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Navigating transitions: A longitudinal exploration of career decision-making process dynamics in adolescents

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ABSTRACT

In times of changing labor markets and rapid technological development, individuals are repeatedly faced with career decision-making to manage frequent and complex transitions within and between learning and work. Thus, it is crucial to understand the dynamic process of career decision-making. Career decision-making models propose specific sequences of key aspects, such as actions of career exploration, gaining career knowledge, and making a career decision. However, how such key aspects are related over time remains not well understood. In this six-wave longitudinal study across 30 months, we investigate the intra-personal dynamics between career self management actions (i.e., environmental exploration), career knowledge (i.e., labor market knowledge), and attitudes (i.e., career decidedness). Based on a sample of 1132 students in 8th grade in Switzerland, we tested a random intercept cross-lagged panel model (RI-CLPM) to examine within-person dynamics while accounting for stable between-person differences. We found a dynamic link between these variables, in that increases in environmental career exploration predicted subsequent increases in career knowledge and career decidedness. Moreover, increased career knowledge and career decidedness predicted subsequent increases in environmental exploration. We discuss the findings considering a dynamic intra-person approach to understanding the career decision-making process.

Amidst a shifting labor market and rapid technological development, recurrent career decision-making is becoming increasingly important for individuals to master frequent and complex transitions within and between learning and work. Contrary to many decisions in everyday life, the career decision process contains many uncertainties, is complex, and has potentially important long-term consequences (Gati & Kulcsár, 2021). Career decisions can involve choosing a field of study or training, selecting a job, moving from one employer to another, or questions about when and how to retire (Gati & Kulcsár, 2021). One of the most influential periods of career decision-making is during adolescence and early adulthood, as this typically represents the first key milestone in lifelong career development (Ashby & Schoon, 2010; Schoon, 2001).

Several career decision-making models and many career counseling applications (Gati & Asher, 2001; Peterson et al., 1996) propose a sequence of how key aspects of career decision-making should be related. For example, they suggest that actions (e.g., environmental exploration) lead to knowledge (e.g., increased knowledge about the world of work or labor market), which fosters

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clarity and confidence in one's career choice (i.e., experience career decidedness). Additionally, models often depict the career decision-making process as a cycle where the steps are repeated in a loop (e.g., feedback from a decision leading to new exploration) (Gati & Asher, 2001), which is also reflected in frameworks that offer a dynamic view. For example, the social cognitive career theory of career self-management proposes that knowledge (in terms of learning experiences) leads to attitudes (e.g., self-efficacy beliefs, clear career goals), leading to actions. These actions can, in turn, lead to new knowledge (i.e., learning experiences), which again can lead to changes in attitudes and actions, and so on (Super & Hall, 1978). Such a dynamic view is also shared by several theoretical perspectives. For example, the happenstance learning theory (Krumboltz, 2009) argues that behavior (e.g., exploration) is a result of planned and unplanned situations, which require continuous re-evaluation and adaptation. In line, the dual-process model of career decision-making (Xu & Flores, 2023) describes a dynamic model where exploration leads to a reduction of confusion (e.g., knowledge about vocations) and containment of ambiguity, which ideally leads to an anchor choice (i.e., career decidedness). Implementing this choice may trigger a reevaluation, which subsequently leads to exploring new alternatives. Similarly, the career self-regulation framework proposed by Hirschi and Koen (2021) provides a dynamic model that integrates different self-regulation and action-regulation theories. It suggests that career self-management (including career decision-making) consists of a dynamic process entailing goal development and selection, mapping resources and barriers, planning and engagement in career behaviors, and monitoring and feedback processing (Hirschi & Koen, 2021). These elements are proposed to create a dynamic process where these elements may influence each other, creating reciprocal relations between goals, actions, and knowledge. For example, goals (i.e., an attitudinal variable) lead to actions in terms of mapping the environment for available supports and constraints for goal achievement, leading to knowledge to formulate more specific action plans, and subsequent actions to implement goals and plans. Based on monitoring and revision processes, these actions can influence goals, knowledge about goal-relevant resources and constraints, and future actions (Hirschi & Koen, 2021).

Moreover, the career self-regulation framework (Hirschi & Koen, 2021) can integrate other career decision-making theories, such as the social cognitive career theory (SCCT; Lent & Brown, 2013; Lent et al., 1994) and Happenstance learning theory (Krumboltz, 2009), because it contains elements from both, explicitly modeling career decision-making as a dynamic, reciprocal process, where career-related actions (e.g., environmental exploration), knowledge acquisition, and attitudes (e.g., career decidedness) continuously influence each other. Similarly, the dual-process model of career decision-making (Xu & Flores, 2023) aligns with this framework by acknowledging that individuals navigate career decisions through deliberate, analytical reasoning and intuitive, affect-driven processes. While the career self-regulation framework focuses on the reciprocal interplay between behaviors, knowledge, and attitudes, the dual-process model highlights the cognitive mechanisms that underlie these processes, offering a complementary perspective. Given our study's focus on within-person changes and reciprocal relations, the career self-regulation framework provides the most comprehensive explanation for our hypothesized effects, as it explicitly accounts for feedback loops and evolving career behaviors over time. Moreover, the self-regulation approach has been proposed to be especially suited for research on the school-to-work transition to more closely understand the theoretical mechanisms that shape this transition and its underlying processes (Akkermans et al., 2024).

Other career decision-making frameworks allude to such dynamics more or less explicitly. However, they are not their focus, and other theories, therefore, lack a more specific theoretical account of how and why core aspects of career decision-making in terms of behaviors, knowledge, and attitudes are dynamically related over time. For example, SCCT includes the notion of feedback loops by acknowledging that outcomes of career choices and career behaviors form new learning experiences, which then affect future career choices and behaviors. However, the nature of such feedback loops and learning experiences is not theorized in detail. Similarly, the happenstance learning theory considers that past experiences affect to what extent and in what way people perceive and act upon unexpected events and that their actions to such events can have consequences on their future career behaviors. However, how such dynamic adaptation processes occur is not the focus of that theory.

However, there exists a limited exploration of these theoretically broadly acknowledged dynamics in the career decision-making process and how key aspects constituting this process are dynamically linked over time. This reflects a general need for more dynamic research in career development, as the assumption that career development is dynamic has been acknowledged but lacks comprehensive investigation (Hirschi & Koen, 2021; Sullivan & Baruch, 2009). Specifically, we lack knowledge on how key aspects of career decision-making in terms of career self-management actions (i.e., environmental exploration), career knowledge (i.e., labor market knowledge), and attitudinal variables (i.e., career decidedness) are mutually related over time. Yet, such knowledge would be critical to better understanding the dynamic decision-making process, especially in career preparation, where these three key aspects of career decision-making might not be linearly related but exhibit mutual effects in different directions.

Because various models of career decision-making propose different orders of sequence and dynamics, intra-individual (or within-person) changes are of particular interest. Assuming that career decision-making aspects vary at the inter-personal level (or between-person, i.e., differences between persons) and at the intra-personal level (i.e., changes over time within a person), stable components of career decision-making need to be separated from alterable components. Examining both within- and between-person dynamics is crucial in career decision-making research because career-related behaviors and attitudes can vary not only between individuals but also within the same person over time. For example, while some adolescents may generally be more career-decided than others (between-person differences), an individual's career decidedness can still fluctuate due to new experiences or insights (within-person changes). Traditional analytical approaches often conflate these levels, making it difficult to determine whether observed effects reflect stable individual differences or true dynamic processes. Because career decision-making models propose different sequences—some suggesting a linear progression from exploration to knowledge to decidedness, while others emphasize iterative feedback loops—separating inter- and intra-individual components helps clarify which mechanisms operate at each level.

For this purpose, an appropriate statistical method is essential. The random intercept cross-lagged panel model (RI-CLPM; Hamaker et al., 2015) is particularly suited as it focuses on intra-person effects by examining cross-lagged paths while controlling for stable between-person differences. It provides insight into whether a within-person deviation from the trait level of a construct (e.g., the state level of career decidedness) predicts subsequent change in the within-person deviation from the trait level of another construct (e.g., state level of environmental exploration). Additionally, the RI-CLPM allows for examining these subsequent changes and cross-lagged, potential reverse, reciprocal, and indirect effects.

To address the issues mentioned above, we longitudinally followed 1132 adolescents in Switzerland in a critical phase of career decision-making shortly before leaving compulsory school and entering working life in vocational education and training (VET). The phase before the transition from school to work (i.e., VET) is ideally suited for the present study, as this time is critical for career decisions. Educational and career paths become clearer during this time, and important occupational decisions are made (Ashby & Schoon, 2010; Schoon, 2001; Zimmer-Gembeck & Mortimer, 2006). We collected data at six time points across 30 months to investigate how different aspects of career decision-making interact over time and how certain aspects of the career decision-making process can promote other aspects over time. As such, the present study aims to extend prior research by (1) investigating how different aspects of the career decision-making process in terms of (a) career knowledge (i.e., labor market knowledge), (b) career attitudes (i.e., career decidedness), and (c) career self-management behaviors (i.e., environmental exploration) are dynamically related over time; (2) exploring potential directional effects among these variables, including possible mutual effects over time; and (3) investigating within-individual changes while accounting for more stable between-person differences.

In sum, this study makes three main contributions to the literature. First, by adopting a within-person approach, we learn how key aspects of career decision-making interact and affect each other over time. Using the RI-CLPM, we can decouple more stable and volatile aspects of the career decision-making process and shed light on the reciprocal relations among critical career decision-making aspects. Second, we enrich the career self-management and decision-making literature by examining how knowledge and attitudes predict changes in career self-management behaviors, and how career self-management behaviors are related to changes in knowledge and attitudes over time. Thus, we add to an enhanced understanding of the dynamic nature of career knowledge, attitudes, and self-management behaviors. Third, our study contributes to the career literature, where dynamics are often assumed but not thoroughly examined by offering an empirical test of dynamics in the career decision-making process.

1.1. Critical aspects of career decision-making models

Although career decision-making models diverge on the exact order and assumed dynamics of the career decision-making process, they typically agree on the important factors. They assume that actions (e.g., environmental exploration) are important for increasing knowledge (e.g., about the world of work or labor market) and that this knowledge informs and facilitates attitudes towards career decision-making, specifically in the form of career decidedness.

1.1.1. Actions: Environmental career exploration

Gathering information on career opportunities, typically called environmental career exploration, facilitates the choice process as students actively acquire and process career-related information (Kleine et al., 2021). Career environmental exploration is defined as “the degree to which one is actively collecting information about various occupations” (Marciniak et al., 2021, p. 30). For example, students may explore the environment by researching career opportunities online, job shadowing, or obtaining information about specific occupations or businesses from personal contacts. Moreover, gathering information about career options can raise students' awareness of their interests, values, and how their behaviors relate to the world of work (Jiang et al., 2019). Furthermore, the concept of gathering information about the environment is a central component of the social cognitive model of career self-management (Lent & Brown, 2013) and in broader career development research (Hirschi & Koen, 2021; Ireland & Lent, 2018; King, 2004). In this line, Lent and Brown (2013) posit that environmental career exploration is a goal-directed behavior predicting career-related outcomes, such as career decidedness and success factors. Consequently, career environmental exploration is viewed as a behavior empowering individuals to navigate and decide on a career path in alignment with their goals.

In a meta-analysis, Kleine et al. (2021) examined the antecedents and outcomes of career exploration based on Lent and Brown's (2013) model of career self-management and affirmed the importance of environmental exploration within the model. Environmental career exploration was positively related to career decidedness and perceived employability and served as a vehicle to reduce doubts, stress, and uncertainty about career decision-making (Kleine et al., 2021). Interestingly, this impact might be more pronounced than the effects of self-exploration alone (Kleine et al., 2021).

1.1.2. Knowledge: Understanding the world of work

Research broadly acknowledges that acquiring occupational information is a cornerstone in career decision-making. According to Sampson Jr. et al. (1999), occupational knowledge is a key basis for career decision-making because it minimizes uncertainty and aids in evaluating career options with factual data rather than relying solely on intuition or anecdotal evidence, enabling individuals to make informed choices. This component is critical for career decision-making, which aims to achieve person-environment fit in terms of personal needs and abilities (i.e., needs-supply fit and demands-abilities fit; van Vianen, 2018). For example, the importance of occupational information is highlighted in Holland (1985), which stresses the matching of individual personality types to suitable work environments. Information on different occupations allows individuals to evaluate their career options against personal preferences and abilities, achieving a more fitting career choice. Conversely, students may be unprepared to make informed career choices if they lack essential information about professions and potential employers (Gati et al., 1996).

The acquisition of occupational knowledge can also have a profound impact on an individual's self-efficacy, a concept critical in SCCT models of career choice and career management (Lent et al., 1994; Lent & Brown, 2013). Knowing the particulars of an occupation, such as the skills required and the challenges involved, can strengthen the belief in one's ability to thrive in that particular field, thereby fostering interest and career decidedness. Moreover, occupational information can also influence occupational outcome expectations by creating more realistic views about what a career in a given occupation might entail. This, in turn, can also shape interest in an occupation and a sense of career decidedness.

1.1.3. Attitudes: Career decidedness

In addition, the ability to crystallize career goals is critical to career decision-making and later success (Hirschi et al., 2011; Super, 1980). Career decidedness is a career-related attitude that reflects an individual's clarity and confidence in their career choice. This conceptualization aligns with prior research, which often positions career decidedness as a decision-related attitudinal construct rather than a mere cognitive state or behavioral intention (e.g., Gati & Kulcsár, 2021). From a career self-management perspective, career decidedness is an attitudinal variable that reflects the type of career goal a person pursues and the clarity and commitment towards that goal (Hirschi & Koen, 2021). Adolescents who have a clear understanding of their career goals not only develop a stronger interest in their chosen field but also make more meaningful decisions aligned with their personal interests and values (Beal & Crockett, 2010). Moreover, adolescents who are clear about their career goals tend to demonstrate greater engagement in their careers (Chan, 2017) and are more successful and satisfied in their career development (Hirschi et al., 2011; Super, 1980).

Career decidedness is typically treated as an outcome in career decision-making (e.g., Guay et al., 2003). However, from a career self-regulation framework perspective (Hirschi & Koen, 2021), the degree of career decidedness can thus function as an input, indicating a potential deviation from one's desired state and spurring further actions (e.g., career exploration) and career knowledge gain to reduce the gap and achieve higher degrees of decidedness. Similarly, higher degrees of career decidedness might motivate to acquire more focused knowledge about desired career options and thus spur further actions and knowledge gain.

1.2. Dynamic links between actions, knowledge, and attitudes

In the present paper, we combine insights from career-decision models (e.g., Sampson Jr. et al., 1999; Van Esbroeck et al., 2005) and dynamic views supported by the social cognitive career theory of career self-management (Lent & Brown, 2013) and the career self-regulation framework (Hirschi & Koen, 2021). These theoretical models underscore the interconnected nature of actions, knowledge, and attitudes, positing that they mutually reinforce and influence each other over time. While conventional career-decision models suggest linear effects from career exploration to knowledge acquisition and ultimately to career decidedness, our synthesis acknowledges the possibility of recursive effects. Indeed, research showed that certain dimensions crucial to decision-making, such as information gathering and processing, locus of control, and effort invested, were malleable in career decision-making (Gadassi et al., 2012; Gadassi et al., 2013). Furthermore, Xu and Tracey (2017) illuminated a reciprocal pattern between career decision ambiguity tolerance and career indecision, while Guan et al. (2017) demonstrated a mutual influence between future work self and career exploration. Furthermore, the career self-regulation framework proposed by Hirschi and Koen (2021) underscores the reciprocal and dynamic interactions between career-related goals, actions, and knowledge. This framework suggests that individuals engage in a continuous process where career goals guide exploratory actions aimed at identifying environmental resources and barriers. Through this exploration, individuals acquire career knowledge, which, in turn, shapes further goal development and action planning. As individuals refine their goals and acquire new knowledge, their engagement in career behaviors, such as environmental exploration, evolves, creating a feedback loop that influences future actions and decisions. In line with this framework, environmental career exploration—defined as the active process of seeking information about career opportunities and environmental factors—can be expected to increase an individual's career knowledge. In turn, this knowledge informs further exploration efforts, creating a mutually reinforcing cycle).

These findings collectively underscore the complexity and evolution of career decision-making, emphasizing the bidirectional nature of interactions among actions, knowledge, and decidedness over time. However, while existing research touches upon cycles and dynamics in career decision-making, there is a notable lack of a detailed investigation of such dynamic elements. To address this issue, we investigate the following hypotheses at a within-person level:

Hypothesis 1. An increase in environmental career exploration is positively related to an increase in career knowledge over time, and vice versa.

According to the career self-regulation framework (Hirschi & Koen, 2021), as career knowledge increases, individuals gain clarity about their career options and resources, leading to greater career decidedness. However, being more decided in one's career can also prompt further actions to more precisely refine career knowledge to be better able to implement action plans to realize the decision. This reasoning supports the second hypothesis:

Hypothesis 2. An increase in career knowledge is positively related to an increase in career decidedness over time, and vice versa.

Finally, individuals who are more career-decided—having clearer career goals—are likely to engage in environmental exploration with greater focus and purpose, seeking information directly relevant to their career aspirations (Hirschi & Koen, 2021). Conversely, environmental exploration may further solidify their career decisions as they gather critical information. This mutual influence leads to the third hypothesis:

Hypothesis 3. An increase in career decidedness is positively related to an increase in career environmental exploration over time, and vice versa.

2. Method

2.1. Sample and procedure

We collected the data in Switzerland, where most adolescents continue to one of over 200 different VETs (65.4 %; Bundesamt für Statistik, 2019) or go to high school (34.6 %; Bundesamt für Statistik, 2019) after completing compulsory education in 9th grade. The VET programs entail 1–2 days of school, with the rest of the time working in companies and organizations where the adolescents are hired and paid as apprentices. To prepare for this transition, adolescents are actively involved in the career decision-making process during the eighth and ninth grades. They participate in compulsory career education classes, which usually start at the beginning of grade eight and end towards the middle of ninth grade. These classes may include various career exploration activities, such as self-exploration workbooks, visiting job fairs, organizing internships, and learning how to apply for a job. Hence, this context provides an optimal setting for our study.

We collected data from 1233 students in 8th grade across six waves (2017–2019) with a time lag of approximately six months through teachers in German-speaking schools in Switzerland. Research on school-to-work transitions frequently applies a time lag of close to two measurement waves per year to study key variables (Akkermans et al., 2024). Such time lags can thus be considered adequate to allow for meaningful change in key career-related constructs. In the current study context of assessing processes during an

Table 1
Means, Standard Deviations, Cronbach's Alphas, and Pearson's Correlations for the Study Variables.

Variables	M	SD	1	2	3	4	5	6	7	8	9
1 Career exploration (T1)	3.45	0.88	(0.80)								
2 Career exploration (T2)	3.61	0.88	0.49***	(0.84)							
3 Career exploration (T3)	3.74	0.90	0.35***	0.57***	(0.85)						
4 Career exploration (T4)	3.97	0.81	0.34***	0.45***	0.56***	(0.85)					
5 Career exploration (T5)	3.90	0.88	0.24***	0.38***	0.54***	0.58***	(0.84)				
6 Career exploration (T6)	4.01	0.82	0.24***	0.36***	0.44***	0.44***	0.52***	(0.86)			
7 Career knowledge (T1)	3.03	0.87	0.67***	0.49***	0.34***	0.33***	0.26***	0.25***	(0.88)		
8 Career knowledge (T2)	3.20	0.88	0.43***	0.70***	0.46***	0.46***	0.30***	0.34***	0.49***	(0.90)	
9 Career knowledge (T3)	3.36	0.93	0.38***	0.55***	0.73***	0.56***	0.46***	0.47***	0.40***	0.56***	(0.91)
10 Career knowledge (T4)	3.61	0.88	0.34***	0.39***	0.51***	0.74***	0.50***	0.37***	0.38***	0.45***	0.56***
11 Career knowledge (T5)	3.47	0.94	0.24***	0.37***	0.45***	0.52***	0.70***	0.49***	0.31***	0.41***	0.49***
12 Career knowledge (T6)	3.51	0.99	0.22***	0.36***	0.35***	0.42***	0.46***	0.67***	0.31***	0.39***	0.47***
13 Career decidedness (T1)	3.83	0.92	0.40***	0.33***	0.17***	0.16**	0.11	0.17***	0.39***	0.29***	0.21***
14 Career decidedness (T2)	3.94	0.91	0.29***	0.44***	0.28***	0.25***	0.19***	0.12*	0.27***	0.40***	0.26***
15 Career decidedness (T3)	4.17	0.85	0.21***	0.40***	0.46***	0.34***	0.26***	0.22***	0.22***	0.27***	0.37***
16 Career decidedness (T4)	4.33	0.82	0.24***	0.25***	0.36***	0.48***	0.34***	0.21***	0.19***	0.25***	0.32***
17 Career decidedness (T5)	4.32	0.77	0.15***	0.20***	0.28***	0.37***	0.48***	0.28***	0.13**	0.23***	0.27***
18 Career decidedness (T6)	4.36	0.74	0.19***	0.25***	0.25***	0.31***	0.29***	0.51***	0.14**	0.25***	0.25***

Variables	M	SD	10	11	12	13	14	15	16	17	18
1 Career exploration (T1)	3.45	0.88									
2 Career exploration (T2)	3.61	0.88									
3 Career exploration (T3)	3.74	0.90									
4 Career exploration (T4)	3.97	0.81									
5 Career exploration (T5)	3.90	0.88									
6 Career exploration (T6)	4.01	0.82									
7 Career knowledge (T1)	3.03	0.87									
8 Career knowledge (T2)	3.20	0.88									
9 Career knowledge (T3)	3.36	0.93									
10 Career knowledge (T4)	3.61	0.88	(0.92)								
11 Career knowledge (T5)	3.47	0.94	0.51***	(0.91)							
12 Career knowledge (T6)	3.51	0.99	0.45***	0.54***	(0.91)						
13 Career decidedness (T1)	3.83	0.92	0.11	0.13*	0.16***	(0.85)					
14 Career decidedness (T2)	3.94	0.91	0.17***	0.25***	0.17***	0.54***	(0.75)				
15 Career decidedness (T3)	4.17	0.85	0.25***	0.26***	0.14**	0.36***	0.53***	(0.92)			
16 Career decidedness (T4)	4.33	0.82	0.34***	0.23***	0.17**	0.30***	0.38***	0.60***	(0.92)		
17 Career decidedness (T5)	4.32	0.77	0.27***	0.42***	0.23***	0.18***	0.33***	0.44***	0.52***	(0.89)	
18 Career decidedness (T6)	4.36	0.74	0.24***	0.28***	0.35***	0.26***	0.26***	0.42***	0.46***	0.52***	(0.93)

Note. $N = 1132$ (missing data estimated with full-maximum likelihood method). In brackets internal consistency (Cronbach's alphas).

*** $p < .001$.

** $p < .01$.

* $p < .05$.

active career preparation period, we deemed a time lag of six months suitable to be long enough to allow a sufficient change in the examined constructs while being fine-grained enough to capture dynamic processes that might occur over shorter periods of time. Questionnaires were administered online during regular class hours. After performing data quality checks, we removed 49 cases (4 % of the participants) from the sample because they showed clear signs of careless responding (e.g., flatliners, speeders). For speeding, we checked the time the participants needed to complete the survey with a cut-off of 2 s/items (Huang et al., 2012) and decided to exclude participants who fell below that threshold ($n = 37$). For flatlining (DeSimone & Harms, 2018), we examined the data for response patterns indicating straight-line answering (e.g., selecting the same option throughout the survey. Participants who exhibited clear, repetitive response patterns were excluded ($n = 12$). Furthermore, we excluded 52 cases (4 % of the participants) that did not fill in their grade and could be only in the 7th grade, which is early for career decision, or already in the 9th grade, which is late for career decision in the VET market. Thus, the final sample comprises 1132 students (50 % male, 50 % female), aged between 12 and 16 years ($M = 13.63$; $SD = 0.649$), and 78 % had a Swiss nationality.

As in all longitudinal studies, we observed some attrition, which was also because some students and/or the class joined the study at later times. In our sample, 1′015 participants filled in at T1, 857 participants filled in at T2, 739 participants filled in T3, 495 participants filled in T4, 484 participants filled in at T5, and 493 participants filled in at T6. Following best-practice recommendations for treating missing data in longitudinal studies (Graham, 2009; Newman, 2014), we included all participating students across the six waves in the analyses to avoid list-wise deletion and estimated missing data with full information maximum likelihood estimators. To test for possible attrition bias, we compared individuals who participated in at least three waves ($n = 798$) vs those who participated in less than three waves ($n = 334$). We conducted several independent samples *t*-tests, comparing T1 demographic and study variables. No differences in career exploration, career knowledge, and career decidedness were found. However, the results showed that gender and age differentiated the participants' response patterns. Specifically, among those who participated in less than three waves, males were more prevalent (57 %) compared to females (43 %). In contrast, for participants who completed at least three waves, the proportion of females (53 %) was higher compared to males (47 %). Additionally, participants who completed less than three waves were slightly older ($M_{age} = 13.70$, $SD = 0.684$) than those who participated in at least three waves ($M_{age} = 13.60$, $SD = 0.684$). We thus included gender and age in our final model as a further robustness test (see also Hypothesis Testing), and the findings remained the same. Moreover, we rerun the model only with participants who participated in at least three waves. The results showed precisely the same pattern. Collectively, these findings indicate that attrition bias was only a minor concern.

2.2. Measures

The variables were answered on a 5-point scale ranging from 1 (*not true at all*) to 5 (*completely true*). Means, standard deviations, and reliability coefficients are reported in Table 1.

2.2.1. Environmental career exploration

We used the *environmental exploration* scale from the German version of the Career Resources Questionnaire for adolescents (CRQ-A; Marciniak et al., 2021). The scale consists of 3 items ("e.g., I have collected information about occupations and jobs"). Marciniak et al. (2021) provide support for the construct validity of the scale in terms of high correlations to other scales measuring closely related constructs. Across all six time points, Cronbach's alpha showed good reliability coefficients ($\alpha = 0.80$–0.86) in our sample.

2.2.2. Career knowledge

We assessed career knowledge with the *labor market knowledge* scale from the German version of the Career Resources Questionnaire for adolescents (CRQ-A; Marciniak et al., 2021). The scale consists of 3 items (e.g., "I am well-informed about the current labor market trends and developments."). Marciniak et al. (2021) provide support for the construct validity of the scale in terms of high correlations to other scales measuring closely related constructs. Across all six time points, Cronbach's alpha showed good reliability coefficients ($\alpha = 0.88$–0.92) in our sample.

2.2.3. Career decidedness

We used the *career clarity* scale from the German version of the Career Resources Questionnaire for adolescents (CRQ-A; Marciniak et al., 2021). The scale consists of 3 items (e.g., "I know which occupational field I am intending to pursue"). Marciniak et al. (2021) provide support for the construct validity of the scale in terms of high correlations to other scales measuring closely related constructs. Across all six time points, Cronbach's alpha showed good reliability coefficients ($\alpha = 0.75$–0.93) in our sample.

2.3. Analytical procedure

For the purpose of this study, we conducted the analyses in R (version 4.2.3; R Core Team, 2023). First, we tested the data for multivariate normality and found deviations from normality. However, it is important to note that we used the robust maximum likelihood estimation method (i.e., "MLR" in "lavaan", Rosseel, 2012), which is known for its resilience to moderate deviations from normality in the data (Gravetter et al., 2021). Model fit was assessed with comparative fit index (CFI), Tucker-Lewis index (TLI), and the root mean squared error of approximation (RMSEA). Common cut-off values indicate values below 0.08 for RMSEA and above 0.90 for CFI and TLI as good model fit (Cheung & Rensvold, 2002; Hu & Bentler, 1999; Vandenberg & Lance, 2000). Besides using common cut-off values, we investigated which model fit indices are necessary for our model. Groskurth and colleagues (2024) argue the goodness of fit indices are highly reliant on the estimated number of indicators, loading magnitudes, and sample size. Based on various simulation studies (e.g., Groskurth et al., 2024; Ximénez et al., 2022; Nye & Drasgow, 2011; Sharma et al., 2005), we conclude that under the given study conditions of low- to medium-size factor loadings and large sample size, our model fit indices indicate a good model fit.

Next, to test the hypothesized model, we conducted RI-CLPM analyses in R 'lavaan' to infer the reciprocal relations. This analytic approach is appropriate given that we assume our focal constructs vary at the between-person (i.e., inter-individual differences) and the within-person level (i.e., intra-individual changes over time). Thus, the RI-CLPM provides insight into cross-lagged within-person effects over time while controlling for stable between-person differences. With these analyses, we can determine whether a within-person deviation from the trait level of one construct (e.g., state-level of career decidedness) predicts subsequent change in the within-person deviation from the trait level of another construct (e.g., state-level of environmental career exploration). In addition, the RI-CLPM allows making statements about subsequent changes, cross-lagged, potential reverse, and reciprocal effects.

As in previous studies (Haenggli et al., 2021; Rudolph & Zacher, 2021), and for simplicity of the model, we used the manifest variable to represent scale-level means of environmental career exploration, career knowledge, and career decidedness at each time point. Specifically, we regressed the observed scores for environmental career exploration, career knowledge, and career decidedness on their own latent factors with the loadings constrained at 1. Additionally, we included three random intercepts (RI) for each of our focal variables in the model and constrained the factor loadings at 1. These RI represent the stable trait-like differences between individuals concerning environmental career exploration, career knowledge, and career decidedness. Their correlations reflect the relations of the stable between-person differences of environmental career exploration, career knowledge, and career decidedness. The autoregressive and cross-lagged effects are modeled using the residual scores rather than the raw observed scores (Orth et al., 2021). The autoregressive paths in the model suggest to what extent within-person deviations in environmental career exploration, career knowledge, and career decidedness can be predicted by deviations from their own expected levels. The cross-lagged paths suggest to what extent a within-person deviation from the trait level of one variable (e.g., environmental exploration) predicts a change in the within-person deviation from the trait level of another variable (e.g., career knowledge) six months later, and vice versa, while the effects are controlled for the autoregressive effects in these deviations (Orth et al., 2021) For example, when individuals exhibit more environmental exploration than usual, they subsequently increase career knowledge. The within-person correlations at given time point x (Tx) reflect to what extent a person's individual deviation from the expected level on one variable is related to the deviation from the expected score on another variable at the same time point.

3. Results

Means, standard deviations and correlations of the study variables are displayed in Table 1. Except for career decidedness at T1 and environmental career exploration at T5, as well as career decidedness at T1 and career knowledge at T4, the bivariate correlations among the focal variables showed that environmental career exploration, career knowledge, and career decidedness were significantly positively related to each other within each measurement point, with correlations ranging between $r = 0.12$ and 0.70 (Table 1).

3.1. *Confirmatory factor analyses and measurement invariance*

Before applying the RI-CLPM, we computed several CFA models to examine the appropriateness of representing the focal constructs separately (i.e., as unique variables) in our statistical models. We then examined the measurement equivalence (i.e., invariance) of the measures across the six time points.

First, we specified five CFA models based on our data to assess whether we can use environmental career exploration, career knowledge, and career decidedness as separate (unique) variables in our statistical models. To evaluate the proposed three-factor model at each time point, we compared it against several alternative models. Specifically, we tested a single-factor model where all items from the three constructs loaded onto one factor. Additionally, we examined three two-factor models, in which two of the three constructs were combined into a single factor: (1) career decidedness as proposed, with environmental career exploration and career knowledge combined into one factor; (2) career knowledge as proposed, with career decidedness and environmental career exploration combined into one factor; and (3) environmental career exploration as proposed, with career decidedness and career knowledge combined into one factor. Based on the results, the proposed three-factor solution (environmental career exploration, career knowledge, and career decidedness) best fit the data across all time points (see Appendix A for details), and significantly better than all other models. Thus, the results suggest that the three constructs are empirically distinct and that it is appropriate to conceptualize them separately in our subsequent models.

Second, based on the suggestions of Vandenberg and Lance (2000) and Putnick and Bornstein (2016), we assessed measurement invariance over time. For this purpose, we fit three measurement models across the six time points for each focal construct (environmental career exploration, career knowledge, and career decidedness) with increasingly restrictive model comparisons ("configural" – "metric" – "scalar" invariance). For the evidence of (in)variance, we observed changes in changes in CFI, RMSEA, and chi-square ($\Delta\chi^2$). The results revealed that all models were invariant, at least with respect to the factor structures that represent each latent variable over time. For environmental career exploration and career knowledge, we found support for strong (i.e., scalar) measurement invariance. For career decidedness, we found evidence for weak (i.e., metric) measurement invariance only. However, this level of measurement invariance is adequate to confirm that latent constructs have the same meaning across time points when using RI-CLPM (Schmitt & Kuljanin, 2008). The more detailed procedure for testing longitudinal invariance, including the criteria and model identification constraint, is described in Appendix B, and the results are displayed in Table 2.

3.2. Hypothesis test

As a first step, we calculated ICC_1 statistics for each variable to quantify the amount of within- and between-person variability among our focal variables. All three variables showed a significant degree of within-person variance (environmental career exploration: $ICC_1 = 0.41$; career knowledge: $ICC_1 = 0.42$; career decidedness: $ICC_1 = 0.39$), suggesting that 61–59 % of the variances in the focal variables occurred within-person.

To establish a basis for our main models, we tested two different RI-CLPMs with a different set of cross-lagged effects. Specifically, to assess stability over time, we tested a model without any mutual effects across the variables (autoregressive only) and a model with a linear causal flow as suggested in standard career decision-making models, where career exploration leads to knowledge, which in turn increases career decidedness. Next, to test the proposed hypotheses, we followed the approach that aligns with previous research in this area (e.g., Haenggli et al., 2021; Nagy et al., 2022; Rudolph et al., 2022; Rudolph & Zacher, 2021) and additionally applied a stepwise approach for constraining the autoregressive and cross-lagged paths (Hamaker et al., 2015; Mulder & Hamaker, 2021; Orth et al., 2021) as it has also been done in other fields (e.g., Hihara et al., 2022). Thus, we specified the full (constrained) cross-lagged RI-CLPM (main model) in four steps. With all the models, we first tested an unconstrained RI-CLPM in which all over-time parameters (i.e., autoregressive and cross-lagged paths) were unconstrained and thus specified to be time-variant (Model 1). Second, we tested a constrained RI-CLPM in which only the autoregressive paths were constrained over time (Model 2). Third, we tested a constrained RI-CLPM in which only the cross-lagged paths were constrained over time (Model 3). Finally, we tested a constrained RI-CLPM where all the over-time parameters were specified as time-invariant (i.e., both autoregressive and cross-lagged paths; Model 4).

In all of the models, the results revealed that the time-invariant model did not fit the data significantly worse than the time-variant model (Models to establish basis: autoregressive only model: $\chi[12] = 10.41$, $p = .058$; linear causal flow model $\chi[20] = 17.737$, $p = .605$; Models for hypothesis testing: Model 2 (time-invariant autoregressive paths): $\chi[12] = 13.599$, $p = .327$; Model 3 (time-invariant cross-lagged paths): $\chi[24] = 31.601$, $p = .137$; Model 4 (main model): $\chi[36] = 42.622$, $p = .208$), justifying restricting the over-time parameters to equality. The fit indices of the baseline model, the autoregressive only and the linear causal flow models, showed worse fit (autoregressive only: CFI = 0.58, TLI = 0.51, RMSEA = 0.115, SRMR = 0.273, $\chi^2(159) = 2547.176$, $p < .001$;linear causal flow: CFI = 0.87, TLI = 0.84, RMSEA = 0.06, SRMR = 0.18, $\chi^2(151) = 845.038$, $p < .001$) compared to the good fit of the main model (CFI = 0.98, TLI = 0.98, RMSEA = 0.03, SRMR = 0.05, $\chi^2(144) = 240.130$, $p < .001$). Fit indices for all the models with the estimates of the autoregressive only and the linear causal flow models (models to establish the basis) are displayed in Appendix C (Tables C1-C4). The fit indices for the models for hypothesis testing, i.e., the unconstrained and the stepwise constrained models (including the main model), are displayed in Table 3, and the estimates of the unconstrained RI-CLPM are provided in Appendix D. Additionally, to test the robustness of the findings, we explored the impact of age and gender as control variables in the final model. However, the results remained consistent even when these controls were incorporated to predict observed variables and random intercepts. Consequently, we present the results without incorporating any control variables for clarity in parameter interpretation.

As the constrained RI-CLPM (main model) showed the best model fit, including trait-like and state-like elements of each construct as well as autoregressive prediction of all state-like elements at later time points by the state-like elements at earlier time points, we only report the results of this model in the manuscript. In Table 4, both the standardized and unstandardized estimates for state variables for both autoregressive and hypothesized cross-lagged effects are displayed. In Table 5, the relations between state and trait variables within each time point are displayed. Fig. 1 represents the RI-CLPM with the autoregressive and cross-lagged paths for state environmental career exploration, career knowledge, and career decidedness. For interpreting the effect sizes, we refer to Orth et al. (2024), which suggest benchmark values of 0.03 for small effects, 0.07 for medium effects, and 0.12 for large effects when assessing the size of cross-lagged effects in the RI-CLPM.

All autoregressive effects were significantly positive, i.e., earlier state environmental career exploration predicted future state environmental career exploration ($\beta = 0.19$, $p < .001$), earlier state career knowledge predicted future state career knowledge ($\beta = 0.16$, $p < .001$), and earlier state career decidedness predicted future state career decidedness ($\beta = 0.30$, $p < .001$). Summarizing the

Table 2
Summary of Measurement Invariance Tests.

	χ^2	df	CFI	RMSEA	AIC	BIC	$\Delta\chi^2$ (df)	p	ΔCFI	ΔRMSEA
Environmental career exploration										
Configural invariance	119.071	75	0.979	0.050	9613.8	10010.1				
Metric invariance	129.390	85	0.979	0.047	9604.1	9965.7	10.3189 (10)	0.413	0.000	0.003
Scalar invariance	137.191	95	0.980	0.043	9591.9	9918.7	10.3189 (10)	0.648	0.001	0.004
Career knowledge										
Configural invariance	89.021	75	0.996	0.028	8453.0	8847.4				
Metric invariance	103.920	85	0.994	0.031	8447.9	8807.7	14.898 (10)	0.136	0.002	0.003
Scalar invariance	114.320	95	0.994	0.029	8438.3	8763.5	10.400 (10)	0.406	0.000	0.001
Career decidedness										
Configural invariance	106.041	75	0.988	0.041	8851.1	9248.3				
Metric invariance	112.712	85	0.990	0.037	8837.7	9200.2	6.672 (10)	0.756	0.002	0.004
Scalar invariance	173.608	95	0.971	0.059	8878.6	9206.2	60.896 (10)	< 0.001	0.019	0.022

Table 3
Summary of RI-CLPM Fit Indices.

Model	χ^2	df	p-value	CFI	TLI	AIC	BIC	RMSEA	90 % CI	SRMR
Model 1: Unconstrained RI-CLPM	198.496	108	0.000	0.981	0.974	25,757.136	26,164.563	0.030	0.023–0.036	0.046
Model 2: Constrained RI-CLPM (time invariant autoregressive paths)	210.439	120	0.000	0.981	0.975	25,752.910	26,099.978	0.026	0.021–0.031	0.049
Model 3: Constrained RI-CLPM (time invariant cross-lagged paths)	230.325	132	0.000	0.979	0.976	25,745.897	26,032.605	0.026	0.021–0.031	0.049
Model 4: Constrained RI-CLPM (time invariant autoregressive and cross-lagged paths)	240.130	144	0.000	0.980	0.979	25,738.711	25,965.060	0.027	0.021–0.033	0.053

Note. All models included environmental career exploration, career knowledge, and career decidedness. Model 1 = baseline model; Model 2 = model with autoregressive paths fixed to be equal over time; Model 3 = model with cross-lagged paths fixed to be equal over time; Model 4 (main model) = model with autoregressive and cross-lagged paths fixed to be equal over time.

Table 4
Summary of Model 2 State Autoregressive and Cross-Lagged Paths.

	β	b	SE	p
Autoregressive paths				
Environmental career exploration T1 – … – Environmental career exploration T6	0.194	0.194	0.040	0.000
Career knowledge T1 – … – Career knowledge T6	0.163	0.163	0.040	0.000
Career decidedness T1 – … – Career decidedness T6	0.303	0.303	0.040	0.000
Hypothesized cross-lagged paths				
Environmental career exploration Tx ➔ Career knowledge Tx + 1	0.175	0.182	0.037	0.000
Environmental career exploration Tx ➔ Career decidedness Tx + 1	0.153	0.144	0.035	0.000
Career knowledge Tx ➔ Environmental career exploration Tx + 1	0.140	0.134	0.032	0.000
Career knowledge Tx ➔ Career decidedness Tx + 1	−0.026	−0.027	0.033	0.415
Career decidedness Tx ➔ Environmental career exploration Tx + 1	0.102	0.104	0.031	0.001
Career decidedness Tx ➔ Career knowledge Tx + 1	0.029	0.030	0.031	0.329

Note. Autoregressive and cross-lagged paths constrained to be equal from Time 1 to Time 6; Specific time points indicated by numbers after each variable. Standardized (β) and unstandardized (b) values are reported. SE refers to standard errors.

Table 5
Summary of Model 2 Correlations for Trait Variables and State Variables.

	r	p
Trait variable (between-person-effects)		
Environmental career exploration with career knowledge	0.899	0.000
Environmental career exploration with career decidedness	0.506	0.000
Career knowledge with career decidedness	0.501	0.000
State variable (within-person-effects)		
Environmental career exploration T1 with career knowledge T1	0.573	0.000
Environmental career exploration T2–6 with career T2–6	0.556	0.000
Environmental career exploration T1 with career decidedness T1	0.354	0.000
Environmental career exploration T2–6 with career decidedness T2–6	0.389	0.000
Career knowledge T1 with career decidedness T1	0.341	0.000
Career knowledge T2–6 with career decidedness T2–6	0.268	0.000

cross-lagged effects from Fig. 1, earlier states of environmental career exploration positively predicted future states of career knowledge ($\beta = 0.18, p < .001$) and vice versa ($\beta = 0.13, p < .001$). These results indicate large effect sizes, providing strong support for Hypothesis 1. Additionally, earlier states of career decidedness positively predicted future states of environmental career exploration ($\beta = 0.10$, $p = .001$) and vice versa ($\beta = 0.14$, $p < .001$). These results indicate medium to large effect sizes, supporting Hypothesis 3. The remaining cross-lagged effects (i.e., between career knowledge and career decidedness and vice versa) were not statistically significant and fell below the threshold for small effect sizes, rejecting Hypothesis 2. At the between-person level, there were moderately strong correlations between the random intercept factors of environmental career exploration and career knowledge ($r_{xy} = 0.90$, $p < .001$), environmental career exploration and career decidedness ($r_{xy} = 0.51$, $p < .001$), career knowledge and career decidedness ($r_{xy} = 0.50$, $p < .001$).

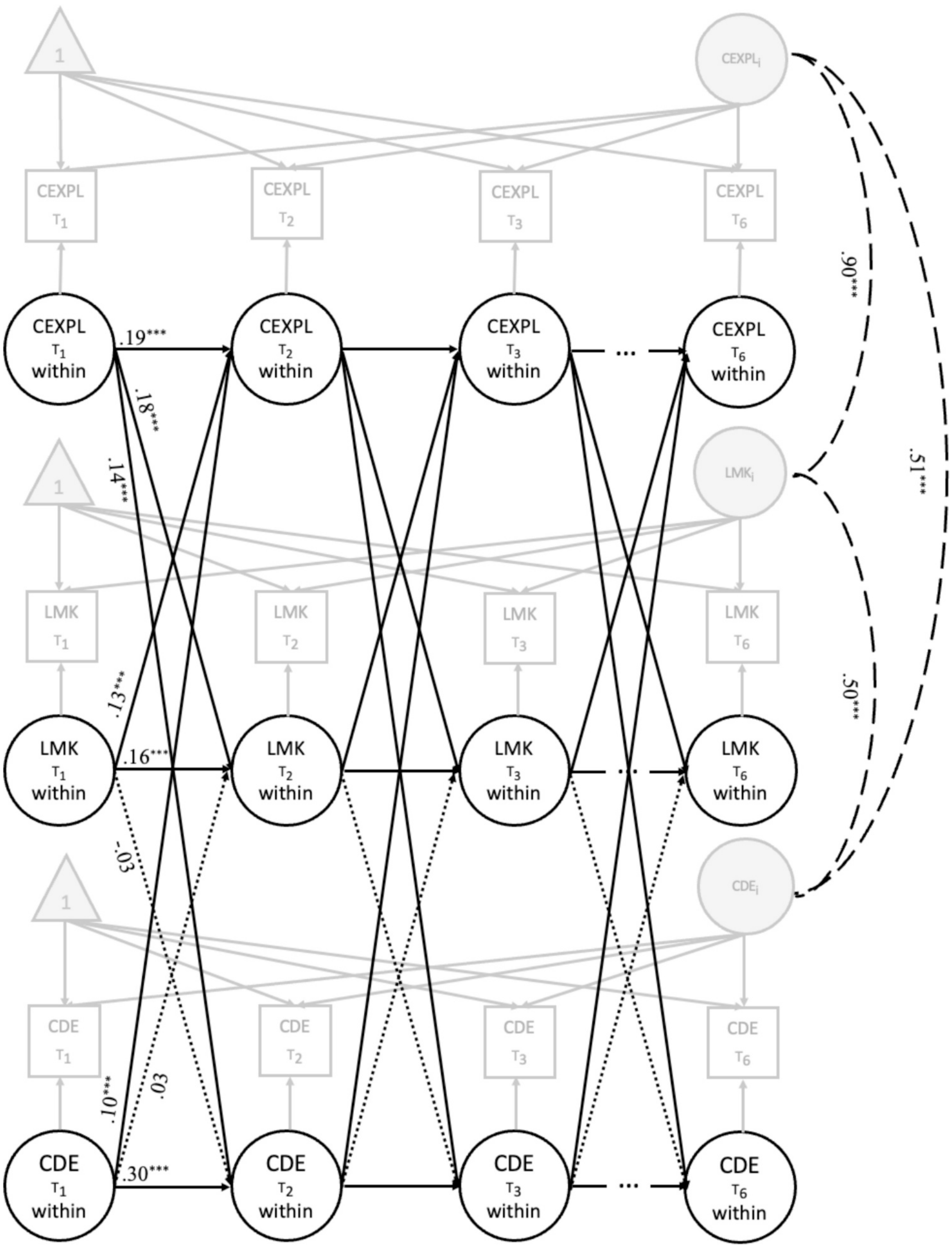

Fig. 1. Grey squares represent measurement from T1 to T6. "Within" circles represent the within-person components of the construct over time. CEXPL$_i$, LMK$_i$,and CDE$_i$ represent random intercepts (i.e., between-person effects) for environmental career exploration (CEXPL), career knowledge in terms of labor market knowledge (LMK), and career decidedness (CDE), respectively. Solid bold directional arrows represent the significant within-person paths according to the postulated hypotheses (non-significant paths displayed as dotted arrows). Dashed bi-directional arrows represent the between-person (i.e., stabile trait component of the variables) correlations. This figure was adapted from Hamaker et al. (2015). Certain parameters and paths have been omitted from this representation for sake of parsimony, for example bi-directional paths representing the state correlations (within-effects) between the variables; see Tables 4 and 5 for additional results.
*** $p < .001$.

4. Discussion

Although recurrent career decision-making has become crucial in the modern labor market, limited attention has been given to the theoretically recognized dynamics in the career decision-making process and how interconnected elements evolve over time. By applying a dynamic within-person approach, we explored potential directional effects among the critical aspects of career decision-making in Swiss adolescents in terms of actions of career self-management (i.e., environmental exploration), career knowledge (i.

e., labor market knowledge), and career attitudes (i.e., career decidedness) over two years. Our dynamic view allows an understanding of how these variables change and influence each other over time within an individual rather than treating them as separate or static traits. It emphasizes these processes' fluid, ongoing nature, highlighting that the variables are not isolated; they interact and continuously influence one another throughout the decision-making process. Using the recently introduced RI-CLPM, we went beyond previous research by examining changes within individuals while controlling for stable differences between individuals.

Our findings suggest a considerable within-person variance in environmental exploration, career knowledge, and career decidedness among adolescents, indicating that all of these variables have both stable trait-like as well as variable state-like aspects while also highlighting their dynamic interplay at the within-person level. On the within-person level, our findings support the dynamics of environmental exploration, career knowledge, and career decidedness. Specifically, we found significant autoregressive effects in all variables and cross-lagged relations between environmental career exploration and both career knowledge and career decidedness, and vice versa. However, no such cross-lagged effect was observed between career knowledge and career decidedness. On the between-person level, the findings suggest that the three components of actions (i.e., environmental exploration), career knowledge (i.e., labor market knowledge), and career attitude (i.e., career decidedness) are strongly and positively related.

4.1. Theoretical implications

4.1.1. Within-person level

Our results showed autoregressive effects in all three variables, which support the notion that earlier states in these variables predict their future states, also called within-person carry-over effects (Hamaker et al., 2015). This means that if someone exhibits a higher level of environmental exploration, career knowledge, or career decidedness than the usual level at a certain time point, the individual will also subsequently conduct more actions of environmental exploration, report more career knowledge, and report higher career decidedness than usual.

Next, our findings demonstrate that the three variables (i.e., environmental exploration, career knowledge, career decidedness) show dynamic linkages over time. We found support for the cross-lagged effects that earlier states of environmental exploration positively predicted later states of career knowledge, and vice versa. Similarly, higher levels of environmental exploration at one time resulted in higher career decidedness at a later time, and vice versa. These results confirm previous results by Okay-Somerville and Scholarios (2021) and the assertion of SCCT (Lent & Brown, 2013), highlighting the critical role of environmental career exploration in increasing career knowledge and fostering a sense of career decidedness. Furthermore, it also confirms the current understanding of career decision-making models (e.g., Gati & Kulcsár, 2021) that more career knowledge can motivate subsequent environmental exploration, which has also been demonstrated empirically by Hirschi et al. (2011). The results are also consistent with Hirschi and Koen's (2021) career self-regulation framework, which emphasizes the dynamic, reciprocal interactions between goals, knowledge, and actions. According to this framework, career exploration helps individuals gain knowledge that informs future decisions, while knowledge gained from earlier exploration can shape the goals and subsequent exploration behaviors. The findings from this study highlight this iterative process, where actions like environmental exploration and knowledge acquisition reinforce one another over time, reflecting the cyclical nature of career self-management.

However, we did not find support for the cross-lagged effects of career knowledge and career decidedness. This means that higher levels of knowledge at one time do not result in higher levels of decidedness at a later time, and vice versa. These results can be explained with current theoretical approaches towards career decision-making (e.g., Xu, 2023, 2021). In Xu and Flores' (2023) model, the authors outline that exploration behavior helps form a broad informational foundation for career decision-making. Ideally, this knowledge can lead to both a reduction in confusion (e.g., through the collection and matching of information) and a reduction of the threat of ambiguity (i.e., uncertainty), which serve as a basis for forming a suitable interim career choice. However, the authors also note that an interim career choice cannot be established without a sufficient reduction of confusion and an acceptable level of ambiguity. In this case, individuals must re-engage in exploration behavior until confusion and ambiguity can be sufficiently managed. Therefore, our results may indicate that the accrued knowledge did not yet sufficiently reduce confusion and ambiguity to establish career decidedness. This might occur because obtained career knowledge can not only clarify and inform but also confuse and cast existing beliefs into doubt if the newly obtained information provides unexpected career information or contradicts existing beliefs or knowledge.

Furthermore, the lack of support for the cross-lagged effects may also be explained by the role of self-knowledge in the career decision-making process. As suggested in various career decision-making models (e.g., Gati & Asher, 2001; Gati & Kulcsár, 2021; Peterson et al., 1996), career decision-making is not solely influenced by the accumulation of occupational knowledge but also by an individual's understanding of their own interests, values, and skills as well as personality traits and meta-cognitions (e.g., self-doubt). Without adequate self-knowledge or in the presence of problematic traits and meta-cognitions, individuals may struggle to integrate the career information they acquire into a coherent career choice.

Our results also partially confirm the dynamic process over time in career decision-making, often described in existing career decision-making models (e.g.,Gati & Kulcsár, 2021; Lent & Brown, 2013). Our study specifically sheds light on this process beyond the content of career decision-making (i.e., the types of careers people choose) or reasons for problems of career indecision (Gati & Kulcsár, 2021). While conventional career-decision models suggest linear effects from career exploration to knowledge acquisition and ultimately to career decidedness, our findings reveal the possibility of some recursive effects. Specifically, environmental exploration increases career knowledge, which, in turn, fosters environmental exploration. As such, we can add knowledge on how key aspects of career decision-making in terms of career self-management actions (i.e., environmental exploration), career knowledge (i.e., labor market knowledge), and attitudinal variables (i.e., career decidedness) are related, though not always mutually, over time.

Further clarifying the dynamics in career decision-making, our results show that although career decidedness is typically treated as an outcome (Gati & Kulcsár, 2021; Lent & Brown, 2013), career decidedness can also lead to more environmental exploration over time, which aligns with previous findings (e.g., Creed & Patton, 2003), as well as the dual-process theory of career decision-making (Xu & Flores, 2023) and the career self-regulation framework (Hirschi & Koen, 2021). The dual-process theory (Xu & Flores, 2023) posits that decidedness can reduce anxiety-provoking uncertainty or ambiguity during exploration. Similarly, in the career self-regulation framework (Hirschi & Koen, 2021), career decidedness can spur exploratory actions to better evaluate resources and constraints for implementing the decision. The degree of career decidedness can also function as an input, indicating a potential deviation from one's desired state and spurring further actions (e.g., career exploration) and career knowledge gain to reduce the gap and achieve higher degrees of decidedness. Similarly, higher degrees of career decidedness might motivate one to acquire more focused knowledge about desired career options and thus spur further actions and knowledge gain. Our analyses found that career decidedness and environmental exploration were mutually linked, and environmental exploration, in turn, was positively linked to career knowledge, and vice versa.

In sum, the within-person results provide support for the utility of applying self- and action regulation theories, like the career self-regulation framework (Hirschi & Koen, 2021), for a deeper understanding of career decision-making processes. While our study could not fully test the complete action regulation process with all its proposed dynamics, it offers support for a dynamic view of career decision-making and several mutual effects suggested by the career self-regulation framework (Hirschi & Koen, 2021).

4.1.2. Between-person level

In addition to our key findings indicating dynamic aspects of environmental exploration, career knowledge, and career decidedness over time, our study also highlights the presence of stable components within these constructs. That is, there are already relatively stable differences among adolescents in these constructs at the outset of their career development process. This finding aligns with existing theoretical and empirical research (Hirschi & Koen, 2021; Lent & Brown, 2013). Understanding these stable components could be the subject of future research exploring the potential influence of certain individual differences and environmental factors contributing to these early differences between individuals. The argument here posits that potentially enduring individual differences, such as proactivity (e.g., Seibert et al., 2001), core self-evaluations (e.g., Koumoundourou et al., 2012), and conscientiousness (e.g., Egan et al., 2017), or influential environmental factors like parental support (e.g., Dietrich & Kracke, 2009) and socioeconomic status (e.g., Eshelman & Rottinghaus, 2015), might play a substantial role in shaping the levels of environmental exploration, career knowledge, and career decidedness observed in adolescents right at the outset of their career decision-making and development process. Hence, while our study sheds light on the existence of stable components, the specific factors contributing to these individual differences were not explored. This aspect presents an important avenue for future research to delve deeper into the relations between stable individual differences, environmental factors, and the process of adolescent career decision-making. Better understanding these underlying mechanisms would allow valuable insights into the complexity of career development and also provide a basis for more focused, research-based interventions.

4.2. Practical implications

The study offers important insights from a practical view. For example, the findings demonstrate that the key aspects of career preparation are volatile to a large extent. This suggests that environmental exploration, career knowledge, and career decidedness could be systematically modified through early career interventions in schools. To implement these findings practically, schools can consider tailoring interventions to address stable individual differences and modifiable aspects related to career preparation. Designing holistic career education programs that go beyond traditional approaches and focus on interactive activities, exposure to diverse career experiences, and mentorship can be instrumental. Such interventions could be especially beneficial when explicitly focusing on environmental career exploration. Instead of providing knowledge about the current labor market or clarifying goals for future careers, one approach could be to focus on supporting adolescents in their environmental exploration behavior. The study showed that this positively impacts decidedness and knowledge about the labor market later on. Moreover, incorporating the career self-regulation framework (Hirschi & Koen, 2021) into career counseling can provide a nuanced understanding of career decidedness as a continuum. Interventions can leverage higher degrees of career decidedness to stimulate further environmental exploration and knowledge acquisition, creating a positive feedback loop. Additionally, developing longitudinal career guidance programs is essential, acknowledging the evolving nature of career decision-making. Providing sustained support over multiple years ensures that interventions adapt to changing needs and circumstances.

4.3. Limitations and future research

This study has some limitations that could be addressed in future studies. First, the data relied on a single source and self-reported information about environmental exploration, career knowledge, and career decidedness. Thus, the possibility of common method bias exists (Podsakoff et al., 2003). Even though using a time-lagged design should reduce concerns about inflation of parameter estimates due to common method bias (Podsakoff et al., 2003), future studies could use multisource data (e.g., assessments of career self-management behaviors by parents, peers, or teachers) to rule out its effects fully. Second, in line with recommendations on school-to-work transitions (Akkermans et al., 2024), we assessed data over six time points, but it is possible that different time lags might produce different results. With the time lags of six months, the findings add important empirical insights into which time spans might and might not be appropriate to discover a meaningful change in the phase of career preparation. The choice of time lag can significantly influence the estimation of autoregressive and cross-lagged effects, potentially leading to misinterpretations if not properly aligned with the underlying processes being studied (Voelkle et al., 2012). Especially when having varying time intervals between measurements, Voelkle et al. (2012) advocate for the use of continuous-time modeling approaches. Third, we focused on intra-individual processes and did not include measures of changes in contexts in which the adolescents are situated. For example, we did not consider whether the observed effects might depend upon parent's educational level, their support, or school-level variables, such as teacher or peer behaviors. We therefore call for future studies that also consider environmental factors and how they might affect the dynamics of career decision-making. Fourth, our study did not assess self-knowledge or vocational identity achievement, which may explain why higher levels of career knowledge did not necessarily lead to higher levels of career decidedness in our study. Exploration of one's own interests, values, personality, and skills are critical aspects of the decision-making process, and future research should investigate how these aspects of self-knowledge interact with occupational information to influence career decidedness. Fifth, while our study examines reciprocal within-person effects using a RI-CLPM approach, we acknowledge the limitation of not testing mediation effects within this framework. Although it is statistically possible to introduce a time-varying covariate as a mediator, we opted against this due to theoretical and methodological challenges that complicate interpretation. Specifically, defining direct and indirect effects within RI-CLPM is not straightforward, as multiple pathways across time create ambiguity in what constitutes a direct effect (Mulder, 2021). Moreover, causal mediation requires strict identification assumptions (exchangeability, consistency, positivity) that RI-CLPM does not inherently satisfy, making causal conclusions problematic (Keele, 2015). Additionally, RI-CLPM relies on strong parametric assumptions, such as linearity and multivariate normality, which differ from traditional mediation models that allow for non-parametric estimation of indirect effects. Given these challenges, we focused on reciprocal within-person effects, for which RI-CLPM is well-suited, rather than testing mediation effects that might lead to misleading conclusions. Future research could explore alternative approaches, such as cross-lagged panel mediation models or structural equation models with latent growth components, to further investigate potential mediation mechanisms.

5. Conclusion

The present study provides an in-depth exploration of the dynamic relations between actions of career self-management, career knowledge, and career attitudes, and their relation over time by using a within-person approach and fully crossed-lagged longitudinal research design. As such, the study offers new insights to understand better the dynamic nature of key aspects of career decision-making.

CRediT authorship contribution statement

Madeleine Haenggli: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Andreas Hirschi:** Writing – review & editing, Supervision, Resources, Methodology, Funding acquisition, Conceptualization. **Julian Marciniak:** Writing – review & editing, Resources, Project administration, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jvb.2025.104125.

Data availability

Data will be made available on request.

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