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Which comes first? Modeling the relationships among future goals, metacognitive strategies and academic achievement using multilevel cross-lagged SEM

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ABSTRACT

Goals are important determinants of learning and achievement. The extant literature has mostly focused on unidirectional effects with goals typically modelled as antecedents of metacognitive strategies and academic achievement. However, the relationships among goals, metacognitive strategy use, and achievement are likely to be dynamic and variables might reciprocally influence each other. This study aimed to examine how future goals, metacognitive strategies, and achievement dynamically influence each other across time. A sample of 6290 students from 16 secondary schools in Hong Kong participated in our three-year study. Survey and achievement test data were collected three times with one-year intervals. Results of multi-level cross-lagged structural equation modeling showed that: (1) intrinsic goals are adaptive because they are associated with lower pursuit of extrinsic goals and higher levels of achievement; (2) the use of meta-cognitive learning strategies is associated with an increase in intrinsic goal pursuit; and (3) higher levels of achievement drive the subsequent use of metacognitive strategies. Theoretical and practical implications are discussed.

Goals and self-regulated learning (SRL) are two crucial factors associated with effective learning (Dent & Koenka, 2016; Pintrich, 2000). Considerable research has examined how different goals and self-regulated learning strategies predict academic achievement (Dent & Koenka, 2016; Elliot, 2005; Paulick, Watermann, & Nückles, 2013). The general consensus is that some goals (e.g., mastery goals and intrinsic goals) are more conducive for learning than others (e.g., performance goals and extrinsic goals) (Deci & Ryan, 2011; Elliot, 2005; Lee, McInerney, Liem, & Ortiga, 2010), and that some SRL strategies (i.e., metacognitive strategies) are likewise more adaptive than others (i.e., superficial learning strategies) (McInerney and King, in press; Zimmerman, 2002).

Although goal and SRL researchers theoretically acknowledge the existence of feedback loops and reciprocal relationships among goals, metacognitive strategies, and achievement (Pintrich, 1999; Zimmerman, 2002), empirical research has often treated both goals and metacognitive strategies as antecedents of academic achievement (e.g., Mega, Ronconi, & De Beni, 2014). Most studies have failed to investigate the causal ordering among these key variables. This is probably because many of the existing studies are cross-sectional. Even among studies that employed longitudinal designs, few investigated alternative causal pathways or reciprocal relationships among goals, metacognitive strategies and achievement.

Existing longitudinal studies of goals and metacognitive strategies usually confine themselves to sampling a relatively short time span (e.g., one semester as in Elliot, Murayama, & Pekrun, 2011). These studies also seldom examine the reciprocal associations among variables, mostly posting goals as antecedents but seldom examining the possibility that goals could also be outcomes of metacognitive strategies and achievement. Studies that cover a wider period and explicitly examine the temporal ordering among the key variables are needed.

Understanding the causal ordering of the variables has the potential to advance theory. Instead of naively assuming unidirectional relationships, this study could present a more dynamic picture of the potential reciprocal relationships among key variables. It could also inform practice by showing which variables are most crucial in optimizing learning and would thereby be a good focus for intervention studies.

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The primary goal of this study was to examine the reciprocal and dynamic relations among different types of future goals, metacognitive strategies and academic achievement. This study addressed the methodological shortcomings of previous research through the following ways: a large longitudinal sample size, assessment of longitudinal measurement validity across multiple groups, control of between-school effect, and use of cross-lagged SEM that are appropriate for exploring reciprocal relationships.

1. Future goals and academic achievement

Future goals refer to “self-relevant, self-defining goals that provide incentive for action” (Miller & Brickman, 2004, p. 14). Instead of focusing on immediate outcomes, these goals are focused on the more distal future.

It is important to focus on future goals for several reasons. First, much of the existing research on motivation and self-regulated learning have focused on more proximal short-term goals. However, future goals influence the adoption of more proximal sub-goals that are adopted in the service of the future goal (Miller & Brickman, 2004). Second, future goals shape many crucial outcomes. According to Future Time Perspective Theory (Simons, Vansteenkiste, Lens, & Lacante, 2004), setting long term future goals is associated with higher motivation, deeper learning, better performance and more persistence. Third, future goals are as important as short-term goals such as achievement goals (task versus ego involvement) in predicting performance (Vansteenkiste, Matos, Lens, & Soenens, 2007). Fourth, future goals give meaning to human behavior. As Bandura (1986, p. 476) noted, “Personal development is best served by combining distal aspirations with proximal self-guidance”. Without future goals, behavior would only be guided by immediate needs and immediate consequences. The higher-order future goals and related constructs give proximal tasks meaning beyond their immediate consequences (Markus & Nurius, 1986).

Future goals can be classified along an extrinsic-intrinsic dimension based on self-determination theory (SDT; Deci & Ryan, 2000). The central assumption of SDT is that “all individuals are born with the basic psychological needs for autonomy, competence, and relatedness” (Vansteenkiste, Timmermans, Lens, Soenens, & Van den Broeck, 2008, p. 388), and individuals' optimal functioning depend on the satisfaction of these psychological needs (Deci & Ryan, 2000). SDT proposes that as intrinsic goals are able to directly satisfy these three basic psychological needs, they are more likely to lead to deep learning and superior performance (Vansteenkiste, Soenens, & Duriez, 2008). In contrast, the pursuit of extrinsic goals may thwart the fulfilment of one's basic psychological needs, thereby leading to poorer learning outcomes (King & Datu, 2017; Vansteenkiste, Soenens, & Duriez, 2008).

Future goal researchers have identified five types of future goals commonly held among adolescents in different cultures. These goals are known as fame-oriented (striving to become a famous person), wealth-oriented (striving for financial success), career-oriented (striving for having a good job), family-oriented (supporting future family), and society-oriented goals (striving to contribute to society) (Nurmi, 2005). Fame and wealth goals classified as extrinsic goals and career, family, and society goals classified as intrinsic goals (Kasser & Ryan, 1996; Lee et al., 2010; Nurmi, 2005; Schmuck, Kasser, & Ryan, 2000).

During the past decade, a growing volume of empirical evidence suggests that extrinsic and intrinsic goals yield differential effects on learning and other crucial educational outcomes. Vansteenkiste, Lens, and Deci (2006) proposed that the content of future goals could affect the experience of learning because the pursuit of different goals could be linked to different level of basic psychological need satisfaction and its associated learning outcomes. Timmermans, Vansteenkiste, and Lens (2004) assessed a set of intrinsic and extrinsic goals among first year college students. They found that students who reported higher extrinsic goals showed signs of academic maladjustment. These findings supported the supposition that intrinsic goals are more beneficial to learning than are extrinsic goals (Vansteenkiste et al., 2006). In a series of experimental studies with 10th–11th graders and college students, Vansteenkiste, Simons, Lens, Sheldon, and Deci (2004) observed that extrinsic goals resulted in poorer learning quality and performance compared to intrinsic goals. The evidence for the adaptive capacity of intrinsic over extrinsic goals has been found among students of different ages and with different outcome variables (Vansteenkiste, Simons, Lens, Soenens, & Matos, 2005).

The studies reviewed above clearly show that intrinsic goals are associated with better learning outcomes, and that extrinsic goals not only negatively affect the quality of learning processes and outcomes, but also reduce the beneficial effects of intrinsic goals. However, the assumption that intrinsic goals are always advantageous and extrinsic goals are disadvantageous might be somewhat simplistic given that peoples' goals evolve over time. Although researchers traditionally draw a sharp distinction between extrinsic and intrinsic goals, it is possible that extrinsic and intrinsic goals also have a dynamic mutual relationship. For example, students could shift their goal pursuits from extrinsic future goals to intrinsic future goals. This is possible through education like career counselling when students gain more understanding about the values and importance of developing oneself and contributing to the society over accumulating money and fame. Moreover, it is also possible that students come to adopt more intrinsic over extrinsic goals over time as a result of psychological integration and maturity (Sheldon, Houser-Marko, & Kasser, 2006).

2. Metacognitive strategies, academic achievement, and future goals

Self-regulated learning (SRL) is an umbrella term that involves various aspects of learning such as cognition, motivation and learning behaviors (e.g., Pintrich, 2000; Winne & Hadwin, 2008; Zimmerman & Schunk, 2011). A core assumption of SRL is that effective learning occurs when students are able to self-regulate their cognitive, motivational behaviors through a series of metacognitive strategies (Pintrich, 2000). These metacognitive strategies are usually distinguished as planning (making a plan of action for performing an academic task), self-monitoring (awareness of performance progress on an academic task), self-control, and self-evaluation (changing/adapting strategies to enhance task performance) (Pintrich, 2000). Numerous studies have been conducted to investigate the effects of metacognitive strategies on learning (Bjork, Dunlosky, & Kornell, 2013; Mega et al., 2014). According to a recent meta-analysis, the effect size of metacognitive strategies on learning achievement was $r = 0.20$ (Dent & Koenka, 2016). Substantially, this means 4% of the total variance of students' academic achievement is contributed by their use of metacognitive strategies.

A critical component of SRL research concerns the interaction between motivational goals and metacognitive strategies. Initially, studies addressing these motivational goals only included short-term achievement goals such as task-specific goals (or task goals) and purpose goals (general reasons for approaching the task) (Pintrich, 2000). Arguing that an exclusive focus on these proximal goals is insufficient to capture the whole picture, Miller and Brickman (2004) proposed a SRL model that emphasizes future-oriented goals. The thesis of their model is that future goals help students to develop proximal sub-goals that can enhance students' perception of task instrumentality, which in turn leads to task-oriented self-regulation (Nett, Goetz, Hall, & Frenzel, 2012; Williamson, 2015). Put another way, future-oriented goals are not only the source of proximal goals, but also the driving force of self-regulated metacognitive strategies during the process of effective learning.

Drawing on Miller and Brickman (2004), Tabachnick, Miller, and Relyea (2008) further distinguished between extrinsic versus intrinsic future goals. They showed that students' intrinsic goals were related to their use of self-regulation strategies while extrinsic goals were not. Building on these findings, the researchers suggested that educators should emphasize intrinsic goals when helping students to develop essential capacities such as metacognitive strategies.

McInerney, Liem, Ortiga, Lee, and Manzano (2008) tested Miller and Brickman's thesis among a large sample of Singaporean secondary students. The researchers examined the effect of extrinsic future goals (i.e., fame-oriented and wealth-oriented) and intrinsic goals (i.e., career-oriented, family-oriented and society-oriented) on self-regulated learning. They found that self-regulated learning was positively related to intrinsic future goals (i.e., career-oriented and society-oriented) but negatively related to extrinsic future goals (i.e., wealth-oriented). McInerney and his colleague's study provided strong evidence for the positive relation between intrinsic future goals and self-regulated learning.

The studies reviewed above show the association between intrinsic goals and metacognitive strategies during learning. However, given their cross-sectional design, these studies cannot shed light on the causal ordering among the variables. We cannot conclude that the relationship is unidirectional from future goals to metacognitive strategies; nor can we exclude the alternative direction from metacognitive strategies to future goals. Perhaps, greater use of metacognitive strategies might result in more efficient future goal selection (Boekaerts, 2010; Boekaerts, de Koning, & Vedder, 2006). The current study attempts to address the issue of how these variables are related to each other across time.

3. Effects of achievement on future goals and on metacognitive strategies

Research on goals and metacognitive strategies in educational settings has predominantly focused on the use of goals and metacognitive strategies for predicting learning outcomes. This is evidenced by a meta-analysis of 40 years' worth of studies on the relationship between extrinsic-intrinsic motivation and performance (Cerasoli, Nicklin, & Ford, 2014) and a meta-analysis of SRL and academic performance (Dent & Koenka, 2016). The long-assumed feedback loops among goals, metacognitive strategies and academic achievement (Carver & Scheier, 1982; Dent & Koenka, 2016; Zimmerman, 2013; Zimmerman & Schunk, 2011) have remained understudied. There are also very few studies that examine how academic achievement can influence subsequent goal adoption and metacognitive strategies. This is surprising, given that students at different levels of academic achievement would likely affect their formulation of different types of future goals and engagement in metacognitive strategies (Boekaerts, 2010; Boekaerts et al., 2006; Zimmerman, 2013; Zimmerman & Schunk, 2011). For example, if students attribute their good exam results to effort or the effective use of certain metacognitive strategies, they would be more motivated to study and to continue to use these strategies (Weiner, 1992; Zimmerman, 2013).

The aforementioned idea is consistent with SDT, which posits that people have a fundamental psychological need for competence (Ryan, Connell, & Deci, 1985). According to SDT, positive feedback (e.g., rewards or high grades) facilitates students' sense of competence, which enhances intrinsic motivation and academic engagement. On the contrary, negative feedback (e.g., low grades) can thwart their sense of competence, which may undermine intrinsic motivation and academic engagement (Ryan & Deci, 2016). The effects of positive and negative feedback have been reported for young adolescents (Poorthuis et al., 2015). Paulick et al. (2013) found that young adolescents' prior GPA (scores combining math, language, and social studies) positively predicted subsequent intrinsicgoals but negatively predicted extrinsical goals. Although their study focused on more proximal achievement goals, the findings suggested that students' academic performance might have important effects on future goal adoption.

To summarize, previous studies have shown that both future goals (especially intrinsic goals) and metacognitive strategies play important roles in facilitating better learning outcomes. However, as most of these studies were not based on longitudinal observations, their findings have led to an impoverished understanding of alternative causal pathways. In existing studies, metacognitive strategies have mostly been treated as an outcome of goals, and academic achievement has always been modelled as an outcome of goals and metacognitive strategies. To advance our understanding of the relationships among these variables, it is essential to account for the possibility that metacognitive strategies might be an antecedent of motivational processes and the possibility of achievement acting as an antecedent of motivational and metacognitive strategies. However, to date, we know of very few studies that have examined how achievement may influence students' future goals and metacognitive strategies.

The current study aimed to investigate the reciprocal relations among extrinsic and intrinsic future goals, metacognitive strategies and academic achievement. We adopted a multilevel longitudinal design with a large sample size from 16 schools. We then analyzed data using multilevel cross-lagged structural equation after controlling for measurement invariance across different student groups. Drawing on the strenghts of our longitudinal design and rigorous statistical analyses, we hope to gain a more in-depth understanding of the co-development of extrinsic and intrinsic goals over time and to clarify the causal ordering among future goals, metacognitive strategies and academic achievement.

4. The present study

4.1. Research questions

The present study explored the dynamic relationships among extrinsic and intrinsic goals, metacognitive strategies, and achievement outcomes. Overall, we addressed four major questions.

1. Do extrinsic future goals (i.e., fame- and wealth-oriented), intrinsic future goals (i.e., career-, family-, and society-oriented), metacognitive strategies, and achievement exhibit stability across time (e.g., are T2 intrinsic future goals predicted by T1 intrinsic future goals)?
2. Do extrinsic future goals positively predict subsequent intrinsic future goals over and above the effects of prior intrinsic future goals? Conversely, do intrinsic future goals positively predict subsequent extrinsic future goals over and above the effects of prior extrinsic future goals?
3. Do extrinsic and intrinsic future goals positively predict subsequent metacognitive strategies over and above the effects of prior metacognitive strategies? Conversely, do metacognitive strategies positively predict subsequent extrinsic and intrinsic future goals over and above the effects of prior extrinsic and intrinsic future goals?
4. Do intrinsic future goals, extrinsic future goals, and metacognitive strategies positively predict subsequent achievement over and above the effects of prior achievement? Conversely, does achievement positively predict subsequent extrinsic future goals, intrinsic future goals, and metacognitive strategies over and above the effects of prior extrinsic future goals, intrinsic future goals and metacognitive strategies?

5. Methods

5.1. Participants

This three-year longitudinal study involved 6290 students roughly equally distributed among 16 Hong Kong secondary schools (each school comprising about 4–7% of the total sample). Hong Kong has a total of 519 secondary schools which can be categorized into Bands 1 (high-ability), 2 (medium-ability), and 3 (low-ability) based on their new intakes' achievement scores.

This classification is based on their school examination scores and the Pre-Secondary One Hong Kong Attainment Test (Education Bureau,

Table 1
An overview of measures and variables (surveys).

Scale	Dimension	No. of items	Sample item	Cronbach's alpha (Time 1/Time 2/Time 3)
Extrinsic future goals	Fame	3	I want to become a famous person in my society.	0.90/0.91/0.92
	Wealth	3	I want to make a lot of money.	0.85/0.86/0.88
Intrinsic future goals	Career	3	I want to get a good work position.	0.88/0.90/0.91
	Family	3	I want to look after my future family well.	0.90/0.93/0.91
	Society	3	I want to help my society.	0.85/0.89/0.89
Metacognitive strategies	Planning	5	I schedule the time to study each subject according to my plan.	0.88/0.89/0.89
	Monitoring	5	I reflect upon my learning strategies to see if they are effective.	0.87/0.87/0.88
	Changing	5	I modify my learning methods to meet the needs of a school subject.	0.85/0.84/0.85

2018). Schools taking Band 1 students gain the prestige of Band 1 schools, so it is with Band 2 and Band 3 schools. Of the 16 schools in our study, 3 were Band 1 (involving 1983 students or 31.5% of the total sample), 9 were Band 2 schools (involving 3387 students, or 53.8% of the total sample), and 4 were Band 3 schools (involving 920 students or 14.6% of the total sample). Of these students, 3253 were males (51.7%) and 3037 were females (48.3%). At the beginning of the study, 2037 (32.4%) students were in Secondary 1 (7th Grade), 2133 (33.9%) in Secondary 2 (8th Grade), and 2120 (33.7%) in Secondary 3 (9th Grade). The mean age at Time 1 was 12.23 (S.D. = 0.65) for Cohort 1 (Secondary 1), 13.27 (S.D. = 0.72) for Cohort 2 (Secondary 2), and 14.27 (S.D. = 0.72) for Cohort 3 (Secondary 3).

5.2. Instruments

All scales were administrated in Chinese.

5.2.1. Future goals

To measure students' extrinsic and intrinsic future goal, the Future Goal Questionnaire (FGQ) developed by Lee et al. (2010) for secondary students was used. The FGQ is rated on a 5-point Likert scale (1 = *strongly disagree*; 5 = *strongly agree*). It consists of five 3-item subscales, each measuring one of the following five types of goals: career-oriented goals (e.g., 'I want to get a good work position'), family-oriented goals (e.g., 'I want to look after my future family well'), society-oriented goals (e.g., 'I want to help my society'), wealth-oriented goals (e.g., 'I want to be wealthy'), and fame-oriented goals (e.g., 'I want to become a well-known person in my society'). The first three types of goals are subsumed under intrinsic goals and the last two under extrinsic future goals (Lee et al., 2010).

5.2.2. Metacognitive strategies

To measure metacognitive strategies, we used the domain-general metacognitive strategy subscales from the Self-Learning Scale (SLS) developed by Mok, Cheng, Kennedy, and Moore (2006). The original SLS consists of 19 subscales measuring different aspects of self-directed learning, such as academic motivation, metacognitive strategies, and cognitive strategies. In the SLS, three subscales were relevant to metacognitive strategies: changing to improve, monitoring and planning. *Changing* to improve refers to the various ways students attempt to improve their learning when identifying mistakes made (e.g., 'When I find that I decline in my achievement, I change my learning methods'). *Monitoring* refers to students' from-time-to-time self-check of their learning and understanding (e.g., 'I keep records of my learning performance in order to monitor how much progress I have made'). *Planning* refers to activities student take to prepare for future work (e.g., 'I schedule the time to study each subject according to my plan'). Each type of strategy was measured using five items on a scale of five points ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). An overview of the survey scales (future goals and metacognitive strategies in English) is show on Table 1.

5.2.3. Academic achievement

Academic achievement was represented using English achievement. English achievement was preferred over other subjects (e.g., science, mathematics) for several reasons. First, English proficiency is the most emphasized factor by the government and the business sector for maintaining Hong Kong's economic advantage (Nunan, 2003). Second, English is used as the medium of instruction in Hong Kong higher education and higher English proficiency means more opportunities for students to pursue their higher education attainment (Curriculum Development Council, 2000). Lastly, it is well known that Hong Kong parents value English more than other subjects such as science or math given its role in helping children get ahead in society.

Students' English achievement was assessed using the English Language Ability Calibrated (ELAC) Scale, a standardized English achievement test developed by Lee (2010). The original ELAC comprised an item bank of over 2500 items designed for the primary and secondary English curricula in Hong Kong. The ELAC scores used in the current study were already calibrated with the Rasch measurement method with > 15,000 students between Primary 1 and Secondary 3 in Hong Kong (Bond & Fox, 2015). A fundamental assumption of the Rasch researchers is that human attributes (e.g., English achievement) are not directly observable but have to be inferred from manifest observations (Bond & Fox, 2015).

5.3. Procedures

The current study was approved by the institutional review board of The Education University of Hong Kong. Before data collection, consent was obtained from all participating schools, parents, and students. Sixteen Hong Kong secondary schools[1] covering three school bands were involved for voluntary participation and each school involved students of all cohorts (i.e., grades students were in when the study began: S1–S3 representing Secondary Grades 1 to 3). All students whose responses were used in our study remained in the same schools.

Data were collected by class teachers at the end of each school year (i.e., end of June 2009, 2020, and 2011). Two data collection sessions were conducted with each session, each lasting for about 30 to 40 min which is equivalent to one class period. The first data collection session focused on administering the psychological self-reported instruments (including future goals and metacognitive strategy use). The second data collection session involved the administration of the standardized achievement test. To ensure the consistency of data collection across schools, a research assistant was trained to assist the teachers in implementing data collection. To cater for students' language preference, each questionnaire had an English version (original) and a Chinese version. The Chinese version was developed using forward and backward translation procedures and further cross-validated using a committee approach to settle inconsistencies in the forward and backward translations. All translators were proficient in both Chinese and English. Students were given the choice to use the English or the Chinese version

[1] There were 519 secondary schools in Hong Kong during the academic year 2012/2013.

but all students chose the Chinese version. Data were collected using paper and pencil questionnaires. The same procedure was applied for all three years.

5.4. Data analyses

As indicated, the data were collected from diverse groups of students (i.e., gender, cohorts or grades, schools and school bands) across three times (i.e., the same scales were used repeatedly). This made our data structure multilevel: gender (=2), cohorts (=3) and times (=3) were nested within students (n = 6290), which in turn was nested within schools (=16). Schools, in turn, were nested within school bands (=3). To focus our attention on the change of student-level variables, the ideal option would be to apply multilevel modeling to control for the aforementioned group effects. However, as school was the only cluster variable that had a relatively sufficient sample size, and in line with the methodology of Muthén (1994) and Cheung and Au (2005), we conducted two-level longitudinal SEM using school as the cluster and treating gender, cohort and school banding (i.e., high-, medium- and low-ability schools) as auxiliary variables.

To analyze these complex data, we developed a two-stage general analytical strategy: one for single-level analyses and the other for multilevel analyses. Stage I was used to explore the general structure of the data without considering the school level effect; while Stage II was to examine the data structure by controlling for school effects.

5.4.1. (Stage I: Single-level analyses)

1) fitting the cross-sectional factorial invariance model through confirmatory factor analyses (CFA; Brown, 2006) to determine the relations of the observed measures to their posited underlying constructs (i.e., intrinsic future goals, extrinsic future goals, metacognitive strategies) and with English achievement at each time (Models 1 to 3 for data collected at T1 to T3, respectively), wherein correlations between different constructs were allowed;
2) fitting the longitudinal factorial invariance model through successively testing the baseline model without placing constraints on across-time estimation (Model 4), the model constraining equal the factor loadings (Model 5), the model constraining equal the intercepts (Model 6), and finally the model constraining equal the error variances (Model 7);
3) fitting the longitudinal factorial invariance across the auxiliary clusters: gender (Model 8), cohort (Model 9) and school band (Model 10);
4) fitting the longitudinal SEM model (cross-lagged SEM) (Model 11);

5.4.2. (Stage II: Multilevel analyses)

5) estimating between-group variation (assessing the necessity of using MSEM), and
6) estimating pooled within-group cross-lagged SEM (Model 12).[2]

This single- to multiple-level analytical flow was in line with Muthén (1994) and Cheung and Au (2005) for conducting MSEM. Among Stage I steps, Step 1 provided an assessment of discriminant validity; Steps 2 and 3 assessed scale stability across time (Heck & Thomas, 2015) and different types of students (i.e., different genders, cohorts, and school bandings), respectively; and Step 4 and Step 6 tested the mutual lagged relationships among key variables with and without considering individual school effect. Our check of the longitudinal measurement invariance during Stage I followed recommendations by Schnettler et al. (2017) for modeling multigroup longitudinal factorial invariance. The longitudinal factorial invariance assessment provided evidence regarding the extent to which the scale(s) were measuring the same thing(s) at different time points.

Mplus 7.4 (Muthén & Muthén, 1998–2015) was used to test the measurement and structural models. To compute model fit and parameter estimates, we used the Maximum Likelihood Robust (MLR) estimator for the most robust performance empirically observed (Satorra & Bentler, 1994). Models were evaluated using four indices recommended in the SEM literature: the root mean square error of approximation, with values < 0.08 and < 0.05 indicating acceptable and good fit (RMSEA; Browne & Cudeck, 1992), standardized root mean square residual (SRMR), with values smaller or closer to 0.09 representing a reasonable fit (Hu & Bentler, 1999), and Tucker–Lewis index (TLI) and comparative fit index (CFI), both with values larger than 0.90 and 0.95 representing acceptable and good fit, respectively (Byrne, 2010). For stepwise model comparison (Steps 2 and 3), we followed Cheung and Rensvold (2002) and took a decrease in the CFI of or < 0.01 as evidence of invariance.

When interpreting SEM results, the current study relied on the standardized path coefficients (β estimates) and considered Hattie's (2009) guidelines for interpreting the effect sizes for educational studies. According to Hattie, the values of 0.05, 0.15, and 0.24 and above are references of small, moderate and large positive effect and the values of −0.10, −0.20, and −0.29 and lower are references of small, moderate and large negative effects. In cross-sectional studies, an effect size (e.g., 0.05 or below for positive effect) falling under the 'small effect' guideline is typically interpreted as trivial and can be ignored. In auto regressive models, however, a small effect size may mean a lot (Abelson, 1985). This is because this effect size is the result of controlling for the effect of the outcome variable on a previous time (Ployhart & Ward, 2011). To overcome this limitation, Adachi and Willoughby (2015) recommended a dynamic approach for interpreting the effect sizes of auto regressive models. According to this approach, the meaningfulness of a predictive effect depends not only on the lagged effect of the predictor variable but also on the stability of the outcome scale. The current study adopted this recommendation for interpreting effect sizes.

6. Results

6.1. Missing values

A common challenge for large-scale longitudinal survey is missing data. The original dataset used in the current study involved 8568 students. Among them, 2278 (27%) cases had whole wave missing value and 6290 cases provided complete responses or within-wave missing values. The missing cases were students who failed to complete at least one wave of data collection. According to missing value research, imputing missing values for whole waves is not advisable (Allison, 2001), as it may introduce unnecessary random errors into the estimates (Von Hippel, 2007; Young & Johnson, 2015). Therefore, we decided to drop cases with whole-wave(s) missing values and to use the 6290 cases with complete or within-wave missing responses. In the cleaned dataset, the missing rates ranged from nearly 0 for auxiliary variables (i.e., gender, cohort, and school band) to 2% for the main variables (i.e., goals, metacognitive strategies, and achievement).

To replace these missing values, we used the multiple imputation (MI) technique (Rubin, 1987; Schafer, 1997) in MPLUS 7.4 (Muthén & Muthén, 1998–2015), by including the nine key variables for each time point that appeared in subsequent analyses, as well as the four auxiliary variables (gender, cohort, and school band). We generated five sets of imputed data, bearing in mind Schafer and Graham's (2002)

[2] The estimation of pooled between-group structure (Step 4) proposed by Cheung and Au (2005) was not included given that the group sample size was only 16, even smaller than the minimum size of 20 required at the group level (Cheung & Au, 2005). To avoid the risk of non-convergence or larger standard errors of estimation (Maas & Hox, 2005), we determined to only perform within-group structural analysis.

Table 2
Descriptive statistics and reliability estimates.

	Extrinsic goals			Intrinsic goals			Metacognitive strategies			Achievement (English)		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
Mean	3.04	3.03	3.02	3.45	3.44	3.41	2.84	2.81	2.84	46.21	48.78	49.52
S.D.	0.60	0.58	0.57	0.45	0.45	0.46	0.53	0.51	0.49	11.52	9.70	9.07
Skewness	−0.27	−0.27	−0.21	−0.88	−0.80	−0.72	−0.31	−0.31	−0.25	−0.92	−0.04	−0.38
Kurtosis	−0.34	−0.15	−0.03	1.04	0.95	1.15	0.98	1.27	1.49	2.60	0.65	1.10
Cronbach's alpha	0.84	0.84	0.84	0.89	0.89	0.90	0.93	0.93	0.93	–	–	–

Table 3
Bivariate correlations among key variables (= 6,290).

	1	2	3	4	5	6	7	8	9	10	11	12
1. T1 extrinsic goals		0.514**	0.454**	0.559**	0.293**	0.261**	0.277**	0.168**	0.177**	−0.005	0.008	0.008
2. T2 extrinsic goals			0.539**	0.300**	0.581**	0.314**	0.183**	0.253**	0.188**	−0.026*	−0.024	−0.009
3. T3 extrinsic goals				0.279**	0.324**	0.611**	0.180**	0.178**	0.294**	−0.024	−0.002	0.013
4. T1 intrinsic goals					0.424**	0.363**	0.381**	0.225**	0.218**	0.034**	0.079**	0.065**
5. T2 intrinsic goals						0.446**	0.255**	0.339**	0.237**	0.032*	0.059**	0.063**
6. T3 intrinsic goals							0.186**	0.215**	0.335**	0.004	0.036**	0.067**
7. T1 metacognitive strategies								0.494**	0.407**	0.066**	0.094**	0.059**
8. T2 metacognitive strategies									0.503**	0.078**	0.087**	0.073**
9. T3 metacognitive strategies										0.067**	0.098**	0.094**
10. T1 achievement											0.449**	0.428**
11. T2 achievement												0.505**
12. T3 achievement												

** $p < .01$.
* $p < .05$.

recommendation that five sets of imputed data provide highly sufficient estimates and more datasets only marginally increase the estimation accuracy. All parameters, standard errors and model fit indices were averaged estimates.

6.2. Descriptive statistics and zero-order correlations

Table 2 shows the descriptive statistics and internal consistency reliabilities of the scales used. For the sake of presentation simplicity, these statistics were calculated based on the mean scores of the subscales within each survey. For instance, extrinsic future goals for each time point was the mean of fame-oriented and wealth-oriented goals for their corresponding time point. The same applied to intrinsic future goals and metacognitive strategies. The internal reliability estimates for each scale across time were roughly the same; they were 0.84 for extrinsic future goal, 0.89 for the intrinsic future goal, and 0.93 for metacognitive strategies, suggesting good to excellent internal consistency.

The bivariate correlations indicate that all variables were positively related to each other (except for part of the correlations between extrinsic future goal and English achievement), which is in line with our theoretical expectations (see Table 3).

6.3. Results of structural equation modeling

We first conducted confirmatory factor analyses (CFAs) at each time point to test whether the measurement model would apply to all individual time points (Brown, 2006). Each of the CFAs contained three latent constructs (i.e., extrinsic future goals, intrinsic future goals, and metacognitive strategies) and one observed variable—English achievement. After freeing two uniqueness covariances (i.e., one connecting career and wealth and the other connecting society and fame) the model fit the data well at all time points (Models 1 to 3 for T1 to T3, respectively) (see Table 4 for details).

Next, we tested the longitudinal factorial invariance model. In doing so, we first combined the three cross-sectional measurement models into a longitudinal measurement model (i.e., T1-T3 extrinsic future goals, T1-T3 intrinsic future goals, T1-T3 metacognitive strategies, and T1-T3 English achievement) and added all across-time error covariances of each indicator (Model 4). The results showed good model-data fit (χ^2 = 4331.695; df = 238; $p < .001$; RMSEA = 0.052 (mean of 5 estimates); SRMR = 0.064; TLI = 0.906; CFI = 0.936).

This model (Model 4) was then used as the configural longitudinal factorial model to test longitudinal measurement invariance. In doing so, we followed Widaman and Reise (1997) and tested successively four models: a weak factorial invariance model constraining equal factor loadings (Model 5), a strong factorial invariance model constraining equal all intercepts within the factor (Model 6), and a restrictive factorial invariance model constraining equal all unique variances (Model 7). Results for all tested models indicated good model-data fit, and the changes in CFI across the increasingly constrained models were all significant at $p < .01$, demonstrating longitudinal measurement invariance despite the increasingly restrictive constraints (see Table 5 for the results of invariance testing).

Third, we conducted a series of invariance tests to see whether the results would hold for students of different genders, cohorts, and school bands. According to Table 6, the most restrictive model was shown to be invariant across male and female students (gender invariance; ΔCFI = 0.003), across students who started at S1, 1 S2, and S3 (cohort invariance; ΔCFI = −0.001), and across students from high-ability, medium-ability, and low-ability schools (school band invariance; ΔCFI = 0.000). Thus, the results held for students of different genders, cohorts, and school band.

Building on the evidence of longitudinal factorial invariance across different groups we then converted the measurement model to a structural model to test the lagged mutual relationships among extrinsic future goals, intrinsic future goals, metacognitive strategies and

Table 4
Cross-sectional CFAs for different time points (n = 6290).

	χ^2	df	χ^2/df	p value	RMSEA	SRMR	TLI	CFI
Model 1 T1 CFA	582.001	20	29.10	< 0.001	0.067	0.045	0.930	0.961
Model 2 T2 CFA	743.324	20	37.17	< 0.001	0.076	0.064	0.910	0.950
Model 3 T3 CFA	796.002	20	39.80	< 0.001	0.079	0.068	0.908	0.949

Note. RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; TLI = Tucker–Lewis index; CFI = comparative fit index.

Table 5
Invariance tests of the measurement model across three time points (n = 6290).

	χ^2	df	χ^2/df	p value	RMSEA	SRMR	TLI	CFI	ΔCFI
Model 4 configural invariance	4331.695	238	18.20	< 0.001	0.052	0.064	0.906	0.936	–
Model 5 weak factorial invariance model	4368.555	248	17.62	< 0.001	0.051	0.065	0.909	0.936	0.000
Model 6 strong factorial invariance model	4421.062	266	16.62	< 0.001	0.050	0.065	0.915	0.935	0.001
Model 7 restrictive factorial invariance model	4417.822	274	16.12	< 0.001	0.049	0.065	0.917	0.935	0.000

Note. RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; TLI = Tucker–Lewis index; CFI = comparative fit index.

Table 6
Longitudinal factorial invariance tests across genders, cohorts and school bands.

Model	χ^2	df	χ^2/df	p value	RMSEA	SRMR	TLI	CFI	ΔCFI
Model 8 gender invariance									
a) Configural longitudinal factorial model	4886.194	508	9.62	< 0.001	0.052	0.065	0.908	0.933	–
b) Weak longitudinal factorial invariance model	4936.315	518	9.53	< 0.001	0.052	0.066	0.909	0.933	0.000
c) Strong longitudinal factorial invariance model	4960.759	534	9.29	< 0.001	0.051	0.066	0.911	0.932	0.001
d) Restrictive longitudinal factorial invariance model	5181.007	558	9.28	< 0.001	0.051	0.067	0.911	0.929	0.003
Model 9 student cohort invariance									
a) Configural longitudinal factorial model	973.309	777	1.25	< 0.001	0.051	0.067	0.912	0.939	–
b) Weak longitudinal factorial invariance model	5017.055	787	6.37	< 0.001	0.051	0.067	0.913	0.935	0.004
c) Strong longitudinal factorial invariance model	5067.446	803	6.31	< 0.001	0.050	0.067	0.914	0.934	0.001
d) Restrictive longitudinal factorial invariance model	5028.396	843	5.96	< 0.001	0.049	0.067	0.919	0.935	−0.001
Model 10 school band invariance									
a) Configural longitudinal factorial model	4179.702	777	5.38	< 0.001	0.046	0.062	0.927	0.946	–
b) Weak longitudinal factorial invariance model	4230.381	787	5.38	< 0.001	0.046	0.062	0.927	0.946	0.000
c) Strong longitudinal factorial invariance model	4259.854	803	5.30	< 0.001	0.045	0.062	0.929	0.945	0.001
d) Restrictive longitudinal factorial invariance model	4357.592	843	5.17	< 0.001	0.045	0.063	0.931	0.945	0.000
Single level cross-lagged model (based on weak invariance)	3970.867	257	15.45	< 0.001	0.048	0.063	0.921	0.942	–
Two level cross-lagged model (based on weak invariance)	3798.525	257	14.78	< 0.001	0.047	0.064	0.920	0.942	–

Note. RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; TLI = Tucker–Lewis index; CFI = comparative fit index.

achievement through cross-lagged SEM (fourth step). We decided to base our analyses on the weakly constrained model to explore the cross-lagged effect for practical reasons. That is, for real longitudinal data (even for cross-sectional data), it is too rigid to expect that strong or restrictive measurement invariance would hold with data that can be grouped in multiple ways such as gender, cohort, and school band. Forcing a strong (or a restrictive) measurement invariance might lead to biased parameter estimates such as the appearance of unreasonable estimates of path coefficients (e.g., standardized path coefficients larger than 1.00).

The fifth step examined the need for conducting multilevel analysis. We examined whether there is variation in the outcome between higher-level units (Heck & Thomas, 2015) and whether there is sufficient sample size at the cluster level. The former concept is referred to as intraclass correlation (ICC) and even small ICCs can impact significance tests (Barcikowski, 1981); the latter is known as design effect and a value larger than 2.0 would suggest the need to do multilevel analysis (Muthén & Satorra, 1995). For our study, the ICCs of all indicators were larger than zero and the design effects were all above 2.0 (see Table 7), both suggesting the need to conduct two-level SEM. However, Heck and Thomas (2015) cautioned that design effect should also be considered together with empirically used cluster size for conducting multilevel analysis, and the recommended range is from 20 to 40 (Cheung & Au, 2005). Given these considerations, we performed two-level analysis while only reporting within-group findings (i.e., controlling for between level variances).

Based on results of between-group variance analysis, in the last step we performed two-level cross-lagged SEM (see Fig. 1a for the conceptual model). The results showed good model fit indices for the within-group analysis (χ^2 = 3798.525; df = 257; p < .001; RMSEA = 0.047; SRMR = 0.064; TLI = 0.920; CFI = 0.942). The results of the within group cross-lagged SEM are illustrated in the diagram in Fig. 1b.

6.4. Results of scale stability and lagged predictive effects

The estimates of autoregression in Fig. 1 provided answers to our question regarding the stability of the four scales (Question 1). As indicated by the standardized autoregression (transition) estimates, all three self-reported scales displayed strong stability. The largest pair of estimates were associated with extrinsic future goals: β = 0.64, p < .01 (for the T1-T2 transition) and β = 0.86, p < .01 (for the T2-

Table 7
The ICCs and design effects of composite indicators across time.

Scale	T1 variable	ICC	Design effect	T2 variable	ICC	Design effect	T3 variable	ICC	Design effect
Intrinsic goals	Fame1	0.009	3.061	Fame2	0.008	4.432	Fame3	0.006	3.574
	Wealth1	0.006	2.374	Wealth2	0.006	3.574	Wealth3	0.005	3.145
Extrinsic goals	Career1	0.012	3.748	Career2	0.018	8.722	Career3	0.012	6.148
	Family1	0.009	3.061	Family2	0.008	4.432	Family3	0.012	6.148
	Society1	0.010	3.290	Society2	0.008	4.432	Society3	0.008	4.432
Metacognitive strategies	Change1	0.016	4.664	Change2	0.023	10.867	Change3	0.022	10.438
	Monitor1	0.013	3.977	Monitor2	0.019	9.151	Monitor3	0.016	7.864
	Plan1	0.013	3.977	Plan2	0.018	8.722	Plan3	0.017	8.293
English achievement	English1	0.280	65.120	English2	0.370	159.730	English3	0.310	133.990

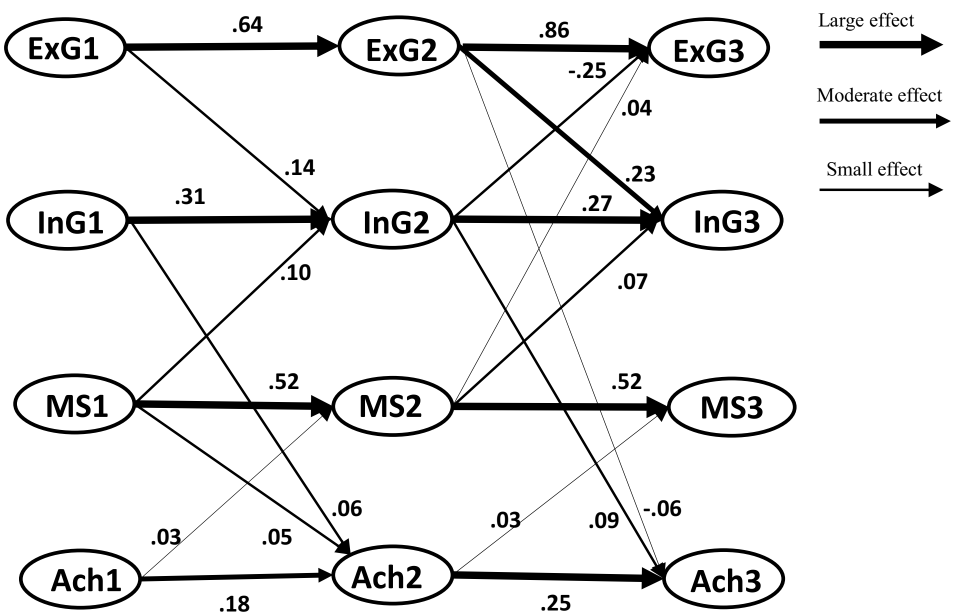

Fig. 1. Reciprocal relations among goals, metacognitive strategies, and achievement
Note: ExG1 to ExG3 = Time 1 to Time 3 extrinsic goals; InG1 to InG3 = Time 1 to Time 3 intrinsic goals; MS1 to MS3 = Time 1 to Time 3 metacognitive strategies; Ach1 to Ach3 = Time 1 to Time 3 achievement; Only statistically significant paths at $p < .05$ are shown.

T3 transition). Compared with the transition estimates of extrinsic future goals, the transition estimates of intrinsic future goals were smaller: the estimates were $\beta = 0.31$ for the T1-T2 transition and $\beta = 0.27$ for the T2-T3 transition. The autoregression estimates for metacognitive strategies fell between the estimates of the two goal scales. For both transitions, the estimates of metacognitive strategies had the same value of 0.52 ($p < .01$). The autoregressions of the achievement tests were 0.18 ($p < .01$) and 0.25 ($p < .01$) for the T1-T2 and T2-T3 transitions, respectively, indicating that achievement was less stable than the self-reported motivational scales.

The estimates of the cross-variable path coefficients represented the lagged predictive effects addressed by Questions 2 to 4. As for Question 2 (i.e., reciprocal relationship between extrinsic-intrinsic future goals), the results showed large predictive effect of extrinsic future goals on subsequent intrinsic future goals (i.e., $\beta = 0.14$, $p < .01$ and $\beta = 0.23$, $p < .01$ for the T1-T2 and T2-T3 transitions, respectively). As for the reverse effect, only one negative predictive effect was found, which was from T2 intrinsic future goals to T3 extrinsic future goals ($\beta = -0.25$, $p < .01$).

With regard to Question 3 (i.e., reciprocal relationships among metacognitive strategies and extrinsic-intrinsic future goals), metacognitive strategies were found to have positive lagged effects on intrinsic future goals ($\beta = 0.10$, $p < .01$, and $\beta = 0.07$, $p < .01$ for the T1-T2 and T2-T3 transitions, respectively), whereas no significant effects were identified in the reverse direction. As for the reciprocal relationship between metacognitive strategies and extrinsic future goals, only T2 metacognitive strategies were found to significantly predict T3 extrinsic future goals ($\beta = 0.04$, $p < .01$).

Finally, all three predictor variables were found to have lagged effects on achievement, though the patterns of the lagged effect and corresponding effect sizes varied. Continuous lagged effect was only observed with intrinsic future goals. The effect was 0.06 ($p < .01$) for the path from T1 intrinsic future goals to T2 English achievement and 0.09 ($p < .01$) for the path from T1 intrinsic future goals 1 to T2 English achievement. The estimate of the path from T1 metacognitive strategies to T2 English achievement was 0.05 ($p < .01$) and the estimate of the path from T2 extrinsic future goals to T3 English achievement was -0.06 ($p < .01$). As for the reverse effect(s), English achievement was found to positively predicted subsequent metacognitive strategies ($\beta = 0.03$, $p < .01$ for both T1-T2 and T2-T3 transition stages). The reverse effects of English achievement on both extrinsic future goals and intrinsic future goals were not significant.

7. Discussion

The aim of this study was to investigate dynamic relationships among future goals, metacognitive strategies, and achievement using a three-wave longitudinal dataset. We discuss our findings in relation to the core research questions:

1. Do extrinsic future goals (i.e., fame- and wealth-oriented), intrinsic future goals (i.e., career-, family-, society-oriented), metacognitive

strategies, and achievement exhibit stability across time (e.g., are T2 intrinsic future goals predicted by T1 intrinsic future goals)?

Our autoregression estimates indicated that all self-reported scales showed strong stability,[3] with extrinsic future goals showing the strongest stability, followed by metacognitive strategies and intrinsic future goals. These results were consistent with previous findings as regards the stability of most psychological constructs such as self-esteem (Marsh, 1993) and intelligence (Thorndike, 1940). Compared with the self-reported scales, the stability of English achievement was relatively weaker. However, the moderate effect size for the T1-T2 transition and the large effect size for the T2-T3 transition suggest that students' English achievement exhibits gradual progression during the observed duration. Taken together, these results provide evidence supporting the stability of the four scales over time, though the extent of the stability varied for different scales. This evidence provided baseline information for determining the meaningfulness of the lagged effects of predictor variables addressed in the remaining three questions (i.e., small effects on these outcome variables should be interpreted as meaningful).

2. Do extrinsic future goals positively predict subsequent intrinsic future goals over and above the effects of prior intrinsic future goals? Conversely, do intrinsic future goals positively predict subsequent extrinsic future goals over and above the effects of prior extrinsic future goals?

Our results showed that both T1 and T2 extrinsic future goals positively predicted subsequent intrinsic future goals. This indicated that students endorsing higher fame- and wealth-oriented goals at previous time points were more likely to endorse higher career-, family- and society-oriented goals at the subsequent time points. This observation is consistent with the findings of McInerney et al.'s (2008) study with secondary school students in Singapore. In the Asian setting, extrinsic and intrinsic future goals are less distinct which may account for these changes (King & McInerney, 2014).

With respect to the path from intrinsic future goals to extrinsic future goals, we detected a non-significant lagged effect of T1 intrinsic future goals on T2 extrinsic future goals but moderate negative lagged effect of T2 intrinsic future goals on T3 extrinsic future goals. This unstable effect of intrinsic future goals on extrinsic future goals suggests that, although individuals have a natural tendency to move away from extrinsic towards intrinsic future goals (Sheldon, Arndt, & Houser-Marko, 2003; Vansteenkiste, Niemiec, & Soenens, 2010), this extrinsic to intrinsic conversion may take time as extrinsic future goals are relatively stable (Sheldon et al., 2003). The findings also suggest that fostering students' intrinsic future goals can potentially constrain the detrimental effects of extrinsic future goals on achievement via reducing the level of subsequent extrinsic future goals adoption.

3. Do extrinsic and intrinsic future goals positively predict subsequent metacognitive strategies over and above the effects of prior metacognitive strategies? Conversely, do metacognitive strategies positively predict subsequent extrinsic and intrinsic future goals over and above the effects of prior extrinsic and intrinsic future goals?

Our results showed that T1 and T2 metacognitive strategies positively predicted subsequent intrinsic future goals, whereas the corresponding paths from intrinsic future goals or extrinsic future goals to metacognitive strategies were not significant. These results suggest that metacognitive strategies are not merely outcome variables, they may also have a role in shaping students' goals. These results, hence, did not support the assumption that goals are the driving force for metacognitive strategy use (Miller & Brickman, 2004). However, our results are in line with the bottom-up mechanism of SRL proposed by Boekaerts and colleagues (Boekaerts, 1996, 2010, 2011). According to their position, when confronted with challenges from task performance, students might choose to use metacognitive strategies to lower their aspiration for the future so as to prevent themselves from 'being damaged' (Boekaerts, 2011, p. 411). This link between task performance and metacognitive strategies could be reflected from the albeit small but significant lagged effects from previous achievement to metacognitive strategies. Applied to our current discussion, secondary school students in Hong Kong appeared to use metacognitive strategies actively when confronted with challenges to adjust their expectations for the future (e.g., career-, family- and society-oriented goals). It is highly possible that students feel that certain extrinsic future goals are harmful for their learning. They are able to recognize this problem, to evaluate the goals they pursue, and to adjust these goals to a level they feel appropriate. Vice versa, they might feel their intrinsic future goals are too low to be able to benefit their learning, and then, they regulate their goals by raising certain intrinsic future goals for the sake of better achievement.

4. Do intrinsic future goals, extrinsic future goals, and metacognitive strategies positively predict subsequent achievement over and above the effects of prior achievement? Conversely, metacognitive strategies over and above the effects of prior extrinsic future goals, intrinsic future goals and metacognitive strategies?

Our results provided evidence that while T2 extrinsic future goals negatively predicted subsequent achievement, both T1 and T2 intrinsic future goals positively predicted their subsequent achievement. In general, these findings are consistent with the SDT position that pursuit of extrinsic future goals can lead to poor learning outcome while pursuit of intrinsic future goals are able to lead to enhanced learning outcomes (Vansteenkiste, Soenens, & Duriez, 2008). However, our results did not support the alternative pathway, namely, the predictive effect of achievement on subsequent extrinsic future goals or intrinsic future goals. The absence of these reverse effects contradicts the existence of feedback loops long-held by SDT researchers (Deci & Ryan, 1985; Ryan & Deci, 2016) and SRL theorists (Zimmerman, 2013; Zimmerman & Schunk, 2011). According to both theories, enhanced academic performance would positively predict future goals, which would again have a positive effect on the use of metacognitive strategies. This inconsistency, however, does not necessarily challenge the entire feedback loop. An alternative interpretation would be available by further considering the role of metacognitive strategies.

Our results showed that metacognitive strategies had significant lagged effect on subsequent achievement only in the short term (i.e., from T1 metacognitive strategies to T2 achievement). The positive lagged effect of metacognitive strategies on achievement in the short term is not surprising, as is consistent with the number of studies reviewed in the meta-analysis by Dent and Koenka (2016). The significance of the lagged effect of metacognitive stage points to the possibility of the causal ordering from metacognitive strategies to achievement.

Our most interesting finding pertains to the significant lagged effects of achievement on subsequent metacognitive strategies. This evidence, on the one hand, verifies the bottom-up mechanism of SRL proposed by Boekaerts and colleagues (Boekaerts, 2010, 2011;

[3] Scale stability in our study refers to the consistency of rank ordering of scores obtained using different scales over time, or 'relative level stability' (Newsom, 2015, p. 91). Controlling for scale stability is regarded as a gold standard in longitudinal studies (Adachi & Willoughby, 2015) because it allows researchers to examine whether the inter-individual differences in change in one variable can predict the inter-individual differences in change in another variable by removing the effect of the outcome variable at previous levels (Taris, 2000). Another advantage of modeling scale stability is that the results can provide information regarding the malleability of different constructs. This type of information, again, is helpful for decision-making regarding the priority of educational interventions.

Boekaerts et al., 2006), that is, use of metacognitive strategies can be activated by external factors such as challenge from task performances. More importantly, the significant lagged effects of achievement on subsequent metacognitive strategies, combined with the significant effect of metacognitive strategies on subsequent intrinsic future goals and with the significant effect of intrinsic future goals on subsequent achievement, offer relevant evidence that the feedback loop flows in a direction opposite to the direction long-held by goal and SRL researchers. Our results support the findings of Paulick et al. (2013) that prior GPA predicted subsequent goal endorsement and those of Poorthuis et al. (2015) that lower grades predicted decreased school engagement. Our finding suggested academic achievement should not only be seen as an outcome, but also as a catalyst of key SRL processes.

8. Limitations and further studies

Our study has a number of limitations. First, although future goals were measured using a scale previously validated and re-assessed using a large sample size of secondary students in an Asian culture, the results may not be generalizable to other age groups or other cultures. While the future goal scale we used included five most common goals, it is important for future studies to identify other important future goals and validate them in other cultures with different age groups. Due to the big challenge of sampling such a large sample and the longitudinal nature of the project, we used convenience sampling instead of more controlled methods such as strictly stratified sampling. Possible confounding effects due to sampling bias remain unknown. Another limitation deals with our use of questionnaires to collect attitudinal data, in such a way students' responses might be biased due to their intention to provide socially-desired answers. Future studies may include other data collection methods such as interview or self-reflections.

9. Conclusions and implications

In summary, the results of our study provided strong evidence supporting the reciprocal relationships among extrinsic and intrinsic future goals, metacognitive strategies and achievement. These included three major findings: 1) students gradually shifted from pursuit of extrinsic to intrinsic future goals; 2) metacognitive strategies influenced subsequent pursuit of future goals; and 3) academic achievement positively predicted metacognitive strategy use.

Our study has key theoretical implications. First, we portrayed a vivid picture of the interplay between extrinsic and intrinsic future goals during learning. We showed how intrinsic and extrinsic future goals are not just static entities but can dynamically influence each other. Students' goals are dynamic and may change across time, and it is important to create contexts that can move students from a more extrinsic to a more intrinsic goal state. Second, we revealed a dynamic picture of the relationship between future goals and metacognitive strategies in affecting subsequent achievement. Our study showed what were typically construed as antecedents (i.e., goals) can also serve as outcomes (metacognitive strategies predict subsequent future goals).

The implication for developing SRL-oriented classrooms is that, teachers need to both focus on developing students' intrinsic future goals and metacognitive strategies, especially the latter, given their role in facilitating the pursuit of intrinsic future goals. There is a large body of research showing specific steps that teachers can undertake to enhance metacognitive strategy use (Tang, 2015; Tanner, 2012; White & Frederiksen, 2005). For example, teachers can ask students to explicitly report on the goals of a particular task, to create plans on how to tackle assignments, and to evaluate cognitive processes during task completion. Metacognitive instruction can also be applied in a collaborative way. For instance, collaborative tasks could be designed in such a way that students will have to plan their steps together, to monitor 'each other' learning progress and evaluate collectively the quality of individual and collaborative outputs.

The current results albeit focused on the Hong Kong context has important implications to the larger international community. The pursuit of money and fame have become prominent in our present-day world. The ways that students learn and perform in a growingly materialistic and capitalistic world become a very important research area (King & Datu, 2017; Ku, 2015; Ku, Dittmar, & Banerjee, 2014). As such the pursuit of intrinsic and extrinsic future goals are likely to be cultural universals.

In addition, Hong Kong has been ranked in the near top worldwide in math, science and reading according to the Program for International Student Assessment (PISA) which is a worldwide study of the scholastic performance of students in 70 nations (OECD, 2016). Therefore, international communities might be interested in the intricacies of the goals and learning strategies of the high-achieving students in Hong Kong. Lastly, the current study could shed light on the universality of the associations between future goals, metacognitive strategies, and achievement.

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