been shown to increase the chances of success (Germeij & Verschueren, 2007).

An underexplored research question is how career exploration, the amount of information about higher education, and study choice commitment interrelate to explain academic success in higher education. Given the established connections between exploration, on the one hand, and the amount of information concerning higher education and commitment, on the other, as well as the relationship of the latter two with academic success, we argue that the influence of exploration on academic success may operate indirectly through information acquisition and commitment. In other words, we hypothesize that differences in career exploration lead to differences in academic success through their effect on students’ acquired information about higher education options and their commitment to their chosen study.

**Study Choice Profiles**

Most studies examining career exploration processes have used a variable-centered approach, investigating correlates of differences in variable scores for
career exploration tasks. Person-centered analysis techniques have become more common in vocational research. They cluster or group individuals based on shared characteristics (Hickendorff et al., 2018; Woo et al., 2018). These techniques allow for the identification of more homogeneous groups of individuals who share communalities concerning the targeted research variables in a sample (Hofmans et al., 2020).

Previous research has identified different exploration profiles of students. In a sample of 5,660 last year secondary school students who made the transition to the first year of higher education, three exploration profiles were identified using latent profile analysis: passive, moderately active, and highly active explorers (Demulder et al., 2022). The ‘passive explorers’ profile consisted of students scoring relatively low on the four exploration tasks (i.e., orientation, self-exploration, broad exploration, and in-depth exploration). Students scoring moderately on all four exploration tasks were labeled the ‘moderately active explorers’. The ‘highly active explorers’ scored relatively high on all four decisional tasks. These profiles were replicated in a subsequent study conducted at two different timepoints; Fall ($n = 9,567$) and Spring ($n = 7,254$) of the last year of secondary education (Demulder et al., 2023). The first study also revealed that boys were more likely to be passive explorers, and that students with more effective regulation and processing strategies were more likely to be highly active than passive or moderately active explorers. Additionally, highly active explorers were more likely to already have a first choice in mind, demonstrated higher scores on commitment to their chosen study, and acquired a greater amount of information about higher education (Demulder et al., 2022). While the identification of these profiles offers valuable insights into the study choice process, the relationship between these exploration profiles and academic success in the first year of higher education remains unexplored. Establishing this relationship is key, as it provides empirical ground for schools’ and counselors’ efforts to support students’
career choice processes. Also, it provides crucial empirical evidence for the assumed importance of exploration in career decision-making models (e.g., Campbell & Cellini, 1981; Gati et al., 1996; Harren, 1979; Tiedeman & O’Hara, 1963) and sheds light on how exploration might affect academic success.

**The Study Choice Process and Academic Success**

Kuh and colleagues (2006) define academic success as “inclusive of academic achievement, attainment of learning objectives, acquisition of desired skills and competencies, satisfaction, persistence, and postcollege performance” (p. 5). Academic success is most often measured by students’ grades or their grade point average (GPA) (York et al., 2015). Most studies use a single outcome measure, whereas considering multiple measures, such as a combination of course grades, GPA, persistence, or retention, would enable a nuanced examination of whether diverse predictors have varying effects on these outcomes. In this study, we will use two indicators of academic success; the credit completion rate, which is calculated by dividing the number of earned credits by the number of enrolled credits, and a study persistence measure, defined as staying in the chosen program during the first year of higher education (as opposed to dropping out or changing programs).

The effect of the study choice process on academic success has only been examined in a few studies, all using a variable-centered approach. Germeijns and Verschueren (2007b) followed a sample of adolescents in the last year of secondary education during their first two years in higher education. Results showed that those who demonstrated a stronger commitment to their study choice at the end of secondary education had a greater chance of actualizing their choice. Students with higher levels of orientation, and broad and in-depth exploration showed more commitment to their studies in higher education. In turn, being committed to the chosen study in higher education decreased the risk of dropping out (Germeijns & Verschueren, 2007b). This
study, however, was performed in a sample of only general track students, an academically preparing study track in Flemish secondary education. Other research by Lacante and colleagues (2001) also suggested that the quality of coping with career decision tasks affects drop-out rates. Students who dropped out of higher education tended to make less informed decisions about their program choice in their first year of higher education. They engaged in less thorough study choice processes, had fewer discussions about their options with others, and participated in fewer related activities, such as reading brochures (Lacante et al., 2001). Prior research has also shown the importance of students’ satisfaction with their chosen program. Satisfaction was positively related to their intention to persist (van Rooij et al., 2018), and the total number of credits obtained at the end of the first year, while being negatively related to drop-out (Jansen & Suhre, 2010). Research by De Clercq and colleagues (2013, 2021) demonstrated that making an informed choice, conceptualized as the number of sources the student consulted when choosing what to study, was positively associated with academic achievement, measured by the average overall percentage for all courses at the end of the first academic year at university. Longitudinal research by Negru-Subtirica and Pop (2016) showed positive reciprocal associations between career concern and academic achievement, measured by self-reported GPA, in adolescents. Adolescents who had a strong future orientation, who already engaged in career planning activities, were more likely to achieve better academically, and the other way around (Negru-Subtirica & Pop, 2016). These studies indicate that the quality of the study choice process is important for academic success. However, none of them have combined a person-centered and longitudinal approach, and the direct assessment of decisional tasks. Therefore, further investigation is needed. This is particularly relevant in higher education contexts with more open admission systems, such as Flanders, in which we expect the study choice
process to play a crucial role in academic success due to the wide range of programs available to students.

Finally, research has shown that students’ background characteristics such as gender, prior educational track, and SES are related to both the study choice process and academic achievement (De Clercq et al., 2013; Richardson et al., 2012; Robbins et al., 2004; Willems et al., 2021). Regarding exploration, girls have been found to exhibit more exploration behavior (e.g., Gamboa et al., 2013; Germeijs & Verschueren, 2006b, 2007a; Lazarides et al., 2016; Seabi, 2012) and were more likely to be in a highly active exploration profile as opposed to boys (Demulder et al., 2022). Evidence regarding the relation between career exploration and educational track and SES is still inconclusive (Demulder et al., 2022, 2023). Concerning academic achievement, students from higher socioeconomic backgrounds (De Clercq et al., 2013; Richardson et al., 2012; Robbins et al., 2004), female students (Richardson et al., 2012), and students from more academically preparing tracks (Willems et al., 2021) generally obtain higher grades. Therefore, we will include these background characteristics (gender, prior educational track, and SES) as control variables.

The Present Study

The main objective of this study was to investigate how different career exploration profiles (i.e., passive, moderately active, and highly active explorers), the amount of acquired information, and study choice commitment in the final year of secondary education interrelate to explain academic success in the first year of higher education. The profiles are an indication of the level of exploration. To evaluate academic success, two measures were used; students’ credit completion rate and a study persistence measure. Our first research question therefore was: “What is the relationship between the exploration profiles, the amount of information about higher education, and study choice commitment among final-year secondary education students and
academic success in their first year of higher education?”. Based on previous research, it was hypothesized that the exploration profiles would be related to the amount of information regarding higher education and commitment to the chosen study. Specifically, more active profiles were expected to show a higher amount of information and more commitment. In turn, it was hypothesized that more information and commitment would increase the chances of academic success. Therefore, it was expected that the exploration profiles would indirectly affect academic success through information acquisition and commitment. The hypothesized model is pictured in Figure 4.1.

**Figure 4.1**
The conceptual model for this study

Finally, since in Flanders students can freely choose a program for higher education, we wanted to exploratively investigate if a differentiated decision-making process exists across academic and professional bachelor’s programs. Our second research question therefore was: “Do the associations between the exploration profiles, intervening variables, and academic success differ across different types of programs, including academic and professional bachelor’s programs?”. For all analyses, we took into account different control variables, including gender, educational track, and socio-economic status (SES).
Methodology

Participants and Procedure

Data used in this study were obtained from the Columbus project, a large-scale research and development project funded by the Department of Education and Training in Flanders, Belgium. Columbus is an exploration feedback instrument with the primary objective of enhancing the career decision-making processes of students in their final years of secondary education opting for higher education (Demulder et al., 2020). The feedback instrument is composed of a collection of validated cognitive tests and self-report questionnaires that help students explore their options, identify their strengths and areas for improvement, and gain insight into potential challenges associated with the transition to higher education. Following the completion of the instrument, students receive normed and individualized feedback, along with appropriate remediation tips for further development.

To ensure an adequate dataset for analysis, data from three cohorts (school years 2017-2018, 2018-2019, 2019-2020) were merged. Our sample consisted of students who completed the Shortened Study Choice Task Inventory (SSCTI, Demulder et al., 2019) during Spring (February, March, and April). We focused on students enrolled in the general and technical tracks who we could track into higher education in the following academic year.

In the first step, the normality of the data was inspected using outlier analyses. Outliers were defined as students who scored more than three standard deviations above or below the mean on the scales. Furthermore, we deleted students who provided incorrect responses to one or both of the included bogus items. A total of 2,080 students were excluded due to providing incorrect responses to the bogus items ($n = 138$), outliers for the four exploration scales ($n = 49$) or Amount of Information or Commitment ($n = 59$), missing data for Amount of Information ($n = 3$) or SES ($n = 5$), or because
they were not subsequently enrolled in an academic or professional bachelor’s program \((n = 84)\). Listwise deletion was used since the Commitment items were not presented to students who did not have a first choice in mind \((n = 1,773)\). This resulted in a final sample size of 5,358 students.

The dataset consisted of 44.1% male and 58.9% female students. Students completed the instrument when they were on average 18 years old. Among them, 61.2% were enrolled in the general track of secondary education, while 38.8% were enrolled in the technical track. There was no specific selection made regarding the higher education programs; instead, all of the programs chosen by the students were included. The final dataset comprised students enrolled in 133 different professional and academic higher education programs. The majority of students opted for programs related to economics (14.9%), engineering (11.6%), healthcare (10.1%), or social work (8.5%), with 49.9% enrolled in an academic bachelor’s program and 50.1% in a professional bachelor’s program.

**Measures**

**Exploration Profiles**

Students completed the validated shortened and updated version of the Study Choice Task Inventory (Demulder et al., 2019). In the Shortened Study Choice Task Inventory (SSCTI) each of the six career-decisional tasks is measured by one of the six scales; Orientation, Self-Exploration, Broad Exploration, In-Depth Exploration, Decisional Status, and Commitment (Germeijs & Verschueren, 2006b). The factor structure of the SSCTI was validated in a previous study (Demulder et al., 2019), using exploratory and confirmatory factor analyses, and measurement invariance analyses. The analyses showed that the items are interpreted in the same way by male and female students and across different educational tracks (Demulder et al., 2019).
For the profiles, the Orientation and Self-, Broad, and In-Depth Exploration scales were used. The Orientation scale ($\alpha = .82$) assesses students’ awareness of the need to make a career decision and their motivation to make that decision. The students rate five items on a 5-point scale. The Self-Exploratory Behavior scale ($\alpha = .81$), which has eight items and is scored on a 4-point scale, measures how much information students have gathered about themselves. While Broad Exploration ($\alpha = .85$) evaluates the degree to which students research general information about higher education, In-Depth Exploration ($\alpha = .75$) measures how much detailed information students explore about specific career alternatives. Both scales have five items answered on a 4-point scale. The students had to list what majors they had previously investigated before responding to the In-Depth Exploration questions. Those who had not gathered information on programs were exempt from filling out the In-Depth Exploration scale.

In a previous study, three exploration profiles were identified in the sample of students who filled out all four exploration scales ($n = 7,254$) using latent profile analysis (Demulder et al., 2023). A combination of the BIC, classification error, and entropy was used to see which model fit the data best. Also keeping theory, parsimony, interpretability, and stability in mind, the three-profile solution was chosen over solutions indicating more profiles. The profile with students scoring relatively low on the four decisional tasks was labeled as the ‘passive explorers’. This profile was the second largest (44%). Students scoring moderately on all four decisional tasks were named the ‘moderately active explorers’. This was the largest profile (45%) in the data. The ‘highly active explorers’ were least present in the data (11%) and scored relatively high on all four decisional tasks. The classification of these three profiles was used in the current study.

We linked the dataset to the administrative database of the Flemish Department of Education and Training, which provided data on students’
secondary education careers. Through this linkage, we obtained data on students’ gender (dummy coded; 1 = males), educational track (dummy coded; 1 = general track), and socio-economic status (SES). The educational level of the mother was used as an indicator of SES, categorizing students whose mothers did not obtain a higher secondary education degree as low SES (dummy coded; 1 = low SES).

**Intervening Variables**

Commitment was measured by the corresponding SSCTI scale ($\alpha = .83$), which assesses students’ level of confidence and attachment to the study choice they have made. The scale consists of five items rated on a 6-point scale, and it was administered only to students who indicated having a first choice in the question regarding decisional status. The amount of information about higher education was evaluated using a scale that assesses students’ understanding of the general structure of higher education and the distinctions between different types of higher education. This scale comprised four items answered on a five-point scale ($\alpha = .70$), based on research by Germeijs (2006).

**Academic Success**

To gather information on students’ academic success, the dataset was linked to the administrative database of the Flemish Department of Education and Training, which provided data on students’ higher education trajectories. Two indicators of academic success were used. The first indicator was the credit completion rate. The credit completion rate is determined by dividing the number of earned credits by the number of enrolled credits. Secondly, a study persistence measure was used. Students were considered non-persistent ($n = 539$) regarding their study choice when they either dropped out or did not re-enroll ($n = 249$) or when they changed programs within their first year of higher education ($n = 313$).
Data Analysis

To answer research question 1, Structural Equation Modelling (SEM) was adopted. The SEM analysis was conducted using the lavaan R package (Rosseel, 2012) in JASP (JASP Team, 2023). To assess the overall fit of the SEM model, several goodness-of-fit indices were utilized. The chi-square test was computed, but since this test is sensitive to sample size (Blunch, 2016), additional fit indices were employed; the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). The model fit indices should meet acceptable thresholds to indicate a good fit between the theoretical model and the observed data. Model fit assessment was conducted following the recommendations of Blunch (2016). A CFI value greater than .95 was considered indicative of a good fit. Moreover, the RMSEA value should be around .05. Additionally, an SRMR value less than .05 was considered an indicator of a good fit (Blunch, 2016).

To assess potential differences between academic and professional bachelor’s programs, a multiple-group SEM was used to make cross-group comparisons between academic and professional bachelor’s programs, following the guidelines by Hirschfeld and Brachel (2014). First, we investigated measurement invariance across those groups for the two latent variables in our model (Amount of Information and Commitment). Therefore, we estimated different models. Firstly, a configural invariance model in which the loading pattern was similar in all groups but the magnitude of all parameters could vary. Secondly, a metric invariance model in which the item loadings were constrained to be equal. Finally, a scalar invariance model in which both item loadings and intercepts were constrained to be equal. Invariance exists if the more restricted model fit is not substantially worse than the less restricted invariance model fit (Hirschfeld & Brachel, 2014). A decrease in CFI greater than .010 (Chen, 2007; Cheung & Rensvold, 2002) and an increase in RMSEA
greater than .015 (Chen, 2007) indicate nonvariance. Next, we used multiple-group SEM to test the full SEM model for equality of structural paths across the two bachelor’s programs. We compared the unconstrained model to a model in which we constrained the structural regression coefficients to be equal across groups, using the same evaluation criteria as in the measurement invariance analyses.

Results

The hypothesized SEM is described graphically in Figure 4.1. To answer research question 1, SEM with maximum likelihood parameter estimation was used. The fit of the hypothesized model was insufficient, \( \chi^2(77, N = 5358) = 2608.22, p < .001 \); the CFI was .85; RMSEA was .078; and SRMR was .059. Based on the modification indices, we added a covariance between two items of the Commitment scale. These items are scored on the same response scale with the same response categories, while the other items of the scale are scored on other response scales. We also added one covariance between the two intervening variables and one between the two profiles, as they are theoretically related to each other. After these modifications, the model appeared to provide a good fit to the data. The chi-square was statistically significant, \( \chi^2(74, N = 5358) = 711.79, p < .001 \), supposedly indicating an unacceptable fit, but since the chi-square is sensitive to sample size and unreliable in large samples (Blunch, 2016), alternative fit measures were used. The other fit measures suggested a good model fit to the data (CFI = .96; RMSEA = .040; SRMR = .028). The final model accounts for a total of 5% of the variance in the credit completion rate and 2% of the variance in persistence. Standardized parameters are reported.

The results show that the exploration profiles were related to Amount of Information (\( \beta_{\text{Moderately}} = .42, p < .001; \beta_{\text{Highly}} = .44, p < .001 \)) and Commitment (\( \beta_{\text{Moderately}} = .23, p < .001; \beta_{\text{Highly}} = .26, p < .001 \)). Students from
highly active or moderately active profiles obtained more information about higher education and showed more commitment than students from the passive profile. Gender was related to both profiles ($\beta_{\text{Moderately}} = -0.09, p < .001$; $\beta_{\text{Highly}} = -0.15, p < .001$); compared to boys, girls were more often highly active or moderately active explorers than passive explorers. Educational track was related to Amount of Information ($\beta = 0.10, p < .001$) with students from more academically preparing study tracks in secondary education (general track) being more knowledgeable about higher education than students from the technical track. SES was also associated with Amount of Information ($\beta = -0.07, p < .001$), in that low SES students showed less information about higher education than high SES students. All three background variables, educational track ($\beta = 0.09, p < .001$), SES ($\beta = -0.13, p < .001$), and gender ($\beta = -0.12, p < .001$) were predictive of the credit completion rate, while only educational track ($\beta = 0.08, p < .001$) and SES ($\beta = -0.06, p < .001$) were predictive of persistence. Girls, students from the general track, and high SES students had a higher credit completion rate. Students from the technical track and low SES students dropped out of or changed programs more. Both Amount of Information ($\beta = 0.07, p < .001$) and Commitment ($\beta = -0.04, p < .05$) were predictive of the credit completion rate, while only Amount of Information ($\beta = 0.06, p < .05$) was predictive of persistence. All significant direct effects are depicted in Figure 4.2.
Figure 4.2
*Standardized SEM results*

There were also indirect effects of both profiles on persistence ($\beta_{\text{Moderately}} = .02, p < .05, \beta_{\text{Highly}} = .02, p < .05$) and the credit completion rate ($\beta_{\text{Moderately}} = .03, p < .001, \beta_{\text{Highly}} = .03, p < .001$) through Amount of Information. Finally, there were indirect effects of both profiles on the credit completion rate through Commitment ($\beta_{\text{Moderately}} = -.01, p < .05, \beta_{\text{Highly}} = -.01, p < .05$). A table summarizing all results can be found in Appendix 4.A.

To address research question 2, multiple-group measurement invariance analyses on the two latent variables, Amount of Information and Commitment, were conducted first. After adding one covariance between two items of the Commitment scale, the configural model showed adequate fit (see Table 4.1). The series of model comparisons indicate that there was no significant decrease in fit, indicating that both the item factor loadings and the intercepts can be assumed to be equal across groups. The results thus suggest that scalar invariance is established, meaning that the items are interpreted in the same way across the two programs.

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*For completeness, we also conducted analyses using the high profile as a reference group. For Amount of Information: $\beta_{\text{Moderately vs. highly}} = -.17, p < .001$; for Commitment: $\beta_{\text{Moderately vs. highly}} = -.10, p < .001$.**
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Table 4.1
Results from the measurement invariance tests

<table>
<thead>
<tr>
<th>Model</th>
<th>CFI</th>
<th>RMSEA</th>
<th>χ²</th>
<th>df</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(ΔCFI)</td>
<td>(ΔRMSEA)</td>
<td>(Δχ²)</td>
<td>(Δdf)</td>
</tr>
<tr>
<td>Configural</td>
<td>.976</td>
<td>.049</td>
<td>349.869</td>
<td>25</td>
</tr>
<tr>
<td>Metric</td>
<td>.975 (.001)</td>
<td>.047 (.002)</td>
<td>398.509 (48.64)</td>
<td>58 (33)</td>
</tr>
<tr>
<td>Scalar</td>
<td>.975 (/)</td>
<td>.045 (.002)</td>
<td>412.635 (14.126)</td>
<td>65 (7)</td>
</tr>
</tbody>
</table>

Next, a multiple-group SEM analysis was conducted to test for invariance across the two bachelor’s programs for the full SEM model. Two models were estimated, one unconstrained model, and one model in which all regression coefficients in the model were set to be equal across the two groups. Model comparison (see Table 4.2) showed no significant decrease in fit between the models, suggesting that the structural paths indicated in Figure 4.2 can be generalized across the two types of higher education programs.

Table 4.2
Model comparison for the multiple-group SEM

<table>
<thead>
<tr>
<th>Model</th>
<th>CFI</th>
<th>RMSEA</th>
<th>χ²</th>
<th>df</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(ΔCFI)</td>
<td>(ΔRMSEA)</td>
<td>(Δχ²)</td>
<td>(Δdf)</td>
</tr>
<tr>
<td>Unconstrained</td>
<td>.959</td>
<td>.041</td>
<td>580.382</td>
<td>152</td>
</tr>
<tr>
<td>Constrained</td>
<td>.958 (.001)</td>
<td>.039 (.002)</td>
<td>895.498 (315.116)</td>
<td>178 (26)</td>
</tr>
</tbody>
</table>

Discussion

The present study aimed to shed light on the relationship between the study choice process of final-year secondary education students and academic success in their first year of higher education. Our first study objective was to investigate how distinct career exploration profiles (i.e., passive, moderately active, and highly active explorers), amount of information, and study choice commitment in the final year of secondary education interrelate to explain academic success in the first year of higher education. First of all, our results demonstrated significant links between the profiles and the amount of
information and commitment. As expected, students with moderately active or highly active profiles exhibited higher levels of knowledge about higher education and stronger commitment compared to passive explorers. This aligns with previous research that revealed that highly active explorers demonstrated a greater amount of information about higher education and showed more commitment to their chosen study than students from the moderately active or passive profile (Demulder et al., 2022). Other research also suggested positive relations between broad and in-depth exploration and commitment (Crocetti et al., 2008; Germeijs et al., 2006a; Germeijs & Verschueren, 2007b; Porfeli et al., 2011), and between the exploration tasks and amount of information acquired (Germeijs et al., 2006a).

Moreover, a positive relationship was observed between the amount of information about higher education and academic success. Students who possessed greater knowledge about higher education had a higher credit completion rate and demonstrated higher persistence. This is an extension of existing research and emphasizes the importance of information gathering about the higher education structure and possible study options. However, a surprising finding emerged when investigating commitment; controlling for the other variables in the model, students who indicated higher commitment to their chosen program had a slightly lower credit completion rate. This contrasts with the research conducted by Germeijs and Verschueren (2007b), which found a positive effect of commitment on choice actualization, academic adjustment, and drop-out (Germeijs & Verschueren, 2007b). One possible reason for this could be the time of measurement; Germeijs and Verschueren (2007b) measured commitment at the beginning of higher education, whereas this study used measures from February to April in the last year of secondary education. However, the negative effect we found was small. Future research could look into possible interaction effects of commitment and amount of information on academic success.
We did not find any direct paths between the exploration profiles and academic success. This contrasts with studies by both De Clercq and colleagues (2013) and Negru-Subtirica and Pop (2016) which did find positive relations between making an informed choice and engaging in career planning activities and academic achievement (De Clercq et al., 2013; Negru-Subtirica & Pop, 2016). One possible reason for this could be the operationalization of the variables in question. For example, informed choice was reported retrospectively (De Clercq et al., 2013).

We also investigated whether the amount of knowledge about higher education and the commitment to the chosen study intervened in the relationship between the exploration profiles and academic success. Our findings indicate that there were indirect effects of the exploration profiles on both persistence and the credit completion rate through the amount of information. Previous research has demonstrated that exploration plays an important role in the acquiring of information (Germeijs et al., 2006a), which in turn increases the likelihood of success in higher education (Germeijs & Verschueren, 2007b). For commitment, there was only an indirect effect of the exploration profiles on the credit completion rate, and it was relatively small and negative. Previous research did show that exploration can foster commitment to the chosen study (Germeijs et al., 2006a; Germeijs & Verschueren, 2007b), which in turn increases the chances of academic success in higher education (Germeijs & Verschueren, 2007b). Our hypothesis that the effect of exploration can occur through amount of information and commitment was thus only partially confirmed.

This study controlled for various background characteristics of students. These characteristics were found to be related to the profiles, amount of information, and academic success. Specifically, girls displayed more exploration and a higher credit completion rate than boys. General track students had higher levels of information about higher education, higher
persistence, and higher credit completion rates than their counterparts from the technical track. Conversely, low SES students obtained less information about higher education, had lower persistence, and lower credit completion rates. This is in line with literature that showed that students’ background characteristics can affect exploration and academic achievement, in that girls show more exploration (e.g., Demulder et al., 2022; Germeijs & Verschueren, 2006b; Lazarides et al., 2016), and girls, students from more academically preparing tracks, and from higher socioeconomic backgrounds tend to achieve better academically (De Clercq et al., 2013; Richardson et al., 2012; Robbins et al., 2004; Willems et al., 2021). Due to the importance of this knowledge for academic success, it is crucial to provide extra attention to technical track and low SES students, who demonstrate lower levels of information about higher education.

Importantly, it should be noted that all of the observed effects were quite small, especially those related to academic success. Furthermore, some background characteristics exhibited a greater effect on academic success compared to the study choice process variables. Amount of information emerged as the best predictor of academic success among the study choice variables. However, gender, educational track, and SES had similar (e.g., educational track) or even larger (e.g., SES) effects. Nevertheless, significant effects of some study choice variables on academic success persisted even after controlling for students’ background characteristics.

Finally, our results demonstrate that the associations between the exploration profiles, intervening variables, and academic success do not differ across different types of programs. Our SEM model was thus generalizable across the two types of programs. This implies that exploration exerts a similar effect, operating through similar mechanisms, regardless of whether one chooses a more theoretically or practically oriented higher education program.
It also implies that supporting exploration and knowledge acquisition about higher education is equally important, regardless of the chosen program type.

Given the demonstrated relationship between the study choice process and academic success, it is important to focus students’ attention on the importance of the study choice process. Especially given the positive association between the amount of information about higher education and academic success, secondary schools should invest in study choice guidance to enhance students' understanding and knowledge of higher education systems and programs. Our findings emphasize the necessity of not only supporting students' exploration activities but also assessing the knowledge they acquire about higher education over time and how it further supports their decisions and commitment. Both broad knowledge (such as having information about the higher education landscape and the available options) and knowledge in depth (such as having detailed knowledge about specific study options) are important. Providing feedback on students’ knowledge of higher education can increase their awareness of their study choice process. By fostering an environment that encourages informed decision-making, such support can play an additional role in guiding students toward academic success.

Limitations and Directions for Future Research

This study has shed light on the relationship between the study choice process and academic success. However, it is important to acknowledge several limitations that may affect the generalizability of the findings and require further investigation. First, we did not consider other variables that are related to academic success, such as self-efficacy or motivation (Robbins et al., 2004), which may influence the observed relationship between the study choice process and academic success. Furthermore, we did not take into account prior achievement, which research has shown to be one of the best predictors of academic success (Richardson et al., 2012; Schneider & Preckel, 2017). We did
however include prior educational track from which research has shown that students from more academically preparing tracks generally obtain higher grades in their first year of higher education (Willems et al., 2021). Future research could take a more comprehensive approach by considering a wider range of potentially influential factors to obtain a more nuanced understanding of the unique contribution of study choice processes to students’ academic success.

Second, the reliance on self-report measures imposes inherent limitations on the accuracy and reliability of the data collected. Participants' responses may be biased and influenced by social desirability effects, which could compromise the validity of the results. We tried to tackle this by removing those students who answered one or more of the bogus items incorrectly. However, future studies could benefit from incorporating other measures alongside self-report instruments. The use of self-report measures did however allow us to gain insights into the study choice process on a large scale. Furthermore, the higher education outcome measures we used were objective indicators of academic success from the Department of Education database.

Finally, it could be interesting for future research to test the effects of certain study choice intervention programs. These programs could be targeted not only at fostering students’ exploration behavior but also at improving their understanding of the higher education system. By investigating the effectiveness of these intervention programs, researchers can shed light on their potential contributions to foster more informed study choices. This, in turn, could benefit students’ academic success in higher education.

In conclusion, this study, by adopting an integrative model to explain academic success, has provided valuable insights into the relationship between the study choice process and academic success in a large and diverse sample of students. Our findings confirmed the importance of career exploration and
related acquisition of knowledge about study options in higher education in explaining student success. This relation was found, even after accounting for relevant background characteristics, such as SES. This research thus provides empirical ground for setting up targeted interventions aimed at fostering students’ study choice processes, as a means of improving their chances of study success. Establishing this relationship is key, as it provides empirical ground for schools’ and counselors’ efforts to support students’ career choice processes. This research also provides empirical evidence for the assumed importance of exploration in career decision-making models (e.g., Campbell & Cellini, 1981; Gati et al., 1996; Harren, 1979; Tiedeman & O’Hara, 1963) and sheds light on how exploration might affect academic success.
DISCUSSION
Introduction

The main goal of this PhD project was to investigate and get a better understanding of students’ study choice process during the transition from their last year of secondary to higher education. More specifically, this dissertation aimed to answer four research questions, as also depicted in Figure 1:

- Is the Shortened Study Choice Task Inventory (SSCTI) a reliable and valid instrument for mapping students’ study choice process? (RQ1)
- Can different career exploration profiles of students be identified (RQ2A), and how do these profiles develop during the final year of secondary education (RQ2B)?
- What is the association between the identified exploration profiles and different antecedents? (RQ3)
- What is the association between the identified exploration profiles and different outcomes related to the study choice process and academic success in higher education? (RQ4)

In this dissertation, we provided an answer to these research questions using a person-centered and longitudinal perspective on the study choice process.

Figure 1
The conceptual framework

This concluding chapter presents a summary of the main findings from the four chapters. It then provides overarching critical reflections on these
findings. Moreover, it discusses the strengths and limitations of the dissertation research, proposes potential areas for future research, and explores possible implications for policy and practice.

Summary of Main Findings

To provide an answer to RQ1, validating an instrument for mapping students’ study choice process, we examined the reliability and validity of the Shortened Study Choice Task Inventory (SSCTI), a modified and shortened version of the Study Choice Task Inventory (SCTI) in Chapter 1. We conducted exploratory and confirmatory factor analyses which resulted in the removal of some items and the addition of some error covariances. This resulted in a reliable and construct-valid instrument for mapping students’ study choice process. Moreover, measurement invariance analyses showed that both males and females, as well as students from different educational tracks, interpreted the items similarly.

RQ2 on the identification of (transitions between) different career exploration profiles of students was examined in Chapters 2 and 3. In both chapters, the first four scales of this instrument were used to identify different exploration profiles of students who were in their last year of secondary education transitioning to higher education (RQ2A). In Chapter 2 we used one sample of students in their final year of secondary education, while Chapter 3 examined two samples in the fall and spring of the final year. Latent profile analysis (LPA) was used and revealed the presence of three exploration profiles: passive, moderately active, and highly active explorers. The moderately active explorers were the largest group in Chapter 2 (52%) and the spring sample of Chapter 3 (45%), and the second largest one in the fall period (41%) as discussed in Chapter 3. Respectively 35%, 48%, and 44% of students were in the passive explorers profile. The highly active explorers were the smallest group in every sample with respectively 13%, 10%, and 11% of students. In
Chapter 3, we also examined the within-person transition probabilities between profiles across the two timepoints (RQ2B). Our results showed that the moderately active explorers profile was the most stable, while the passive profile was the most variable.

In Chapters 2 and 3 we also provided an answer to RQ3, by investigating the association between the (transitions between) identified exploration profiles and different antecedents. In Chapter 2, different regulation and processing strategies were associated with the exploration profiles; students who scored higher on self-regulation, relating and structuring, concrete processing, and memorizing, and lower on lack of regulation were more likely to be highly active explorers than passive or moderately active explorers. Furthermore, male students were more likely to be passive or moderately active explorers than their female counterparts, who were more likely to be highly active explorers. Chapter 3 demonstrated that girls were more likely than boys to transition to the moderately active profile instead of remaining in the passive profile. In terms of educational track, students in the general track were found more likely to be moderately active than highly active explorers compared to those in the technical track (Chapter 2). However, Chapter 3 did not confirm this finding, and educational track also did not have an effect on the transition probabilities. Finally, with regard to the socioeconomic status (SES), there was no significant effect of SES on the profiles or the transition between profiles (Chapter 3). In addition, Chapter 3 showed that academic self-concept, motivation, and test anxiety were associated with the initial states, while motivation and test anxiety were associated with the transition probabilities. For both academic self-concept and motivation, students scoring higher were found to be less present in the passive or the moderately active than in the highly active profile. Furthermore, compared to students who remained in the passive profile, higher levels of motivation were associated with a higher probability of transitioning to the
moderately active profile. Additionally, compared to students who remained in the highly active profile, higher levels of motivation were associated with a lower probability of transitioning to the moderately active profile. Results on anxiety showed that students with higher scores were less likely to be included in the passive profile than in the highly active profile. Regarding the transition probabilities, higher levels of test anxiety were associated with a higher probability of transitioning to the highly active profile compared to staying in the moderately active profile and associated with a higher probability of staying in the passive profile compared to transitioning to the highly active profile.

Finally, Chapters 2 and 4 addressed RQ4, which examined the association between the identified exploration profiles and different outcomes related to the study choice process and academic success in higher education. Chapter 2 examined outcomes related to the study choice process. The different profiles were associated with decisional status, commitment, and the amount of information acquired about higher education. Highly active explorers were more likely to have made a decision than moderately active or passive explorers, while passive explorers were more likely to be undecided. In terms of both the amount of information and commitment, the highly active explorers scored significantly higher than the moderately active explorers, who in turn scored significantly higher than the passive explorers. Chapter 4 looked at outcomes related to academic success in higher education. It describes how the three distinct career exploration profiles, amount of information, and study choice commitment in the final year of secondary education interrelate to explain academic success in the first year of higher education. The Structural Equation Modeling (SEM) results showed that the exploration profiles had a significant impact on the amount of acquired information and commitment. Moderately active and highly active explorers had higher levels of commitment and more information about higher education than passive explorers. The amount of information acquired had a positive direct effect on academic
success, as students who possessed greater knowledge about higher education had a higher credit completion rate and demonstrated higher persistence. Additionally, an indirect effect of the exploration profiles on academic success through the amount of information was observed. Regarding commitment, there was only a direct effect on the credit completion rate, and an indirect effect of the exploration profiles on the credit completion rate, and these effects were relatively small and negative. This chapter controlled for various background characteristics of students. Finally, differences in relationships across academic and professional bachelor’s programs were examined. Multiple-group SEM analysis showed that there were no differences in the structural paths between academic and professional bachelor’s programs, indicating the generalizability of the model across program types.

**Critical Reflections**

**Person-centered Research**

The present dissertation used latent profile analysis (LPA) to identify different exploration profiles of students transitioning to higher education (RQ2A). Germeijis and colleagues (2012) based their analyses on the six SCTI scales and identified four decision-making profiles: achievement, foreclosure, moratorium, and diffusion, which correspond to Marcia’s (1966) identity status paradigm (Germeijis et al., 2012). However, this dissertation solely focused on the Orientation and Exploration scales of the SSCTI, excluding the Decisional Status and Commitment scales. As a result, profiles with equal amounts of exploration but varying levels of commitment could not be identified. For instance, we did not investigate whether all students from the passive profile show lower commitment to their chosen higher education program. Perhaps some of these students have decided early on, reducing their need to further explore other options. Research from Germeijis and colleagues indeed identified a ‘foreclosure’ profile of students who scored low on the Exploration
scales but high on Commitment (Germeijss et al., 2012). However, it is important to note that Commitment is a conditional scale. Students only complete it when they already have a first choice in mind, as indicated in the Decisional Status scale. By focusing on the Exploration scales, we were able to perform our analysis on a larger group of students, including those who had not yet made a decision. This made the sample(s) more diverse in terms of their study choice process, including in the LPA also those who were still considering many options. The levels of the Decisional Status and Commitment scales were assessed as outcomes of the exploration process for each of the identified profiles.

Person-centered approaches have several advantages. They can help to account for the heterogeneity in the career exploration process (Hickendorff et al., 2018; Woo et al., 2024). Given that careers and career choices result from the unique interplay of a broad set of different characteristics (Hofmans et al., 2020), person-centered approaches are particularly useful in this field. By identifying different career exploration profiles, we can gain further insight into how students navigate the career exploration process and its associations with different antecedents and outcomes. This can lead to the development of interventions that target specific profiles (Hickendorff et al., 2018), as explained later on. Since latent transition analysis (LTA), which was used in Chapter 3, aligns well with the concept of careers as developing and evolving over time, examining study careers in this way may also provide new information (Hofmans et al., 2020).

Depending on when we measured the exploration tasks, the number of students in the passive profile varied. The passive profile was the largest one in the fall sample from Chapter 3, while the moderately active profile was the largest one in Chapter 2 and the spring sample from Chapter 3. The highly active explorers were consistently the smallest profile in all samples. The moderately active explorers were the most stable profile (78% stayers), while
the passive explorers were the most variable profile in comparison with the other profiles, with 44% of them being able to transition to the moderately active profile between fall and spring, and 4% even being able to transition to the highly active profile (Chapter 3). In contrast, almost no students transitioned from the moderately active to the passive profile (0.1%). According to Hickendorff and colleagues (2018), such asymmetry of transition probabilities suggests a developmental ordering of profiles, in this example from passive to moderately active but not the other way around.

The added value of a person-centered approach may be criticized when only a ‘low’, ‘average’, and ‘high’ profile are found, as was the case in our research. “In cases like these, where profiles are defined mainly by (quantitative) levels without much configurational (qualitative) difference, one might question the unique value of person-centered approaches.” (Woo et al., 2023, p. 18). The latent profiles may represent the same underlying continuum, in which the classes are ordered (Bouwmeester et al., 2004). However, according to Hickendorff and colleagues (2018) latent profiles can still be useful for providing statistically sound categorizations instead of using arbitrary cut-off points. In this dissertation, a combination of different parameters was used to evaluate which model fit the data best, including the BIC, entropy, and the classification error (J. K. Vermunt & Magidson, 2005).

Also, when starting the analysis, it may not always be possible to clearly specify the exact nature of the results that are expected. Then replication becomes especially important (Morin et al., 2018), which also adds to the rigor of the research (Woo et al., 2024). “To support a substantive interpretation, construct validation is necessary and involves demonstrating that the profiles: (a) have heuristic and theoretical value; (b) are meaningfully related to key covariates; and (c) generalize to new samples or present some degree of stability over time.” (Morin et al., 2018, p. 808). We were able to successfully replicate our profile solution in multiple larger samples of both general and technical
track students. Results from Chapters 2 and 3 showed that the identified three-profile solution is robust across different samples and timepoints. The profile solution was replicated across different cohorts, but also, in the preparing steps, across general and technical education students (c). Furthermore, we investigated associations between the exploration profiles and different antecedents and outcomes (b). Finally, we determined the optimal number of profiles not only based on the statistical fit indices, but also considered theoretical justification, parsimony, and ease of interpretation (Jung & Wickrama, 2008; J. K. Vermunt & Magidson, 2003) (a).

**Knowledge about Higher Education**

This dissertation demonstrated the importance of students’ knowledge about higher education when making a study choice for higher education (RQ4). Passive explorers obtained less information about higher education compared to moderately and highly active explorers, as discussed in Chapter 2. This finding was further supported in Chapter 4, where the SEM analysis revealed that students from highly active or moderately active profiles obtained more information about higher education than the passive explorers. This is in line with previous variable-centered research which suggested a positive relationship between the exploration tasks and the amount of information acquired (Germeijss et al., 2006a). In addition, in Chapter 4, the amount of information predicted the credit completion rate and persistence in higher education. Students with greater knowledge about higher education had higher credit completion rates and were less likely to reorient or drop out. Finally, there was an indirect effect of the profiles on persistence and the credit completion rate through amount of information. These effects were present even after controlling for important background characteristics of students.

The positive association between the amount of information and higher education outcomes extends previous research and highlights the
importance of gathering information about the higher education structure and possible study options. Furthermore, although the amount of information about higher education scale only consists of four items and was measured during the spring of the last year of secondary education, it was found to be associated with academic success after the first year of higher education, 1.5 years later. The impact of the knowledge about higher education thus resonates throughout students’ entire first year of higher education. In conclusion, this dissertation emphasizes the importance of the amount of information in shaping students’ educational outcomes.

Commitment

Similar to the results we found for the amount of information, highly active explorers showed more commitment to their chosen program compared to moderately active and passive explorers, both in Chapters 2 and 4. This is in line with previous variable centered research, which has shown that broad and in-depth exploration were associated with higher levels of commitment (Germeijs et al., 2006a; Germeijs & Verschueren, 2007b; Porfeli et al., 2011). It is important to note that not all students completed the commitment scale as it was conditional. Only those who indicated having a first choice in the decisional status scale completed it. However, Chapter 4 also revealed an unexpected finding: after controlling for the other variables in the model, students who reported higher commitment had a slightly lower credit completion rate. This contrasts with the findings of Germeijs and Verschueren (2007b), who found higher commitment to relate with more choice actualization, higher academic adjustment, and lower drop-out rates (Germeijs & Verschueren, 2007b). However, the effect we found was very small \( \beta = -.04, \ p < .05 \), and there was no significant bivariate correlation between commitment and the credit completion rate \( r = -.003 \). Despite this, the expected positive association of commitment with academic success was not
found. It is also important to note that there was no significant association with our other academic success outcome, study persistence.

A first potential explanation for the unexpected finding that commitment was not positively associated with academic success may be the time of measurement. Whereas Germeijs and Verschueren measured commitment at the beginning of higher education, we used measures from February to April during the final year of secondary education. Possibly, this is too early in the study choice process to reveal effects. It would be interesting to conduct further research on how commitment evolves over time and whether later measurements have greater predictive value for academic success. Furthermore, Germeijs and Verschueren (2007b) used a sample consisting only of general track students, while we used a more diverse sample that included both general and technical track students, trying to predict higher education outcomes for a wide range of 133 professional and academic higher education programs, more than one year later.

**Strengths, Limitations, and Suggestions for Future Research**

**Sample**

This dissertation used multiple large and diverse samples of students in their final year of secondary education which could also be followed into higher education, ranging from 672 (the longitudinal sample in Chapter 3) to 11,559 (Chapter 1) students. All samples were drawn from the student group using the Columbus tool, which reaches about one third of all first-time students. Chapter 1 took into account general, technical, and vocational track students, while Chapters 2, 3, and 4 focused on general and technical track students who transitioned to higher education. This selection was made because in Flanders the vocational track is not typically designed to prepare students for higher education. The arts track was too small to be included in this dissertation. In
Chapter 4, we further focused on students from the general or technical track who transitioned specifically to an academic or professional bachelor's program in higher education. The use of these large and diverse samples offered several methodological advantages. These substantial samples allowed for more generalizable results. Furthermore, we were also able to replicate some of our findings, such as the identification of the exploration profiles, across multiple (sub)samples (e.g., educational track) and thus ensure their robustness.

However, focusing mainly on the general and technical track and on the academic and professional bachelor’s programs also has its limitations. First, all fields of study within these tracks and programs were grouped and analyzed together. Future research could take a more fine-grained perspective and look further into specific fields of study in secondary and higher education. Second, we were not able to include the associate’s degree programs as a separate category in our analyses in Chapter 4, due to a lack of sufficient data. Future research should include the associate’s degree programs, as they are a growing part of the Flemish higher education landscape, and their inclusion would enhance the comprehensiveness of our findings.

**Included Measures**

This dissertation focused on multiple antecedents and outcomes of the exploration process. The data used in this dissertation were obtained from the Columbus tool, which includes mainly self-report measures. Additionally, we linked our datasets to the databases of the Department of Education and Training to obtain further administrative data. This approach allowed for insights into the study choice process on a large scale. We were able to investigate the effect of different antecedents from the framework by Jiang and colleagues (2019) on the exploration profiles in Chapter 3. Furthermore, Chapter 2 revealed that different processing and regulation strategies were
associated with the exploration profiles. As the Columbus data can be linked to the databases of the Department of Education and Training, we were able to examine how the three career exploration profiles, amount of information, and study choice commitment in the final year of secondary education interrelate to explain academic success in the first year of higher education. Academic success was measured using two objective criteria: the credit completion rate (the number of earned credits divided by the number of enrolled credits) and a study persistence measure (whether or not students dropped out or changed programs).

However, the dissertation also had some limitations regarding the included measures. The majority of the variables were measured through self-reports, which could have influenced the accuracy and reliability of the collected data. Students’ responses may have been biased or answered in a socially desirable way. Where possible (in Chapters 3 and 4), we attempted to address this issue by removing those students who answered the bogus items incorrectly (Chauliac et al., 2023). This enabled us to detect careless invalid responses (Curran, 2016). Furthermore, we also considered some more objective variables, such as students’ background characteristics, and their credit completion rate and study persistence in higher education, by linking our data to the Flemish Department of Education and Training databases. Future studies could incorporate multiple complementary careless response detection methods (Chauliac et al., 2023; Curran, 2016). Also involving additional informants could be useful to gather a more comprehensive understanding of the study choice process. For example, parents could be asked to evaluate the amount of exploration behavior of their children. However, it is important to note that these informants may not have a complete understanding of the study choice process of their children, and certain variables, such as commitment, may still require self-reports.
This dissertation only used quantitative data, enabling the examination of large samples of students, resulting in generalizable and replicable results. However, future research could supplement a quantitative analysis with a qualitative perspective, such as conducting focus groups to gain deeper insights into the experiences of students during or after the study choice process. The present survey research could also be supplemented by conducting experiments to investigate the effects of interventions, for example those targeted at counseling type or at promoting exploration, and to investigate causality. These focus groups and experiments could offer valuable insights to complement the quantitative findings.

Additionally, we should be aware of possible bidirectionality. For instance, we have examined the effect of the antecedents on the career exploration profiles, but there may be a reciprocal or mutual relationship between these variables as well. Chapter 3, for instance, has shown that (academic) motivation is positively associated with the career exploration profiles and the transitions between them, but investing more in exploration, such as researching websites of higher education institutions or visiting them, could also enhance their motivation for school.

Moreover, it is important to consider that there may still be unaccounted-for variables or contextual factors that could influence students’ career exploration. Other variables that could play a role and may provide additional insight are for instance personality characteristics such as openness or conscientiousness (S. D. Lee et al., 2023; Li et al., 2015; Nauta, 2007; Reed et al., 2004). For instance, conscientious individuals tend to be hardworking, achievement-oriented and goal-directed. As a result, they are more likely to persist in completing exploration activities (S. D. Lee et al., 2023; Reed et al., 2004). Future research could investigate the role of these personality characteristics in addition to the antecedents already examined in this dissertation. For this dissertation, however, we analyzed data from the
Columbus tool, in which it was deliberately decided to include variables that are important in the transition to higher education but are also remediable, meaning that students receive feedback and tips so they can take action to improve them. A component of the Columbus tool that was not used in this dissertation are the RIASEC interests of students. Future research could investigate these interests as they appear to be associated with career exploration (Nauta, 2007; Tracey et al., 2006). Future research could also focus on the relation between the career exploration profiles and other important outcomes in higher education. We took into account the credit completion rate and study persistence of students, but other higher education outcomes that are worth examining are for instance students’ satisfaction with their choice, choice actualization, and academic or social integration (Germeijs et al., 2012; Germeijs & Verschueren, 2007b). This dissertation defined study persistence as not dropping out or changing programs in the first year of higher education. Future research could examine reorientation in more detail, such as the difference between whether students change within academic bachelor's programs or from an academic to a professional bachelor's program. This dissertation focused on the relationship between the study choice process and academic success in the first year of higher education. Future research could investigate academic success over an even longer period, for instance by focusing on the time to graduation. This could provide additional evidence on the importance of the study choice process.

Finally, and unfortunately, we were not able to take into account contextual factors. For example, the Self-Exploration scale of the SSCTI measures whether students have discussed their study choice with others (such as parents, family, friends, teachers,...), but it does not provide us with information about guidance on the study choice process as it may occur in schools. Although we are aware that there may be variations in the guidance provided to students by different schools, as we have learned from our
discussions with teachers and schools (Willems, 2022), we were not able to take these differences into account in the present dissertation. Although some items of the SSCTI assess whether students have discussed their study choice with others, we did not include measures to assess parental support of the study choice process, nor did we take into account possible peer influences. Future research could investigate the contextual supports and barriers in the school and home contexts more thoroughly to address these limitations.

Furthermore, the administration of the Columbus tool could be extended to include questions about the circumstances under which students use the tool, such as whether they use it at home or at school, as well as the guidance they receive when completing the questionnaires and are consulting the feedback. Chapter 1 showed that a shortened and updated version of the SCTI could be validated. However, it is important to note that the SSCTI does not measure all the dimensions of the complex study choice process. It may be interesting to include additional tasks or aspects that are currently not captured by the SSCTI. The SSCTI could be extended with items measuring other dimensions, tapping into current social developments, such as the study choice and exploration process increasingly taking place online. Supplementing the quantitative data with qualitative data, such as conducting focus groups with students who completed the questionnaire, could be useful.

Measurement Times

The current dissertation is based on data from the Columbus tool. Since the 2017-2018 school year students can complete the ‘How do I choose?’ component, in which they fill out the SSCTI, multiple times throughout the school year. Initially, this was limited to specific time periods: once between the start of the school year and February’s winter break, once between the winter break and Easter, and a final time before the end of the school year. Since 2019-2020 the administration of the ‘How do I choose?’ component
changed from these fixed periods to a delayed administration with at least six weeks or 42 days in between. Students have the autonomy to decide when and how often they want to fill out the ‘How do I choose?’ component. This dissertation used different cohorts measured at different timepoints.

Chapters 2 and 3 indicate that a significant proportion of students are (still) passive explorers during the two measured periods. It is possible that fall and even early spring are too early for students to have fully engaged in the exploration process. In Flanders students have the freedom to choose from a wide range of higher education programs due to the open access policy. This can be overwhelming for some students, which may explain why their exploration and decision-making process takes longer. In Chapter 3, the passive profile was the most variable profile, with 48% of students transitioning to the moderately active (44%) or highly active (4%) profile between fall and spring. Additionally, 22% of students were able to move from the moderately active to the highly active profile. Previous variable-centered research showed general increases in the degree of exploration during the last year (Germeijs & Verschueren, 2006b). From fall to spring in the last year of secondary education, students appear to be making progress in their exploration. However, students from the highly active profile also commonly transitioned to the moderately active profile (42%). Since this profile was the smallest in the data, it represents only a small fraction of students in absolute numbers. For these students, it is possible that after a period of high exploration behavior, they experience a decrease in exploration. This may be because they have already completed the most important phase of their decision-making process. Fortunately, there were very few transitions from the highly or moderately active profiles to the passive profile.

As previously stated, students have the autonomy to decide when and how often they complete the ‘How do I choose?’ component. According to our data, students tend to complete this component at the beginning of the
school year, with little to no data available for the months after April or for more than two timepoints, which makes it difficult to assess the study choice process at a later timepoint. It is important to note that the longitudinal sample in Chapter 3 was smaller than the other samples used in this dissertation, as it only included students who completed the ‘How do I choose?’ component twice, during two specific time periods. This selection may have introduced bias, as these students may be experiencing difficulties in their decision-making process, which could explain why they feel the need to complete the component a second time. Alternatively, it could be that these students are simply more motivated to make work of their study choice. Future research could measure the decision-making tasks at a later timepoint, such as May or June, as we expect students to make progress in self-, broad, and in-depth exploration behavior between the beginning and end of their final year in secondary education (Germeijs & Verschueren, 2006b). As a result, we hypothesize that more students would be highly active explorers. Another option is to administer the Decisional Status and Commitment scales separately, so that students would not have to complete the entire SSCTI questionnaire multiple times, but only these two subscales. Administering the Commitment scale later might also be useful when examining its association with academic success in higher education. Recent developments, such as the introduction of positioning tests (‘ijkingstoetsen’), have made it interesting to consider adding an even later timepoint. These tests usually take place in July and August and provide valuable feedback on students’ abilities to succeed in their provisionary choice. By the end of the final year of secondary education, students may also have completed relevant assessments or examinations that could influence their study choices. These evaluations may provide them with additional insights into their strengths and weaknesses, which could affect their decisions regarding future studies. This allows them to have a full
understanding of themselves and their possibilities, which can help them to better choose the path that best suits their individual needs and goals.

**Other Theoretical Perspectives**

This dissertation examined the study choice process from a decision-making approach that considers the career decision-making process as a process consisting of different decisional tasks. Other theories view career choices from different perspectives, such as a matching, developmental, or social-cognitive approach (S. D. Brown & Lent, 2020). They emphasize different facets of career decision-making, such as the role of personality or lifespan considerations, and can provide complementary insights into the psychological, developmental, and contextual factors that shape individuals' career choices.

While the focus of this dissertation, and the Columbus tool in general, is on ‘how’ students go through the decision-making process, other theories focus more on the ‘what’ of students’ choices. For instance, Holland’s RIASEC model focuses on the degree of fit or congruence between the person’s characteristics and the chosen work or educational environment (Nauta, 2020).

Furthermore, this dissertation did not examine the ‘why’ of students’ exploration process; the reasons for starting their exploration process were not investigated. It is unclear whether they were intrinsically motivated to start the process, or if they for instance were encouraged by external factors, such as feeling pressured by their parents (Vermote et al., 2023) or their teachers, since the Columbus tool is provided to students by schools and is usually completed in class.

The focus of the SSCTI and this dissertation in general is solely on one specific decision, namely the study choice for higher education. This allows for a thorough investigation and better understanding of students’ study choice process during the transition from the final year of secondary to higher education. This dissertation provided empirical evidence supporting the
assumed importance of exploration in career decision-making models (e.g., Campbell & Cellini, 1981; Gati et al., 1996; Harren, 1979; Tiedeman & O’Hara, 1963). It is important to note, however, that choosing a study for higher education is just one of many career-related decisions individuals have to make throughout their lives, which other theories might place more emphasis on.

Identity-related theories offer a more comprehensive framework for understanding how adolescents and emerging adults navigate challenges or decisions across diverse domains of identity formation; including career paths, relationships, personal values, or societal roles. They examine exploration and commitment in a broader sense, beyond the decision-making process for higher education (Luyckx et al., 2013). While our focus is solely on students in their last (two) year(s) of secondary education, they examine identity development during, and even before or after adolescence. Further research could combine the SSCTI with other instruments focusing on other career decisions or decisions in general.

**Implications for Practice and Policy**

**Detection and Support of At-Risk Students**

As mentioned above, using LPA to identify different profiles can lead to the development of interventions that target specific profiles (Hickendorff et al., 2018). This dissertation identified students from the passive profile as ‘at-risk’. We revealed that they most often have not yet made a decision, may exhibit less commitment to their chosen higher education process, as well as less knowledge about higher education (Chapter 2). Ultimately, this lack of knowledge about higher education was related to a lower credit completion rate and study persistence in higher education (Chapter 4). The insights from this dissertation can lead to more tailored support for the three identified profiles throughout their decision-making process. Tailored assistance or intervention programs could be developed to more effectively match students’
exploration profiles. Passive explorers, who have yet to fully start their decision-making process, could benefit from being activated to start and invest effort in their exploration process. Additionally, they could benefit from support in how to start gaining information about themselves and possible career options. Students with less effective processing and regulation strategies are more often passive explorers. Therefore, this profile may benefit from increased external guidance in their decision-making process. The moderately active explorers have slowly started their exploration process, which is why they may require assistance in identifying and organizing the different options available to them as they progress through the career decision-making process. Since the highly active explorers have already conducted extensive exploration, they may benefit from additional assistance in committing to their provisional decisions. This could include help with identifying the necessary steps to turn a decision into a tangible and committed reality.

The results on the transitions between profiles in Chapter 3 emphasize the importance of the timing of interventions to support students in their decision-making process. Being in the passive explorers’ profile in fall is not as concerning as (still) being in the passive profile in spring. Whether being in the passive profile is worrisome depends on when in the educational career we measure the exploration tasks. Targeted actions can be taken to prevent passive explorers from remaining in this profile over time when they can already be identified in fall. Particularly since more than half of them appear to remain passive between fall and spring, effective interventions might have a beneficial impact on this group of students. This can also be incorporated into the Columbus feedback. Currently, students receive textual feedback on each of the SSCTI scales in the ‘How do I choose?’ feedback in Columbus. If they fill out the component more than once, the feedback is automatically updated to provide comparative feedback in which their administration at the new timepoint is compared to their administration at the old timepoint. Based on
the results presented in this dissertation, feedback in the Columbus tool could also be tailored according to the three identified profiles, and provide more specific recommendations for remediation. Students could be assigned one of the three profiles that best match their combination of scores on the orientation and exploration subscales, and feedback could be tailored accordingly. This type of feedback provides a more comprehensive overview of students’ exploration process. This holistic perspective better captures the heterogeneity in the career exploration process. As careers and career choices are influenced by a complex interplay of a wide set of personal and contextual characteristics (Hofmans et al., 2020), providing feedback in this manner may better match the exploration process than providing feedback in a dimensional way for each of the SSCTI scales. Students may perceive this type of feedback as more individualized and personalized, which could enhance their engagement with it. However, it may also be too complex for some students. Achieving the right balance of detail can be challenging and depends on the students, their expertise, and how they receive the feedback (Lipnevich et al., 2016; Lipnevich & Smith, 2022). This could lead to problems with interpreting and even misinterpreting the feedback. The feedback provided to students should be comprehensible, allowing them to effectively process the information (Lipnevich et al., 2016; Lipnevich & Smith, 2022). Additionally, this type of feedback may oversimplify the complexity of the exploration process and lack nuance or specificity, providing less detailed information than giving feedback on each scale individually. For example, students may not be able to identify the type of exploration they demonstrate less and how to improve.

Chapters 2 and 3 demonstrated that different antecedents (such as academic self-concept, motivation, and learning strategies) were associated with the profiles and transitions between them. These findings suggest that when providing interventions or counseling to students in the study choice
process, it may be important to also address these antecedents. It is important to note that these antecedents are changeable and can be remedied. For example, offering interventions tailored to improving students’ learning strategies may enhance their ability to process information during the exploration process. This, in turn, could result in a more beneficial exploration profile and better outcomes of the decision-making process. As another example, working on a more clear and certain self-concept could improve students’ exploration process and profile by enabling them to match new information with their existing knowledge about themselves. Interventions aimed at enhancing self-concept (Haney & Durlak, 1998; O’Mara et al., 2006), increasing motivation (e.g. Lazowski & Hulleman, 2016), or improving learning strategies (e.g. Hattie et al., 1996; Pandey et al., 2018; Weinstein et al., 2000) have proven to be effective. It may not always be possible to address the antecedents prior to the study choice process. In such cases, counseling could be tailored to students’ learning strategies, self-concept, motivation, and other antecedents. For instance, as previously mentioned, students with less effective processing and regulation strategies may benefit from increased external guidance in their decision-making process.

Knowledge about Higher Education

This study demonstrated the importance of students’ knowledge about higher education when making a study choice for higher education. Both broad knowledge, such as having information about the higher education landscape and the available options, and in-depth knowledge, such as having detailed information about specific study options, are important. Schools could facilitate this by, for example, organizing information sessions on the structure of higher education and available study options. Inviting staff from higher education institutions to provide information about their programs and financial aid options can also be helpful. Furthermore, many schools already
organize visits to the ‘SID-ins’ or study information days (‘Studie-informatiedagen’), where students can learn about different study and career options at various higher education institutions. The different institutions provide students with general and specific information about studying in higher education. Online assessment tools, such as Columbus, may also play a role, especially if they are followed by individualized counseling based on the feedback from the tool. The Columbus instrument focuses more on self-exploration than on exploration of the environment, while this dissertation highlights the importance of knowledge about the structure of higher education and possible study options. To improve the Columbus ‘How do I choose?’ feedback, information about the organization of higher education could be included, for instance by providing students with access to information about higher education (via links, etc.), or by adding short informational videos (video clips), possibly followed by a knowledge test.

Chapter 4 demonstrated that the amount of information was positively related to academic success, even after controlling for students’ gender, educational track, and SES. However, SES was also positively related to the amount of information and to both academic success indicators, with high SES students displaying more knowledge about higher education, having a higher credit completion rate and being less likely to drop out or change programs compared to low SES students. It is important to give extra attention to these students, who demonstrate lower levels of knowledge about higher education, as this knowledge is important for academic success. Schools should be aware of this and offer additional support to these students during their decision-making process.

Implications for Policy
In Flanders, higher education is generally accessible to all. However, this results in low success rates and high drop-out rates. A significant 15% of students who
started higher education in the 2020-2021 academic year dropped out after one year. Additionally, only 31% of students who started higher education during the 2019-2020 academic year finished their bachelor’s degree within the prescribed study period (Statistiek Vlaanderen, 2023a, 2023b). To increase the study efficiency in higher education, the government agreement (Vlaamse Regering, 2019; Weyts, 2019) introduced the so-called ‘viertrapsraket’ (a four-stage approach) of which Columbus is one component. It consists of the results from secondary education and the recommendation of the class council, the online assessment tool Columbus, compulsory but non-binding entrance exams, and a rapid reorientation process (Vlaamse Regering, 2019; Weyts, 2019). This dissertation confirms that the way students handle their study choice process can impact their academic success in higher education, even after controlling for students’ gender, educational track, and SES (Chapter 4). This emphasizes the government’s efforts to focus on students’ decision-making process and the malleable factors associated with it, by implementing the Columbus tool. Future research could expand on investigating the effectiveness of Columbus as an exploration tool, for instance by further examining the factors that influence students’ engagement with the feedback and its effectiveness in supporting students in their study choice process.

Another important aspect of the policy coalition agreement was the implementation of Flemish tests (‘Vlaamse toetsen’): validated, standardized, and normed tests to improve the quality of Flemish education by measuring whether pupils achieve the final attainment levels, as well as the learning gains of pupils and schools (Vlaamse Regering, 2019; Weyts, 2019). These tests will focus on the Dutch language and mathematics and will be conducted twice during elementary school and twice during secondary education. In 2024, the first assessment will take place in the fourth year of elementary school and the second year of secondary school. The first assessment in the last year of secondary education is scheduled for the 2026-2027 school year (Onderwijs &
Vorming Vlaanderen, 2024). As Columbus also targets students in their final year of secondary education, it is important to avoid overburdening the students and their schools with assessments. The Flemish tests will assess whether students reach the attainment level for Dutch language and mathematics, while the Columbus tool evaluates a broader range of skills including numerical skills, reasoning, vocabulary, and academic language proficiency, by mapping individual variations in cognitive scores across a wide range of cognitive tests. The Flemish tests focus solely on knowledge, while the Columbus instrument also considers students’ study choice process, their study and learning strategies, and interests. In the future, information from the Flemish tests may provide complementary insights for the statistical analyses of the Columbus tool, for instance by supplementing information on additional student background characteristics.

In the past years, Columbus has reached an increasing number of students, highlighting the need for support in the decision-making process. It is widely used, reaching about one third of all first-time higher education students. Although it was initially proposed to make the tool mandatory for all students transitioning to higher education (Kabinet Vlaams minister van Onderwijs, 2016), this idea has received less attention in recent years. However, it may be beneficial to require all students to use Columbus when making their study choice, in order to make more informed decisions regarding higher education. Choosing which program to study in higher education is one of the most important decisions students have to make, and the choice is significant for both the individual and society (Gati & Asher, 2001b; Skorikov, 2007). Furthermore, it is related to academic success in higher education, as demonstrated by previous research (De Clercq et al., 2013; Germeijs & Verschueren, 2007b; Negru-Subtirica & Pop, 2016) as well as in Chapter 4.

Since Flemish higher education has quite high study delay and drop-out rates, and tuition fees are intentionally kept very low to ensure accessibility for all
students, society currently pays the price for these delays. Students may avoid disappointment by choosing a program that aligns with their interests and by ensuring that they have the necessary skills and attitudes to succeed in the chosen program. Columbus can support students in making their study choice and hopefully help them in selecting the program that best suits them. The Columbus feedback does not prescribe ‘what’ this choice should be, but provides information at the level of study domains and aims to encourage exploration behavior.

**Conclusions**

This dissertation aimed to enhance the understanding of students’ study choice process during the transition from secondary to higher education. First, we demonstrated the measurement invariance of the SSCTI, an instrument to evaluate students’ engagement in (different decisional tasks within) the study choice process. Secondly, we identified three exploration profiles of students: passive, moderately active, and highly active explorers. Transitions between these profiles were examined, and it was found that the passive profile was the most variable profile. When they transition, most students were able to make positive transitions to more active profiles. Thirdly, we examined associations of the profiles and the transitions with different antecedents. The results indicated that students with more effective learning strategies, a more positive academic self-concept, and higher levels of motivation, were more likely to be categorized as highly active explorers than as moderately active or passive. Finally, we examined the associations between the identified exploration profiles and different outcomes related to the study choice process and academic success in higher education. The findings demonstrated that students from the highly active profile were more likely to have made a study choice decision, showed greater commitment to their chosen program, and possessed more knowledge about higher education. Furthermore, the profiles
significantly predicted the amount of information and commitment, with the former having a positive direct effect on academic success. Additionally, an indirect effect of the exploration profiles on academic success through the amount of information was observed. Our findings demonstrated the importance of students’ engagement in the study choice process in the transition to higher education. The Columbus assessment tool can play an important role in supporting students in their decision-making process.

In conclusion, this dissertation identifies three exploration profiles based on four scales of the SSCTI. It also highlights the importance of the knowledge that students acquire about higher education, which is related to academic success in higher education.
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APPENDICES
Appendix 1.A

*Items SSCTI in Dutch*

<table>
<thead>
<tr>
<th>Oriëntatie</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Or1</td>
<td>Ik denk vaak na over welke studie ik volgend jaar zal kiezen.</td>
</tr>
<tr>
<td>Or2</td>
<td>Ik wil mijn best doen om een goede studiekeuze voor volgend jaar te maken.</td>
</tr>
<tr>
<td>Or3</td>
<td>Ik ben nu bereid om tijd te besteden aan het zoeken van een studie.</td>
</tr>
<tr>
<td>Or4</td>
<td>Ik dagdroom vaak over welke studie ik zal aanvatten.</td>
</tr>
<tr>
<td>Or5</td>
<td>Ik wil me nu al graag inspannen zodat ik een correcte studiekeuze zou maken.</td>
</tr>
<tr>
<td>Or6</td>
<td>Ik denk vaak aan het feit dat ik een studiekeuze moet maken.</td>
</tr>
<tr>
<td>Or7</td>
<td>Ik heb zin om nu al na te denken over welke studie ik zou kiezen.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Exploratie van zichzelf</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EZ1</td>
<td>Ik heb zelf nagedacht over wat ik goed en minder goed kan.</td>
</tr>
<tr>
<td>EZ2</td>
<td>Ik heb zelf nagedacht over wat ik graag en minder graag doe.</td>
</tr>
<tr>
<td>EZ3</td>
<td>Ik heb zelf nagedacht over wat ik belangrijk en minder belangrijk vind voor mijn toekomst.</td>
</tr>
<tr>
<td>EZ4</td>
<td>Ik heb zelf nagedacht over mijn studie-aanpak.</td>
</tr>
<tr>
<td>EZ5</td>
<td>Ik heb met anderen (bijvoorbeeld ouders, familie, vrienden, leerkrachten,…) een gesprek gehad over wat ik goed en minder goed kan.</td>
</tr>
<tr>
<td>EZ6</td>
<td>Ik heb met anderen (bijvoorbeeld ouders, familie, vrienden, leerkrachten,…) een gesprek gehad over wat ik graag en minder graag doe.</td>
</tr>
<tr>
<td>EZ7</td>
<td>Ik heb met anderen (bijvoorbeeld ouders, familie, vrienden, leerkrachten,…) een gesprek gehad over wat ik belangrijk en minder belangrijk vind voor mijn toekomst.</td>
</tr>
<tr>
<td>EZ8</td>
<td>Ik heb met anderen (bijvoorbeeld ouders, familie, vrienden, leerkrachten,…) een gesprek gehad over mijn studie-aanpak.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Exploratie in de breedte</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EB1</td>
<td>Ik heb een overzicht doorgenomen van hoe de structuur van het hoger onderwijs eruit ziet.</td>
</tr>
<tr>
<td>EB2</td>
<td>Ik heb brochures of websites van verschillende studierichtingen bekeken.</td>
</tr>
<tr>
<td>EB3</td>
<td>Ik heb zelf overzichten met de korte inhoud van studierichtingen doorgenomen.</td>
</tr>
<tr>
<td>EB4</td>
<td>Ik heb zelf overzichten met opleidingsnamen doorgenomen.</td>
</tr>
<tr>
<td>EB5</td>
<td>Ik heb zelf overzichten van adressen van onderwijsinstellingen doorgenomen.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Exploratie in de diepte</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ED1</td>
<td>Ik heb een brochure of website over een studierichting grondig bekeken.</td>
</tr>
<tr>
<td>ED2</td>
<td>Ik heb de brochures of websites van verschillende studierichtingen met elkaar vergeleken.</td>
</tr>
<tr>
<td>ED3</td>
<td>Ik ben naar een infodag van een onderwijsinstelling geweest waar één van de studierichtingen ingericht wordt.</td>
</tr>
<tr>
<td>ED4</td>
<td>Ik heb gepraat met studenten die nu in het hoger onderwijs zitten over één van de studierichtingen.</td>
</tr>
<tr>
<td>ED5</td>
<td>Ik heb een cursusboek van een bepaalde studierichting bekeken.</td>
</tr>
<tr>
<td>ED6</td>
<td>Ik heb gepraat met mensen met beroepservaring over hun studie en/of beroep.</td>
</tr>
<tr>
<td>ED7</td>
<td>Ik heb gepraat met anderen (bv. ouders, vrienden, leerkracht, …) om meer te weten te komen over een studierichting.</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Binding</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>Bi1</td>
<td>Ben je zeker van de keuze voor deze studierichting?</td>
</tr>
<tr>
<td>Bi2</td>
<td>Geeft de keuze voor deze studierichting je het gevoel dat je jouw toekomst met vertrouwen en optimisme tegemoet kunt zien?</td>
</tr>
<tr>
<td>Bi3</td>
<td>Zou de keuze voor deze studierichting even goed weer kunnen veranderen?</td>
</tr>
<tr>
<td>Bi4</td>
<td>Zou je gemakkelijk kunnen afstappen van de keuze voor deze studierichting?</td>
</tr>
<tr>
<td>Bi5</td>
<td>Ben je onzeker over de keuze voor deze studierichting?</td>
</tr>
<tr>
<td>Bi6</td>
<td>Is deze studierichting helemaal jouw eigen keuze?</td>
</tr>
</tbody>
</table>

*Noot.* Cursief gedrukte items werden later, op basis van betrouwbaarheid- en factoranalyse op data van de cohorte 2016-2017, verwijderd.
### Appendix 1.B

*Goodness-of-fit-indices CFA and Cronbach’s alpha per scale for different subgroups*

<table>
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<th>Sample</th>
<th>n</th>
<th>CFI</th>
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<th>SRMR</th>
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### Appendix 1.C

*Mean and standard deviation of the raw sum scores across different subgroups*

<table>
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<th>Orientationa</th>
<th>Self-Explorationb</th>
<th>Broad Explorationb</th>
<th>In-Depth Explorationb</th>
<th>Commitmentc</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
<td>SD</td>
</tr>
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<td>2.71</td>
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<td>Male</td>
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<td>Female</td>
<td>4.10</td>
<td>.66</td>
<td>2.77</td>
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<td>2.67</td>
<td>.53</td>
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</table>

*Note.* a) Answering categories = 1-5; b) Answering categories = 1-4; c) Answering categories = 1-6
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Appendix 2.A

Multinomial logistic regression results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Passive versus Moderately active</th>
<th>Highly active versus Moderately active</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$ (SE)</td>
<td>95% CI for Odds Ratio</td>
</tr>
<tr>
<td></td>
<td>Lower</td>
<td>Odds Ratio</td>
</tr>
<tr>
<td>Intercept</td>
<td>2.77 (.22)</td>
<td>-</td>
</tr>
<tr>
<td>Self-regulation</td>
<td>-.56** (.06)</td>
<td>.51</td>
</tr>
<tr>
<td>Lack of regulation</td>
<td>.12* (.04)</td>
<td>1.04</td>
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<tr>
<td>Relating and structuring</td>
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<tr>
<td>Concrete processing</td>
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<td>Memorizing</td>
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<tr>
<td>Gender</td>
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<td>Educational track</td>
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</table>

Note. The reference category includes moderately active explorers; females were the reference group for gender; technical track was the reference group for educational track.

* Significant at the <.05 level
** Significant at the <.001 level
## Appendix 3.A

*Means, Standard Deviations, and One-Way Analyses of Variance in the four exploration tasks for the three profiles in Fall*

<table>
<thead>
<tr>
<th></th>
<th>Passive</th>
<th>Moderately active</th>
<th>Highly active</th>
<th>$F(2, 9564)$</th>
<th>$\eta^2$</th>
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<td>$M$</td>
<td>$SD$</td>
<td>$M$</td>
<td>$SD$</td>
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* $p < .001.$
### Appendix 3.B

*Means, Standard Deviations, and One-Way Analyses of Variance in the four exploration tasks for the three profiles in Spring*

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<th>Task</th>
<th>Passive M</th>
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<th>Moderately active M</th>
<th>Moderately active SD</th>
<th>Highly active M</th>
<th>Highly active SD</th>
<th>F(2, 7251)</th>
<th>η²</th>
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</thead>
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*p < .001.
Appendix 4.A

Summary of the SEM results

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<tr>
<td>Moderately active profile → Commitment</td>
<td>.23**</td>
</tr>
<tr>
<td>Moderately active profile → Study persistence</td>
<td>-.01</td>
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<tr>
<td>Moderately active profile → Credit completion rate</td>
<td>-.02</td>
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<td>Moderately active profile → Amount of Information → Study Persistence</td>
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<tr>
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</tr>
<tr>
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* *p < .05, ** *p < .001
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