NON-COGNITIVE FACTORS OF EDUCATIONAL ACHIEVEMENT: MOTIVATION AND ANXIETY

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Declaration

I declare that the work presented in this thesis is my own. All experiments and work detailed in the text of this thesis is novel and has not been previously submitted as part of the requirements of a higher degree.

Signed ____ Date ____________

Abstract

Educational achievement has traditionally been closely associated with general cognitive ability (*g*). Although *g* explains a substantial portion of variance in educational attainment, several non-cognitive factors have been found to relate to achievement beyond *g*. The present thesis focuses on exploring the association between achievement and two such factors: motivation and anxiety. The five empirical chapters included in the present thesis address several questions regarding the relation between motivation, anxiety and achievement, which to date remained unexplored. The present thesis includes data from two samples: the Twins Early Development Study (TEDS), a large-scale developmental twin sample from the United Kingdom (UK), and a sample of students attending the first year of secondary school in the UK, who contributed data longitudinally. The results showed that academic anxiety and motivation are domain-specific constructs. This observed domain-specificity of motivation and anxiety was also found to apply to their association with academic achievement. Motivation and anxiety constructs were moderately heritable, and the remaining variance explained by nonshared, individual specific, environmental influences. The cross-sectional and longitudinal links between motivation, anxiety and achievement were largely due to genetic influences common to all measures within a specific academic domain. The present thesis also explored the directionality of effects in the longitudinal associations between educational achievement and motivation; partly supporting the view of reciprocal links between the two constructs in several academic domains. However, a reciprocal relation between motivation and achievement was not observed in the domain of second language in a sample of naïve learners. The results of the present thesis have important implication for future research and practice. For example, it is argued that future interventions aimed at reducing the academic anxiety should consider three main factors: (1) its domain specific; (2) the directionality of effects in its association with achievement; (3) possible factors moderating or mediating the association between anxiety and achievement (i.e. motivation).

Personal contribution to the Study

The majority of the data presented in this thesis were collected as part of the Twins Early Development Study (TEDS), a large-scale developmental twin study funded by the Medical Research Council. I was personally involved in developing the measures and collecting the data when the TEDS twins were 18-20. The present thesis also includes data collected by other researchers at earlier waves, when the twins were 9, 12 and 16.

I personally recruited the sample described in Chapter 6. I have piloted the measures, and co-ordinated the data collection in schools and the data entry.

I have conducted all the data analyses reported in the present thesis on my own, with the exception of the novel ACE cross-lagged model reported in Chapter 5; this model was developed by Ivan Voronin at the Psychological Institute of the Russian Academy of Education, and Ivan conducted this analysis.

A slightly modified version of Chapter 1 of the present thesis has been submitted as a publication to the journal *Translational Psychiatry*, and it is currently under review. Chapter 5 has also been submitted and accepted for publication by the journal *Developmental Psychology*. All co-authors have provided comments and feedback on these drafts.

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I dedicate this thesis to my mum, Mariacristina, and my dad, Marco, for having believed in me, against all odds. My love goes beyond words.

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Author's Publications

- **Malanchini, M**., Wang, Z., Voronin, I., Schenker, V., Plomin, R., Petrill, S.A., & Kovas, Y. (in press). A genetically informative longitudinal study on the relations between reading achievement and motivation. *Developmental Psychology*

- **Malanchini, M.**, Rimfeld, K., Shakeshaft, N.G., Rodic, M., Selzam, S., Schofield, K.L., Dale, P.S., Petrill, S.A., & Kovas, Y. (in press). The genetic and environmental aetiology of spatial, mathematics and general anxiety. *Scientific Reports*

- Shakeshaft, N.G., Rimfield, K., Schofield, K.L., Selzam, S., **Malanchini, M.**, Rodic, M., Kovas, Y., & Plomin, R. (2016). Rotation is visualisation, 3D is 2D: using a novel measure to investigate the genetics of spatial ability. *Scientific Reports*, 6, 30545

- Rimfeld, K., Shakeshaft, N.G., **Malanchini, M.**, Rodic, M., Selzam, S., Schofield, K.L., Dale, P.S., Kovas, Y., & Plomin, R. (in press). Spatial ability or spatial abilities? Investigating the phenotypic and genetic structure of spatial ability. *PNAS*

- **Malanchini, M.**, Tosto, M., Garfield, V., Czerwik, A., Dirik, A., Arden, R., Malykh, S., & Kovas, Y. (2016). Preschool Drawing and School Mathematics: the nature of the relationship. *Child Development*, 87(3), 929-943.

- **Malanchini, M.**, Voronina, I.D., Soldatova, E.L., Maslennikova, E.M, Malykh, S.B., & Kovas, Y. (2015). Private Environment And The Ability To Draw At An Early Age: A Study Of Differences In Monozygotic Twins. *Theoretical and Experimental Psychology*, 8(4), 22-35.

- Savostyanov, A.N, Dolgorukova, T.A, Esipenko, E.A., Zaleshin, M.S. **Malanchini**, M.,…& Kovas, Y. (2015). EEG Correlates of Trait and Mathematical Anxiety during Lexical and Numerical Error-Recognition Tasks**.** *World Academy of Science, Engineering and Technology Linguistics and Language Sciences*, 2 (7), 303.

- Bogdanova, O., Ginku, E., Bogdanova, E., Zueva, D., **Malanchini, M**., & Kovas, Y. (2014). Mathematical Anxiety and mathematical learning: Multidimensional approach. Abstract. *Personality and Individual Differences, 60, Supplement, p. S9*.

- Filer, K., **Malanchini, M**., Voronina, I.D., Akimova, K.K., Zueva, D.E., & Kovas, Y. (2013). Longitudinal relationship between second language motivation and achievement feedback. *Teoreticheskaya i Eksperimentalnaya Psihologiya (Theortetical & Experimental Psychology)*, 6(4), 61-75. In Russian

Papers submitted and or in preparation:

- **Malanchini, M.**, Voronin, I., Wang, Z., & Kovas Y. (under review). Motivation and Achievement in Literacy and Mathematics across Secondary School. *Journal of Personality and Social Psychology*.

- **Malanchini, M.,** Rimfeld, K., Shakeshaft, N., Wang, Z., Schofield, K., Petrill, S., Kovas, Y., & Plomin, R. (submitted). Common genetic influences underlie the aetiology of the domain-specific association between mathematics anxiety, motivation and performance. *Journal of Child Psychology and Psychiatry*

- **Malanchini, M.**, Dale, P.S., Filer, K., Jones, A., & Kovas, Y. (in preparation). The emergent relations among motivation, anxiety and second language learning. *Psychological Science*

The Structure of the present thesis

The present thesis aims to addresses numerous questions related to academic anxiety, motivation, and academic performance which to date remain unexplored. **Chapter 1** presents a literature review of the main theoretical frameworks that have emerged form decades of investigations in the fields of academic anxiety and motivation, and identified some of the unresolved issues in the literature.

Chapter 2 explores the association between general anxiety and two domain-specific anxieties: mathematics anxiety and spatial anxiety in a large sample of young adult twins from the UK. A modified version of this chapter is in press in the journal *Scientific Reports*. For this study, I have developed and piloted the spatial anxiety measures, contributed to the organization of the data collection, analysed all the data and written the manuscript, which has subsequently been made into a paper.

Chapter 3 investigates the origins of the association between mathematics anxiety and several subcomponents of mathematical ability and mathematics motivation in the same twin sample from the UK. The chapter examines how mathematics anxiety relates to different aspects of mathematics performance phenotypically and aetiologically. I have designed the study, conducted all data analyses and written the entire chapter. This chapter has been made into a paper that will be submitted to the *Journal of Child Psychology and Psychiatry*.

Chapter 4 explores the longitudinal association between motivation and achievement in reading and mathematics within and across academic domains. A modified version of this chapter is under review in the *Journal of Personality and Social Psychology*. I have written the entire chapter and conducted data analysis. The data were analysed in collaboration with a colleague, Ivan Voronin.

Chapter 5 applies a newly developed method, the ACE cross-lagged design, to the investigation of the origins of the longitudinal links between reading motivation and reading achievement in a large sample of 9 to12-year-old twins from the UK. A modified version of this chapter is in press in the Journal *Developmental Psychology*. I have designed the study and written the entire manuscript. The data were analysed in collaboration with Dr Zhe Wang and Ivan Voronin.

Chapter 6 investigates the longitudinal association between academic motivation, anxiety and achievement in the domain of L2 learning in a sample of 11 year-old students from the UK. I am currently working at preparing this chapter for publication. For this study I have planned the design and data collection, collected all the data, supervised data entry, analysed the data and written the manuscript.

Chapter 7 of the present PhD thesis presents a general discussion of the findings that have emerged from the five empirical chapters and outlines future directions stemming from the current work.

Chapter 1

Introduction

Education is one of the major investments undertaken by contemporary society. The level of educational attainment is continuously increasing, with 10% more of the population in OECD countries completing tertiary education in 2013, if compared to the year 2000 (OECD, 2013). Educational attainment is often considered a measure of human capital and indicative of the skills of a population. Higher levels of educational attainment are associated with higher employment rates, better job opportunities and higher earnings. Higher levels of achievement are not only associated with professional success, but also with better health and wellbeing (Cutler & Lleras-Muney, 2012). As countries' economies are moving away from mass production, and shifting towards becoming knowledge economies, governments are eager to increase the skills and wellbeing of the population through educational attainment (OECD, 2013).

Due to its association with favourable societal and life outcomes, a large body of research has explored which factors contribute to the observed differences in achievement between students at all ages. Extant literature has identified general cognitive ability as the main factor associated with variation in educational achievement. Several studies have investigated the association between achievement and general cognitive ability, finding moderate to strong correlations (Mackintosh & Mackintosh, 2011). In addition to general cognitive ability, the literature describes numerous other non-cognitive factors associated with variation in achievement, including: motivation (e.g. Spinath, Spinath, Harlaar, & Plomin, 2006; Zuffianò, Alessandri, Gerbino, Kanacri, Di Giunta, Milioni, & Caprara, 2013) emotion regulation (e.g. Owens, Stevenson, Hadwin, & Norgate, 2012), curiosity (e.g. Von Stumm, Hell, & Chamorro-Premuzic, 2011), and personality (e.g. Briley, Domiteaux, & Tucker-Drob, 2014).

This introductory chapter starts by describing the well-established association between educational achievement and general cognitive ability, and its aetiology. Subsequently, the chapter introduces the topic that is central to the present thesis: the association between educational achievement and two non-cognitive characteristics: academic anxiety and motivation. This first chapter focuses on introducing the most influential evidence-based accounts of the association between anxiety and achievement, and motivation and achievement. The chapter concludes with a description of the aims of the current thesis and how these are addressed in the following empirical chapters.

Educational achievement and general cognitive ability

Educational achievement has traditionally been closely associated with general cognitive ability. Indeed, the first test of general cognitive ability (Binet, 1905) was developed with the aim of predicting individual differences in educational outcomes. Predicting educational and occupational outcomes has been to date the main target of cognitive tests (Deary, Strand, Smith & Fernandez, 1997). General cognitive ability (*g*) is a psychometric construct that emerged at the beginning of the past century from observations that almost all cognitive tests correlate substantially and positively (Spearman, 1904). Individuals performing highly in one cognitive test are also likely to show good performance in other tests of cognitive abilities, and *g* indexes this covariance observed between cognitive measures. As such, the *g* score is calculated taking the first unrotated component emerging from the principal component analysis (PCA) of several cognitive tests. If the tests included in the analysis are sufficiently diverse and reliable, studies found that the *g* factor explains around 40% of the total variance in a battery of cognitive tests (e.g. Jensen, 1998).

General cognitive ability is thought to represent individual differences in the domain-general abilities to plan, learn, think abstractly, and solve problems that are necessary for successfully completing cognitive tests (Deary, 2013). The *g* factor is universally observed and is highly stable across development, with one investigation observing a strong correlation (r = .63) between *g* scores taken at age 11 and measured again 68 years later, when participants were 79 years-old (Deary, Whalley, Lemmon, Crawford, & Starr, 2000). The *g* score is a good predictor of several important life outcomes including mental and physical health (e.g. Deary, Weiss, & Batty, 2010), occupation and educational attainment (e.g. Stenze, 2007).

The fact that cognitive assessments reliably predict educational outcomes is a fascinating phenomenon that has been extensively studied in the literature. Taken at any point across development, *g* shares a moderate to strong correlation with educational achievement, ranging from .40 to .70 (e.g. Bartels, Rietveld, Van Vaal, & Boomsma, 2002; Stemberg, Grigorenko, & Bundy, 2001). Substantial associations between cognitive abilities and educational achievement are also observed longitudinally. One of the largest prospective studies exploring the association between cognitive ability an educational achievement included over 70,000 children from England (Deary et al., 2007). The investigation found that *g* at age 11 was strongly correlated (r = .81) with educational achievement at age 16, calculated using the first principal component from national examinations grades in 25 different subjects. Moreover, *g* at 11 predicted individual differences in every school subject, explaining from a very large portion of variance in mathematics (59%) and English (48%) exam scores to 18% of individual differences in Art and Design exam grades (Deary et al., 2007).

Even more strikingly, tests of cognitive abilities taken very early in life are reliable predictors of educational achievement and abilities later in development. Several longitudinal investigations have found significant associations between early cognitive ability and later academic achievement. For example, a study found that two sub-tests of the Wechsler Preschool and Primary Scale of Intelligence (Wechsler, 1990) taken at the age of 5, the block design test and the object assembly test, predicted achievement in mathematics six years later. The investigation showed that non-verbal intelligence assessed at the end of kindergarten predicted 17% of the variance in numeracy skills at the end of primary school (Alloway, & Alloway, 2010).

Two recent studies explored the predictive validity of another cognitive test taken in early childhood, the human-figure drawing test (McCarty, 1972).

The human-figure drawing test is widely used as part of the cognitive assessment of children as young as 3-4 years old. Human figure drawing ability measured at age 4 was found to be modestly associated with general cognitive ability ten years later (r = .20), when the children were 14 (Arden, Trzaskowski, Garfield, & Plomin, 2014). Another study found that, in the same large sample of over 13,000 twins, early drawing predicted mathematical ability and teacher-rated mathematical achievement when the children were 12. The drawing test taken at age 4 explained between 5% and 12% of the variance in mathematical outcomes at age 12 (Malanchini, Tosto, Garfield, Dirik, Czerwik, Arden, Malikh, & Kovas, 2016).

Genetically informative investigations of general cognitive ability

Studies using genetically informative methodologies have explored the origins of individual differences in general cognitive ability and of its well-established association with educational achievement. Indeed, one of the main focuses of behavioural genetics research has been the investigation of why individuals differ in their cognitive capacity (Plomin & Deary, 2015). Genetic differences between individuals have been found to play an important role in explaining variation in general cognitive ability. The heritability of *g*, the extent to which genetic differences between individuals explain differences in their observed performance, was found to increase substantially from early childhood to adulthood. Genetic factors were found to explain around 20% of individual differences in *g* in infancy, around 40% in adolescence, and about 60% of the variation in *g* in adulthood (e.g. Davis, Haworth, & Plomin, 2009; Haworth, Wright, Luciano, Martin, de Geus, van Beijsterveldt et al., 2010). Although the heritability of *g* increases over development, strong genetic stability has been observed in *g* from age to age, indicating that largely the same genes are involved in individual differences in *g* across development. In fact, strong genetic correlations (r_A) have been reported between *g* at age 7 and age 12 (r_A = .75), as well as between *g* at age 11 and at age 69 (r_A = .62; Deary, Yang, Davies, Harris, Tenesa, Liewald, 2012).

Genetically informative investigations of educational achievement

Educational achievement is also highly heritable. Studies found that genetic differences between individuals explain a substantial portion of their differences in achievement at any stage in development (e.g. Kovas, Haworth, Dale & Plomin, 2007; Shakeshaft, Trzaskowski, McMillan, Rimfeld, Krapohl, Haworth, Dale & Plomin, 2013; Bartels et al., 2002). It may be plausible to assume that the high heritability of academic achievement is mostly due to its association with *g*; however, academic achievement in literacy and numeracy in the early years of education was found to be significantly more heritable than *g* (Kovas, Voronin, Kaydalov, Malykh, Dale, & Plomin, 2013). Individual differences in literacy and numeracy at age 7 were found to be 68% and 66% attributable to genetic factors, respectively. Similarly, literacy and numeracy at age 9 were 77% and 73% heritable, respectively. These estimates were significantly higher than the estimates observed for *g* at age 7 and 9. As the heritability of *g* increases over development (Plomin & Deary, 2015), by age 12 the heritability of numeracy and literacy was found to be similar to that of *g,* estimated at 65% for literacy, 56% for numeracy and 49% for *g* (Kovas et al., 2013).

Educational achievement was also found to be highly heritable at the end of compulsory education in the UK, when children are 16 years old. The General Certificate of Secondary Education (GCSE) exam scores were found to be substantially heritable, with genetic factors accounting for 58% of individual differences in GCSE compulsory subjects. Genetic differences explained 52% of the variance in English, 55% of the variance in mathematics and 58% of the variance in science GCSE grades. Individual differences in GCSE scores for every school subject were also substantially heritable (Shakeshaft, et al., 2013). Educational attainment was found to be heritable also beyond compulsory education, with genetic factors explaining a major portion of A level results in several subjects (Rimfeld, Ayorech, Dale, Kovas, & Plomin, 2016). After compulsory education, students in the UK can choose to continue studying for two years in preparation for university studies, freely choosing the subjects they want to focus on. Genetic factors explained 35-76% of individual differences A level achievement. The choice of continuing onto A levels was also found to be substantially heritable (44%). Furthermore, 52-80% of variability in specific subject choice was explained by genetic factors (Rimfeld et al., 2016).

The aetiology of the association between educational achievement and general cognitive ability

Genetic factors were also found to explain a substantial portion of the association observed between *g* and educational attainment (Calvin, Deary, Webbink, Smith, Fernandes, Hong Lee, et al., 2012; Johnson, Deary, & Iacono, 2009; Krapohl, Rimfeld, Shakeshaft, Trzaskowski, McMillan, Pingault, et al., 2014). The study previously described, exploring the association between early drawing performance and *g* and later mathematical achievement, found that their association was largely genetic in origins. Genetic factors explained around 80% of the association between preschool drawing ability and later mathematics outcomes and between early *g* and later mathematics (Malanchini et al., 2016).

Another study found that the strong correlation between GCSE scores and *g* at the same age (r = .58) was 75% explained by shared genetic variance (Krapohl, et al., 2014). This indicates that a substantial part of the same genes are implicated in the variation of both general cognitive ability and educational attainment. Although *g* was found to be the best predictor of GCSE scores, several other factors were also found to contribute to variation in GCSE scores beyond *g*. Self-efficacy, personality, well-being, parent-rated behavioural problems, child-rated behavioural problems, health, perceived school environment, and perceived home environment, were all found to be associated with GCSE scores beyond *g*. (Krapohl et al., 2014). Furthermore, *g* was found to explain only part of the heritability of GCSE exam grades (50%). Similarly, the other non-cognitive and environmental predictors considered in the study explained all together around 50% of the GCSE heritability. When combined, *g* and the other non-cognitive predictors explained 75% of the heritability of GCSE (Krapohl et al., 2014). These findings show that several other factors, beyond general cognitive ability, are associated with academic achievement and paly a role in promoting educational success.

The association between non-cognitive factors and achievement beyond general intelligence

Academic anxiety

The role of numerous non-cognitive and emotion regulation constructs has been explored in association with academic achievement at several developmental stages. One of the main non-cognitive constructs that have been implicated in contributing to variation in educational attainment is academic anxiety. The association between academic anxiety and educational attainment has been mostly investigated in the domain of mathematics. Although research in other academic domains has been recently emerging (see **Chapter 2** for an overview of the existing research in the domain of spatial anxiety and **Chapter 6** for an overview of the research into second language anxiety), mathematics anxiety has been the most widely investigated emotion regulation construct in relation to educational achievement.

Mathematics anxiety describes the negative feelings that are elicited by performing a mathematics task, or even by the prospect undertaking a mathematics-related activity (Maloney and Beilock, 2012). Mathematics anxiety has been associated with lower levels of mathematics achievement, avoidance of mathematics, and a decline in the selection of careers in the Science, Technology, Engineering, and Mathematics –STEM fields (Ashcraft & Moore, 2009; Suárez-Pellicioni, Núñez-Peña & Colomé, 2016). Participants with high levels of mathematics anxiety struggle significantly more in performing mathematics tasks ranging from basic numerical operations (Maloney, Risko, Ansari & Fugelsang, 2010) to tasks that involve mathematical reasoning - considered extremely important for succeeding in the STEM fields (Wu, Barth, Amin, Malcame & Menon, 2012). Importantly, the negative association between mathematics anxiety and performance in mathematics was found to be partly independent from general cognitive ability (Ashcraft & Moore, 2009).

The most recent results of the Program for International Student Assessment (PISA; Organisation for Economic Co-operation and Development –OECD, 2013) found that the prevalence of mathematics anxiety is more widespread than previously reported (Ashcraft & Redley, 2005; Betz, 1978). In a student population of 15-year-olds from OECD countries, 61% reported feeling concerned at the prospect of getting low grades in mathematics, and around 30% reported feeling anxious or incapable when solving a mathematics problem or doing mathematics homework (Suárez-Pellicioni, Núñez-Peña & Colomé, 2016). The fact that mathematics anxiety constitutes such a prominent problem has sparked a great deal of interest in the educational research community.

The main theories of mathematics anxiety and of its association with mathematics achievement

From a large body of research on mathematics anxiety and its association with performance and career choice (see **Chapter 3** of the present thesis for a review of the research in this field), several theoretical accounts have emerged. The leading cognitive theories explaining the mechanisms influencing the relationship between mathematics anxiety and performance have identified working memory as the main moderating process involved in their association (Ashcraft & Kirk, 2001; Young et al., 2012, Beilock & Carr, 2005). Working memory is defined as the cognitive system that manipulates, integrates and temporarily stores information that are obtained through individuals' attention focusing (Miyake & Shah, 1999). Working memory is involved in performance in most mathematics-related tasks, such as, for example, simple subtractions (Sayler, Kirk & Ashcraft, 2003), mental calculations (Raghubar, Barnes, & Hecht, 2010), and mathematics understanding and fluency (Le Fevre et al., 2013).

As working memory was found to be crucial for mathematics performance, disruptions in working memory functioning, in part caused by the intrusive thoughts related to anxiety which consume working memory resources, are likely to impair mathematics performance (Moore, McAuley, Allred, & Ahcraft, 2014). This is in line with the *Processing Efficiency Theory* developed to account for the association between general anxiety and lower cognitive performance (Eysenck, Derakshan, Santos, & Calvo, 2007). This theory is has been supported by several studies linking heightened cortisol levels to lower working memory functioning and problem solving ability in humans (Mattarella-Micke, Mateo, Kozak, Foster & Beilock, 2011) and animals (Roozendaal, McReynolds, & McGaugh, 2004). Particularly, mathematics anxiety was found to be associated with a disruption in the visual working memory subsystem (Miller and Bichsel, 2004).

One of the first theories linking mathematics anxiety to reduced working memory functioning proposes that mathematics performance would be most disrupted in individuals with a lower working memory capacity (Ashcraft, 2001; 2007). This account emerged from a series of studies that investigated the effects of working memory load on mathematics performance. The experiments found that an increase in task difficulty had detrimental effects on performance, but only for mathematically anxious individuals (Ashcraft & Kirk, 2001). The theory explains the findings by suggesting that, for those mathematically anxious, a consistent chunk of working memory capacity is invested in ruminating about the anxiety towards mathematics. Consequently, the availability of fewer working memory resources is likely to impact on their mathematical performance (Ashcraft & Krause, 2007). The disruptive effects of anxiety on working memory and their consequent impact on performance are thought to be most apparent when individuals are dealing with relatively difficult tasks, requiring more working memory resources (Ashcraft & Krause, 2007). Moreover, for those equipped with high working memory capacity, performance would be relatively spared, if compared to that of individuals with lower working memory capacity. The theory proposes that a greater working memory capacity may protect anxious individuals from the negative effects of mathematics anxiety on performance (Ashcraft, & Kirk 2001; Ashcraft & Krause, 2007).

Stemming from this early theory, the *Affective Drop* account (Ashcraft & Moore, 2009; Moore & Ashcraft, 2013) proposes that mathematics anxiety brings about additional cognitive load to that already produced by the task in hand. In fact, those experiencing high levels of mathematics anxiety are required to allocate their available cognitive resources to the demands of the task, while at the same time processing irrelevant distractors and experiencing negative affect, which are both triggered by their anxiety. Therefore, the account suggests that the decline in mathematics performance that is associated with mathematics anxiety depends partly on the strains that anxiety puts on cognitive resources, but also on the negative affect associated with experiencing the anxiety. At a higher risk of experiencing this negative affect, or "*affective drop*" as termed by the authors, are those with lower mathematical ability and/or working memory capacity, as they would be more likely to receive negative feedback on their performance from teachers and parents. The negative feedback received from teachers and parents is likely to contribute to experiencing lower levels of motivation and interest in mathematics (negative affect), which are likely to lead to avoidance of the subject and further deficits in mathematics performance. The theory proposes that the *affective drop* imposed by mathematics anxiety becomes most apparent when individuals are performing difficult mathematics tasks, requiring a greater deal of cognitive resources, and also when performing tasks under a time constraint (Ashcraft & Moore, 2009).

This is in line with evidence showing that intrinsic motivation mediated the association between mathematics anxiety and performance in two large samples of students from the United States at different ages (Wang, Lukowski, Hart, Lyons, Thompson, Kovas, et al., 2015). As described by Maloney et al. (2014) students who, when facing a challenging mathematics task, adopt an avoidant motivational style, in order to avoid experiencing anxiety, might be more likely to perceive the tasks as a threat rather than a challenge. On the other hand, students who adopt an approach motivational style would tend to see a difficult mathematics task as a challenge and less as a threat. This will encourage them to face the challenge rather than avoiding it because of the experience of threat associated with it (Maloney, Sattizahn, & Beilock, 2014). This creates a feedback loop for which those experiencing higher levels of mathematics anxiety would perform poorly in mathematics, and consequently they would tend to avoid mathematics-related situation and classes, and develop negative affect towards mathematics. This model, named the *Feedback Loop* model proposes that the combination of avoidance and negative affect will create in turn higher levels of mathematics anxiety, increasing avoidance of mathematics even further. Avoidance of mathematics will correspond to diminished practice of the discipline (e.g. less classes and homework) and in turn lead to lower achievement. Lower achievement will in turn increase the anxiety towards mathematics, starting a circular chain reaction (Wu, Barth, Amin, Malcarne, & Menon, 2012).

An alternative account to the *Affective Drop* theory proposes that mathematics anxiety would disrupt performance more for those with higher working memory capacity. This is because students and adults with a higher working memory capacity would tend to rely more on it when solving a complex task (Beilock and Carr, 2005). As working memory resources are limited, those who rely more on working memory when solving a task would suffer the most when these resources are allocated towards attending to the anxiety and not to the task. This theory, known as the *Chocking Under Pressure* account (Beilock & Carr, 2005) is supported by evidence collected in samples of adults (Beilock & Carr, 2005; Beilock & De Caro, 2007) and children (Ramirez et al., 2013: Vukovic et al., 2013). In fact, several studies found that mathematics anxiety was negatively associated with performance only in subgroups of adults and children showing good working memory capacity. Additionally, longitudinal research also supported this account, finding the that the mediating effects of working memory were stable over development in a sample of children followed from 7 to 9 years-old (Vokovic, Kieffer, Bailey & Harari, 2013). Therefore, evidence is inconclusive in elucidating the mechanisms through which mathematics anxiety, working memory and performance interrelate.

The directionality of effects in the association between mathematics anxiety and achievement

A further topic under debate in the mathematics anxiety literature concerns the directionality of the association between mathematics anxiety and performance. Namely, does the negative association between mathematics anxiety and achievement starts as a product of high anxiety or low achievement? Two opposing theoretical models have been developed to account for the developmental origins of the relation between mathematics anxiety and achievement. The first is the *Deficit Theory,* which proposes that their association starts from performance. Following this account, poor performance in tests of mathematical ability, or in the mathematics classroom, is thought to lead to the development of anxiety towards mathematics (e.g. Hembree, 1990). The Deficit Theory is supported by a number of investigations, including a longitudinal study using structural equation modelling that found that previous achievement significantly predicted the development of later mathematics anxiety, but not vice versa (Ma & Xu, 2004, the study is discussed in greater details in **Chapter 3** –Introduction section). However, it is argued that anxiety and performance operate following different time frames, and that the effects of anxiety on performance may be better observed in the short rather than long term. These short-term effects of anxiety are difficult to capture in longitudinal studies that include collection waves that are substantially far apart (Carey, Hill, Devine & Szucs, 2015). Studies finding particularly high levels of mathematics anxiety in samples with dyscalculia also seem to support this model (Rubinsten & Tannock, 2010). Nevertheless, samples of participants with learning difficulties may be characterized by cognitive and emotion regulation profiles that are qualitatively different from the general population.

On the contrary, the second model of causal direction, the *Debilitating Anxiety Model*, proposes that mathematics anxiety reduces performance by impacting on the pre-processing, processing and retrieval of mathematics information. Studies have found that mathematics anxiety had a greater effect on performance when tasks required a higher working memory load (Ashcraft & Krause, 2007). Additionally, it has been proposed that mathematics anxiety has an impact on the selection of simpler and less effective cognitive strategies when solving a mathematics task. This is also in line with studies that have used manipulations such as stereotype threat, and have found a negative effect of the experimental manipulation on performance (Beilock & Decaro, 2007). Functional magnetic resonance imaging (fMRI) data also suggests that anxiety has an impact on performance, and not the other way around. One fMRI study showed that participants with high levels of mathematics anxiety, who were able to supress the negative cognitive interference of anxiety (indexed by increased fronto-parietal activity in the brain), performed better than those with high anxiety but low fronto-parietal activity (Lyons & Beilock, 2012). By being able to control the negative cognitive consequences of mathematics anxiety, their performance was less disrupted, suggesting that anxiety has an impact on performance, rather than the opposite. However, longitudinal investigations have not supported the Debilitating Anxiety model, and replications and additional studies are needed.

Evidence is therefore inconclusive with respect to the directionality of the association between mathematics anxiety and achievement, as some investigation have supported the Deficit Theory and some others the Debilitating Anxiety model. However, a third approach has been proposed, the *Reciprocal Theory*, advocating that the relation between mathematics anxiety and performance is mutual (Ashcraft & Krause, 2007). To date, very few longitudinal investigations have explored the association between mathematics anxiety and performance, and no longitudinal investigations have supported the *Reciprocal Theory*. However, lack of decisive evidence supporting either the Deficit Theory or the Debilitating Anxiety account could be interpreted as a sign of a reciprocal association. Furthermore, the only study to date that explored the aetiology of the association between mathematics anxiety and performance found that they shared a genetic link. In fact, part of the same genes implicated in variation in mathematics anxiety was also found to influence individual differences in mathematics problem solving performance (Wang, Hart, Kovas, Lukowski, Soden, Tompson, et al., 2014). Longitudinal, genetically sensitive investigations are likely to shed some light on how the relation between mathematics anxiety and performance emerges and what are the causes behind it. **Chapter 5** of the current PhD thesis presents an example of such methodologies, but applied to exploring the aetiology of the longitudinal association between reading motivation and reading achievement.

Unexplored research questions on the association between mathematics anxiety and achievement: the current thesis

Although several theories and a large body of scientific investigations have explored the association between mathematics anxiety and mathematics performance (reviewed in **Chapter 3** of the present thesis –Introduction section), numerous questions remain unanswered. The present thesis sets out to address two main questions that remain unexplored in the mathematics anxiety literature. Firstly, it remains unclear whether mathematics anxiety is a construct that is separate from general anxiety and other context-specific anxiety constructs, such as for example spatial anxiety. **Chapter 2** of the present thesis explores this topic in a genetically informative sample of twins from the United Kingdom. The chapter investigates how mathematics anxiety relates to general anxiety and spatial anxiety and the origins of their association; ultimately addressing the question of whether mathematics anxiety is a domain-specific construct, different from general anxiety and other academic anxieties. Only one study to date has explored the origins of the association between mathematics anxiety and general anxiety, finding that the two constructs were party independent in their aetiology (Wang et al., 2014). Nevertheless, the study included a number of limitations, among which a small sample size, and did not include other measures of context-specific anxiety. These limitations do not apply to **Chapter 2** of the present thesis, which applies a multivariate genetically informative approach to the investigation of this research question.

Secondly, it remains unclear how mathematics anxiety relates to different aspects of numerical and mathematical processing. In fact, some skills relevant to mathematics performance may be relatively spared from the effects of mathematics anxiety. Furthermore, the reasons behind the association between mathematics anxiety and the different components of mathematics remain unexplored. For example, recent evidence has suggested that number sense is only weakly associated with mathematics anxiety, and only for specific groups of students (Hart et al., 2016). Another question that remains unexplored regards the nature of the well-established negative association between mathematics anxiety and motivation (see **Chapter 3** for a review of the existing literature on this topic). **Chapter 3** of the present PhD thesis aims to address these outstanding questions by exploring the aetiology of the association between mathematics anxiety, mathematics motivation, and several aspects of mathematics performance. Measures of performance include school achievement, understanding numerical content, mathematics problem solving ability and number sense. By investigating the association between these mathematics related constructs within a genetically informative design, the study presented in **Chapter 3** of the present thesis addresses the questions of what are the factors that influence the co-occurrence of mathematics anxiety, performance and motivation.

The studies presented in **Chapter 2 and Chapter 3** of the present thesis provide new evidence on the mechanisms at the heart of why individuals differ in experiencing mathematics anxiety and bring us a step closer to the identification of the mechanisms through which anxiety relates to performance and motivation

Academic motivation

In addition to mathematical anxiety, another non-cognitive factor that has been associated with educational achievement beyond general cognitive ability is academic motivation (Chamorro-Premuzic, Harlaar, Greven, & Plomin, 2010). Academic motivation refers to beliefs, attitudes, and values individuals hold towards academic activities (Ryan & Deci, 2000; Wigfield, 1997). Extant literature describes academic motivation as a multifactorial construct, including several subcomponents, which are all positively correlated, and share modest to moderate associations with educational achievement (e.g. Luo, Kovas, Haworth, & Plomin, 2011; Wigfield, Eccles, Fredricks, Simpkins, Roeser, & Schefele, 2015). The academic motivation umbrella includes constructs such as: *self-efficacy, self-concept, interest and enjoyment, self-control, achievement/goals orientation, and expectancies and* values (Tucker-Drob et al., in press). The present thesis focuses on two main subcomponents of academic motivation: academic self-efficacy, also described in the literature as self-perceived ability, and academic interest, which is also described as enjoyment.

Academic self-efficacy, defines individuals' perceptions of their cognitive and academic competence (Wigfield, 1997). Numerous investigations have explored the association between self-efficacy and academic performance. Moderate positive associations between self-efficacy and achievement are consistently observed in several academic domains (e.g. Guay, Marsh, & Boivin, 2003; Morgan & Fuchs, 2007; Greven, Harlaar, Kovas, Chamorro-Premuzic & Plomin, 2009; Chamorro-Premuzic et al., 2010). Academic self-efficacy is not only associated with performance, but also with students' academic effort, with how much students enjoy academic activities, and with their effort and perseverance when they are presented with more challenging tasks (e.g. Wigfield et al., 2015; Baker & Wigfield, 1999).

Academic interest, or enjoyment, describes the pleasure gained from academic activities (Wigfield, 1997). There are several reasons why students may enjoy academic activities, including curiosity and eagerness for intellectual development and positive feedback on their cognitive and academic skills. Academic interest has been associated with a greater involvement in academic activities, and better academic performance (e.g. Tucker-Drob, & Briley, 2012; Schiefele et al., 1992; De Naeghel, Van Keer, Vansteenkiste, & Rosseel, 2012).

Several theories have been developed to account for the observed association between academic motivation, including self-efficacy and enjoyment, and academic achievement. Two of the most influential frameworks that have been proposed in this field are the Expectancy-Value Theory (Wiggfield & Eccles, 2000) and the Self-Determination Theory (Ryan & Deci, 2000; 2002)

Theories accounting for the association between academic motivation and achievement: Self Determination Theory and Expectancy Value Theory

The *Expectancy-Value Theory* of achievement motivation proposes that individuals' choice, persistence and performance depend on two main processes: (1) Expectancy –how well they believe they will do in the task; and (2) Value –the value that the task has for them. The theory suggests that the processes through which motivation acts are not only affective, but also cognitive, as awareness and self-evaluation are central to the model (Wigfield et a., 2015). These two main motivational processes, expectations and values, are proposed to be associated with students' choice of academic interests, their persistence in engaging in studying, and ultimately with their academic performance.

The model proposes that students' choice, persistence, and performance in an academic subject would partly depend on the expectancies and the values students give to the subject (Eccles, 2005; 2009). Socio-cognitive processes are seen as the main influence on development of the expectancies and values that students hold for a certain academic subject. The socio-cognitive processes described by the model as important are: beliefs specific to the academic subject, perception of difficulty of the subject, perception of one's own competence in the academic domain and individual's goals. The importance of competence-related beliefs is supported by cross-cultural research that found they predicted not only subsequent performance in different academic domains, but also subject choice, and students' levels of engagement and persistence (e.g. Bong, 2001; Denissen, Zarrett, & Eccles, 2007; Simpkins, Davis-Kean, & Eccles, 2006).

These socio-cognitive factors are themselves thought to be partly dependent on individuals' perception of what other people's expectations are for them. For example, what parents and teachers expect from them in that particular academic field. Additionally, individuals' interpretations of their previous achievement are also seen to have an impact on the development of confidence and beliefs for that specific academic domain. This is supported by evidence showing that parents play a role in promoting involvement in academic activities, particularly in the early years of primary school. Parental expectations and involvement were also found to be associated with motivation to progress in the academic domain, and to choose more extra-curricular course-work in the field (Simpkins, Fredricks, Davis-Kean, & Eccles, 2006).

The model finally proposes that perceptions of other people's expectations and of one's own achievement will depend on socio-cultural factors (Eccles, 2005; Wigfield et al., 2015). The importance of socio-cultural factors to the development of motivated behaviour has been supported by recent investigations, particularly by several studies that have linked socio-economic status (SES) to academic motivation and performance (e.g. Mahoney, Vandell, Simpkins, & Zarrett, 2009). Additionally, several factors, such as culture, school and classroom environment have been found to play a role in the development of motivated behaviour (Wigfield et al., 2015).

Therefore, the Expectancy-Value Theory emphasizes the role of beliefs, confidence and autonomy as essentials factors in promoting motivated behaviour. These factors are proposed to play a role in the choice, persistence and engagement in specific academic subjects, consequently leading to academic performance. Within this framework, beliefs, confidence and autonomy are not independent from socio-cultural factors, such as for example classroom, school and home environment, which therefore are thought to play a major role in the development of motivated behaviour.

An alternative account of the association between motivation and achievement is *Self-Determination Theory* (Ryan & Deci, 2002). This theory of academic motivation shares some core features with the Expectancy-Value Theory. In fact, the idea that beliefs, confidence, and autonomy are fundamental for the development of motivated behaviour is also central to Self-Determination Theory. However, Self-Determination Theory focuses on the role that different “types” of motivation play in performance and life outcomes. The main distinction proposed by the model is between two “types” of motivation: autonomous motivation, also described as intrinsic motivation, and controlled motivation, also defined as extrinsic motivation. Intrinsic motivation is based on interest for new experiences, challenges and learning. Extrinsic motivation refers to a behaviour that is guided by the desire for an outcome, usually a reward or approval (Ryan & Deci, 2002). This differentiation between intrinsic and extrinsic goals is central to Self-Determination Theory, which suggests that intrinsic goals are more closely associated with achievement, if compared to extrinsic ones (e.g. Vansteenkiste, Simons, Lens, Sheldon, & Deci, 2004).

Both intrinsic and extrinsic motivations have been investigated in relation to academic achievement (Ryan & Deci, 2000; Deci & Ryan, 2008), in domain general or domain specific contexts (Wigfield & Eccles, 2015), with some indication that domain-specifically assessed motivation is more predictive of academic achievement than domain-general motivation (Steinmayr & Spinath, 2009).

Several studies found links between school achievement and extrinsic motivation, in the form of parental involvement and encouragement (e.g. Karbach, Gottschling, Spengler, Hegewald & Spinath, 2012; Hong, Yoo, You, & Wu, 2010). One recent study found that parental involvement accounted for an additional small portion of the variance in school achievement beyond that explained by *g*. The study found that measures of achievement-oriented control and the structure provided by parents were negatively associated with academic achievement beyond the influence of *g* (Karbach et al., 2012). Another study, using longitudinal structural equation modelling (SEM) found that mathematics achievement and parental encouragement (the value that parents attached to learning) mutually influenced each other over time (Hong et al., 2010).

Supporting the prediction of Self-Determination Theory, research found that the links between academic attainment and intrinsic motivation are stronger than those with extrinsic motivation (Ryan & Deci, 2000; Deci & Ryan, 2008). In one study academic achievement and self-concept - one aspect of intrinsic motivation - were measured multiple times over one academic year in three cohorts of primary school children (Guay, Marsh, & Bovin, 2003). The results showed that achievement and academic self-concept were highly stable over time. Self-concept was related to later achievement and achievement was related to later self-concept, with similar modest to moderate effects (Guay et al., 2003).

In sum, existing evidence supports both Expectancy-Value Theory and Self-Determination Theory. This is not surprising as beliefs, goals, autonomy, and confidence are central constructs to both accounts. While the Expectancy Value Theory focuses on motivation as a unitary construct and on the role played by socio-cultural influences, Self-Determination Theory distinguishes between two main different types of motivated behaviour, intrinsic and extrinsic motivation. The different goals that characterize intrinsic and extrinsic motivation result in the prediction that intrinsic motivation would share a stronger association with academic achievement than extrinsic motivation; a prediction supported by several investigations (Deci & Ryan, 2008).

The directionality of effects in the association between academic motivation and achievement

As observed in the field of academic anxiety, extant literature is inconclusive with regards to how the motivation-achievement association emerges and develops. Early theories, such as the Self-Enhancement Model and the Skill Development Model, favoured unidirectional approaches. The *Self-Enhancement Model* (Calsyn & Kenny, 1977) proposes that are individual differences in motivation that influence the development of subsequent achievement. More motivated students would invest more time in studying and practicing their academic skills, and this frequent practice would result in higher achievement (Calsyn & Kenny, 1977). Support for this model comes from educational experimental programs showing that interventions designed to increase motivation lead to significant improvements in children's ability (e.g. Guthrie et al., 1996; Wigfield, Guthrie, Tonks, & Perencevich, 2004). However, most of these studies did not consider the potential opposite link from prior academic achievement to the development of later motivation.

On the other hand, the *Skills Development Model* (Calsyn & Kenny, 1977) argues that motivation emerges from previous academic achievement. Students who achieve highly are likely to be praised and encouraged to engage more in academic activities, and consequently will develop greater interest and self-efficacy in that field. At the same time, students with lower academic abilities are more likely to encounter difficulties and frustration when approaching academic activities, which may in turn lead to decreased academic motivation. Longitudinal studies have supported this theory by finding a developmental link from previous achievement to later motivation, but not the opposite link from early motivation to later achievement (e.g. Aunola, Leskinen, Onatsu-Arvilommi, & Nurmi, 2002; Chapman & Tunmer, 1997; Skaalvik & Valas, 1999). However, studies that found support for the Skills Development Model have mostly involved small samples; consequently, they may have been underpowered to detect reciprocal, possibly weaker, links from motivation to achievement.

Contemporary theories argue for a reciprocal association between achievement and motivation. According to the *Reciprocal Model* (Morgan & Fuchs, 2007), both academic achievement and motivation contribute to the emergence and development of one another. The Reciprocal Model has been supported by longitudinal studies that have explored the association between motivation and achievement in domain-general (e.g. Chamorro-Premuzic et al., 2010; Luo, Haworth, & Plomin, 2010) and domain-specific contexts (e.g. Guay et al., 2003; Marsh & Martin, 2011; Muijs, 1997; Luo, Kovas, Haworth, & Plomin, 2011). These studies have found reciprocal links between motivation and achievement over development. However, results are mixed regarding the effects of these associations, as some studies found reciprocal associations of similar strength (e.g. Luo et al., 2010; Chamorro-Premuzic et al., 2010) whereas others suggest that previous achievement has a stronger effect on predicting later motivation than the other way around (Retelsdorf, Köller, & Möller, 2014). This issue of reciprocity in the association between motivation and achievement will be explored in Chapter 4, 5 and 6 of the current PhD thesis. These three chapters apply cross-lagged design to the investigation of the association between motivation and achievement within and across several academic domains.

One of the most influential theories arguing for a reciprocal relationship between motivation and achievement is the *Reciprocal Internal/External Frame of Reference Model* (Möller, Retelsdorf, Köller, & Marsh, 2011). The model was developed to account for the longitudinal association between academic self-concept (closely related to self-efficacy) and achievement. The Reciprocal Internal/External Frame of Reference (rI/E) Model proposes that self-concepts are based on two main comparisons, or ‘frames of reference’: a social (external) comparison –judging one’s own performance against that of other peers; and a dimensional (internal) comparison – comparing one’s accomplishments in one domain with one's own achievement in another academic subject. This differentiation between frames of references would predict that students who achieve highly in one academic domain would also show high levels of self-concept for the same domain (external frame of reference). On the other hand, the internal frame of reference would lead those students who are high achievers in one academic domain (e.g. mathematics) to develop lower self-concept for another, often contrasting, academic domain (e.g. literacy; Möller et al., 2011). This creates a model in which the links between self-concept and achievement within domains are positive and moderate to strong, and the links between self-concept and achievement across academic domains negative and characterised by smaller effect sizes (Marsh et al., 2015). The rI/E model is described in details in **Chapter 4** of the present thesis.

The role of genotype-environment correlation in the association between academic motivation and achievement: The transactional model

A further theory that has been proposed in order to account for the association between non-cognitive factors and academic achievement is the *Transactional Model*. The Transactional Model of cognitive development is founded on the concept of genotype-environment correlation. Genotype-environment correlation (*rGE*) describes the fact that environments do not just randomly happen to people; instead they are experienced, partly depending on genetic predispositions. In fact, children who are raised by their biological parents share with them both genetic predispositions and environmental exposure. Parents with higher cognitive skills are also more likely to have better jobs and higher earnings. As well as inheriting the predisposition towards higher cognitive skills, their children will also be raised in an enriched environment, which will likely foster their genetically influenced cognitive skills. Following the same logic, children who have a genetic risk for lower cognitive skills are more likely to be raised by parents with less successful jobs, in more disadvantaged environments (Tucker-Drob, in press). This process is known as *passive genotype-environment correlation* (Plomin, DeFries, & Lohelin, 1977).

Two additional types of *r*GE have been identifies: *Active and evocative genotype-environment correlation*. Active *r*GE is observed when children actively seek environmental experiences depending on their genetic prepositions. For example, children who are genetically predisposed towards high cognitive skills are more likely to pursue cognitive stimulating activities, which will improve their cognitive skills even further. Evocative *r*GE describes the idea that children are likely to elicit reactions from other people based on their genetic predisposition. For example, children with a genetic predisposition for high cognitive skills are likely to be praised more for their abilities by the adults surrounding them, and these environmental praises are likely to increase confidence in their abilities further, which in turn will lead to more practice and ultimately improve abilities (Plomin et al., 1977; Plomin, 2014).

The transactional model proposes that genotype-environment correlation promotes differences in environmental experiences, which in turn impact on cognitive development and academic achievement. It has been proposed that this genetically influenced environmental exposure would increase the heritability of cognitive abilities and academic achievement (Briley & Tucker-Drob, 2013). One of the genetically influenced environmental experiences that have been associated with selecting, evoking and experiencing environments related to academic achievement is academic motivation (Tucker-Drob & Harden, 2012b). In line with the transactional model, students are believed to select, evoke and experience learning environments, partly depending on their differences in academic motivation, which are genetically influenced.

Tucker-Drob et al. propose six main criteria that are necessary in order to find empirical support for the transactional model of the association between non-cognitive traits and academic achievement. First, a correlation between the non-cognitive trait and achievement is necessary, although not sufficient. Second, their correlation should be significant beyond their association with general cognitive ability. Third, the model requires non-cognitive factors to be moderately heritable. Fourth, there should be a degree of genetic correlation between the non-cognitive trait and academic achievement. Fifth, the direction of causation, evaluated though longitudinal panel analyses (e.g. cross-lagged analysis presented in **Chapter 4, 5 and 6** of the present thesis), should be significant from the non-cognitive trait to achievement. Sixth, environmental experiences should mediate the association between non-cognitive traits and achievement though a genetic pathway (Tucker-Drob, in press). Evidence largely supporting the transactional model has been found for both academic self-efficacy and interest.

Academic self-efficacy and interest within the Transactional Model framework

Academic self-efficacy and other closely associated constructs, such as self-concept (discussed in **Chapter 4** of the present thesis), have been extensively studied in relation to academic achievement. Extant literature shows positive moderate correlations between self-efficacy and academic achievement in several domains, and these correlations have been observed beyond general intelligence (Chamorro-Premuzic et al., 2010). Academic self-efficacy was found to be moderately heritable, both when measured as a domain-general construct (Greven et al, 2009; Luo et al., 2010) and when specific domains, such as mathematics were considered (Luo et al., 2011). This evidence is in line with what is required by the first three criteria proposed by the Transactional Model. Additionally, a genetic correlation between mathematics self-efficacy and achievement has been observed (Luo et al., 2011), supporting the fourth criteria necessary for the model. Additionally, longitudinal investigations have found significant links from academic self-efficacy to achievement (Luo et al., 2010; Luo et al., 2011), meeting the fifth criteria. To date, no studies have found evidence supporting the sixth criteria proposed by the transactional model, and more research investigating self-efficacy using genetically informative designs is needed in order to confirm the predictions of the Transactional Model.

Only a few studies have explored the association between academic interest and achievement. Evidence is particularly limited when considering longitudinal and genetically sensitive investigations into the association between academic interest/enjoyment and achievement. Nevertheless, some support for the Transactional Model of cognitive development has been found. A large meta-analysis found a moderate positive correlation between interest and academic achievement across several studies (average r = .31; Schiefele et al., 1992). Furthermore, the moderate correlation between academic interest and achievement, observed in another sample of students from the United States, was found to remain significant after accounting for general intelligence (Tucker-Drob, & Briley, 2012a). These studies support the first two criteria necessary for the transactional model. Investigations have also found evidence for the third criterion proposed by the Transactional Model. In fact, measures of academic interest and enjoyment have been found to be moderately heritable cross-culturally from age 9 to age 12 (Kovas et al., 2015). Evidence supporting this third criterion will also be discussed in **Chapter 3** and **Chapter 5** of the present thesis across two different fields: reading and mathematics interest and enjoyment.

Evidence supporting the fifth criterion has also been observed in one cross-lagged investigation that found a reciprocal longitudinal association between academic interest and achievement (Marsh, Trautwein, Lüdtke, Köller & Baumert, 2005). **Chapter 4**, **Chapter 5**, and **Chapter 6** of the present thesis explore this issue further by investigating the longitudinal associations between academic interest/enjoyment and achievement in the domains of: mathematics, literacy, reading and second language. By investigating the aetiology of the correlation between interest and achievement in the domains of reading and mathematics (**Chapter 3** and **5**), the present thesis aims to find evidence for the fourth prediction of the transactional model, which to date remains unsupported.

In summary, in relation to motivation, the present thesis aims to explore several outstanding research questions. The investigations presented in **Chapter 4** and **5** of the present thesis focus on two main motivational constructs: self-efficacy and interest. On the other hand, **Chapter 6** of the current thesis explores the longitudinal association between achievement in the domain of second language (L2) learning and several subcomponents of motivation, including: ideal L2 self, intrinsic motivation, instrumental motivation, self-efficacy, peer pressure, parental encouragement, self-regulation, and international orientation. By applying longitudinal and genetically informative methodologies, **Chapter 4**, **5** and **6** of the present thesis aim to address several unresolved issues in the motivation-achievement literature.

The aims of the present thesis: summary

The present work addresses several unexplored issues related to academic anxiety, academic motivation, and their association with cognitive and academic performance. This first chapter has reviewed some of the main theoretical frameworks that have emerged form decades of investigations in the fields of academic anxiety and motivation, and identified some of the unresolved issues in the literature. The following chapters of the present thesis aim to address outstanding research questions by applying longitudinal and genetically informative methodologies.

Chapter 2 of the current PhD thesis presents the first genetically informative investigation into the association between domain-general anxiety and domain specific anxiety. The chapter explores the association between general anxiety and two domain-specific anxieties: mathematics anxiety and spatial anxiety in a large sample of young adult twins from the UK. This chapter addresses some fundamental outstanding research questions: Is anxiety unifactorial phenotypically and aetiologically? Are mathematics and spatial anxiety partly independent in their aetiology from general anxiety? Are mathematics anxiety and spatial anxiety different constructs phenotypically and aetiologically?

Chapter 3 investigates the origins of the association between mathematics anxiety and several subcomponents of mathematical ability and mathematics motivation in the same twin sample from the UK. This third Chapter addresses for the first time in the mathematics anxiety literature questions related to the origins of its association with different aspects of mathematics motivation. Furthermore, the chapter examines how mathematics anxiety relates to different aspects of mathematics performance phenotypically and aetiologically. This question has never been explored within a multivariate genetically informative design.

Chapter 4 of the current PhD thesis empirically evaluates a theoretical model of academic motivation: the Reciprocal Internal/External Frame of Reference model (Marsh & Martin, 2011) using cross-lagged design. The chapter aims to answer several questions related to the association between motivation and achievement within and across academic domains, and their links over development. This investigation is the first to explore their association over a developmental time of 8 years in a very large population-representative sample.

The study presented in **Chapter 5** of the present thesis applies a newly developed method, the ACE cross-lagged design, to the investigation of the origins of the longitudinal links between reading motivation and reading achievement in a large sample of 9 to12-year-old twins from the UK. This study is the first to explore this issue, and is likely to improve our understanding of the mechanisms though which reading motivation and achievement interact longitudinally.

Chapter 6 of the current thesis investigates the longitudinal association between academic motivation, anxiety and achievement in the domain of L2 learning in a sample of 11 year-old students from the UK. The association between achievement and motivation and anxiety in the field of L2 is a topic that remains largely under investigated in the literature. The study presented in chapter six explores how several subcomponent of L2 motivation and L2 anxiety relate to achievement over time. The study is particularly significant as the participants had just started formally learning a second language, and it is therefore ideal to explore how the trivariate link between motivation, anxiety and achievement emerges.

Chapter 7 of the present PhD thesis presents a general discussion of the findings that have emerged from the five empirical chapters and outlines future directions stemming from the current work.

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Chapter 2

Anxiety: unitary or multifactorial? The genetic and environmental aetiology of spatial, mathematics and general anxiety

Abstract

Individuals differ in their level of general (trait) anxiety as well as in their level of anxiety towards specific activities, such as mathematics and spatial tasks. Both specific anxieties have been found to relate phenotypically to general anxiety, but the aetiology of their association remains unexplored. Moreover, the factor structure of spatial anxiety is unknown, as to date it has only been investigated with respect to navigation and way finding, and not in relation to other spatial tasks such as rotation or visualization. The present study explored the factor structure of spatial anxiety, its aetiology, and the origins of its association with general anxiety and mathematics anxiety. The sample included 1,464 19-21-year-old twin pairs from the UK representative Twins Early Development Study (TEDS). Participants completed self-report measures of general, mathematics and spatial anxiety as part of an online test battery. We found spatial anxiety to be a multifactorial construct, including two main components: navigation anxiety and rotation/visualization anxiety. All anxiety measures were moderately heritable (30% to 41%), with non-shared environmental factors explaining the remaining variance. Multivariate genetic analysis showed that, although there were genetic and environmental factors that contributed to all anxiety measures, a substantial portion of genetic and non-shared environmental influences were specific to each anxiety construct. This suggests that anxiety is a multifactorial construct phenotypically and aetiologically. Our findings highlight the importance of studying context-specific anxiety, particularly when exploring its association with performance.

Introduction

The negative association between anxiety and cognitive and academic performance

The negative relationship between general anxiety and cognitive and academic performance is now well documented (Breslau, Lane, Sampson, & Kessler, 2008). High levels of anxiety have been associated with a wide range of negative educational outcomes, including poor academic achievement, early school leaving and failure to succeed in higher education (Owens, Stevenson, Hadwin, & Norgate, 2012). A large literature review (Hembree, 1988) and a meta-analysis (Seipp, 1991) have observed moderate effects in the negative associations between general anxiety and academic performance (average $r = -.25$), and similar associations were found between general anxiety and IQ scores ($r = -.23$). To date, the origins of the associations between general anxiety and academic performance and cognitive abilities remain unexplored.

Extant literature has also examined their association within specific contexts. One domain that has received extensive interest is mathematics. Mathematics anxiety refers to the negative feelings and emotional reactions elicited by mathematics or even by the prospect of doing a task related to it (Maloney & Beilock, 2012). Mathematics anxiety varies in degrees of severity and is observed independently from levels of mathematical knowledge (Ashcraft, Krause, & Hopko, 2007). Numerous studies have observed a moderate negative correlation between mathematics anxiety and mathematics achievement across ages and educational curricula (average $r = -.30$, Hembree, 1990; Ashcraft & Krause, 2007; Devine, Fawcett, Szűcs, & Dowker, 2012; Ma, 1999), with the exception of basic numerosity skills, which were found not to share an association with mathematics anxiety (Hart, Logan, Thompson, Kovas, McLoughlin, & Petrill, 2016).

In addition to a direct relationship with mathematics attainment, mathematics anxiety is associated with lower rates of involvement in activities that require mathematics (Hembree, 1990), from taking any optional STEM

(Science, Technology, Engineering and Mathematics) subject in school or university, to not choosing professional careers in the STEM fields (Ashcraft et al., 2007a). This in turn is negatively associated with the opportunity to develop mathematical skills further (Ashcraft, 2002).

Similar cognitive mechanisms were found to characterise the association between anxiety and performance in domain-general contexts and in the domain of mathematics. One of the leading cognitive theories of anxiety, the attentional control theory (Eysenck & Derakshan, 2011) proposes that a disruption in working memory capacity is central to the negative link observed between general anxiety and performance. The framework suggests that high levels of anxiety interfere with working memory processes, leading to reduced performance efficiency and effectiveness. Several studies have supported the account (Eysenck & Derakshan, 2011; Visu-Petra, Cheie, Benga, & Alloway, 2011). Similarly, research has identified a disruption in working memory as characteristic of the association between anxiety and attainment in the domain of mathematics (Ashcraft & Kirk, 2001; Beilock & Carr, 2005; Young, Wu, & Menon, 2012).

The association between general anxiety and mathematics anxiety

As well as being characterised by similar underlying cognitive mechanisms in their association with performance, the two anxieties are associated with similar physiological indicators – including rapid pulse, nervous stomach, palpitations, dizziness, and tension headaches (Adams, 2001; Cemen, 1987). Recent studies, using neuroimaging and electrophysiological methods, have found an overlap in the brain areas associated with general and mathematics anxiety (Young et al., 2012; Suárez-Pellicioni, Núñez-Peña, & Colomé, 2013). One study found that when children with high mathematics anxiety were presented with mathematical stimuli, they experienced increased activation and connectivity in the amygdala, which has also been associated with experiencing general anxiety, fear and negative emotions (Young et al., 2012). Another study using electro-encephalography (EEG) found that the same component (the error-related negativity –ERN; Moser et al., 2013) involved in error-monitoring behaviour in participants suffering from general anxiety (Weinberg, Olvet, & Hajcak, 2010), was also implicated in error monitoring in mathematics anxiety (Suárez-Pellicioni et al., 2013).

Although similarities between general and mathematics anxiety were observed in their physiological manifestations, as well as in cognitive and brain networks, the two anxieties share only a moderate association (average r = .35, Hembree et al., 1990). This suggests that they may be separate constructs, manifesting themselves independently from one another, and characterised by different aetiologies.

Only one study to date has explored the aetiology of general and mathematics anxiety and of their association, in a sample of 12-year-old twins from the United States (Wang, Hart, Kovas, Lukowski, Soden, Thompson et al., 2014). In this study, genetic factors contributed moderately to individual differences in general and mathematics anxiety. Individual-specific environmental factors explained the remaining variance and remaining variance in general and mathematics anxiety was explained by environmental factors specific to each child. Approximately 20% of the same genetic effects and 7% of the same nonshared environmental effects contributed to the origins of both general and mathematics anxiety. However, the majority of the aetiology was specific to each construct (Wang et al., 2014). These findings suggest that, although the origins of general anxiety and mathematics anxiety partially overlap, their causes are also partly independent. However, the small sample size calls for caution when interpreting findings from this investigation.

Spatial anxiety: a largely unexplored construct

Another context-specific anxiety construct that has received considerably less attention in the literature is spatial anxiety: the fear of performing tasks that have a spatial component (Lawton, 1994). Spatial anxiety has been linked to a decreased efficiency of orientation strategies (Lawton, 1994) and increased errors in a navigation task (Hund & Minarik, 2012). Spatial anxiety was found to emerge very early on, with students in the early years of elementary school already showing variation in their degree of spatial anxiety (Ramirez, Gunderson, Levine, & Beilock, 2012). In the same study, a negative association was observed between spatial anxiety and performance in a mental rotation task. Consistent with findings in the domain of mathematics anxiety (Beilock & Carr, 2005), this negative association was found predominantly in children with higher working memory skills. In fact, a similar disruption in working memory processes has been proposed to moderate the negative association between spatial anxiety and performance in spatial tasks (Shea, Lubinski, & Benbow, 2001). Because spatial ability is a predictor of positive academic outcomes such as achievement in mathematics and science (Shea et al., 2001; Casey, Nuttall, & Pezaris, 1999), and success in STEM careers (Wai, Lubinki, & Benbow, 2009), exploring the structure and origins of its affective correlates is of substantial importance.

To date, several aspects of spatial anxiety remain unexplored. Spatial anxiety has mostly been investigated in the context of navigation and orienting. Most of the existing self-report measures designed to assess spatial anxiety (e.g. the Way-Finding Strategy Scale; Lawton, 1994) have focused on exploring anxiety towards navigation or map reading skills. Only one instrument to date has been designed to assess anxiety in relation to other spatial abilities, such as mental rotation, visualization and object manipulation in young children (the Child Spatial Anxiety Questionnaire –CSAQ; Ramirez et al., 2012). However, information on the factor structure of the CSAQ is not available, and only a total score for the questionnaire, combining items assessing several putative aspects of spatial anxiety, is recommended based on the internal validity of the measure (alpha = .56; Ramirez et al., 2012). Therefore, it remains unclear whether spatial anxiety is a unitary construct encompassing anxiety towards all spatial abilities (e.g. navigation, map reading, mental rotation, visualization, scanning etc.), or a multifactorial construct, characterized by several subcomponents. The aetiology of individual differences in spatial anxiety (or anxieties) also remains unexplored.

Up to now, only one study (Ferguson, Maloney, Fugelsang, & Risko, 2015) has explored the association between spatial anxiety and other anxiety constructs including mathematics anxiety and general anxiety, finding only moderate correlations between spatial anxiety and mathematics and general anxiety. However, their differentiation remains poorly understood. Importantly, their association has not been explored within a genetically informative design. It is plausible that the aetiology of spatial anxiety is mostly independent from the other anxiety measures, as it was observed for mathematics and general anxiety (Wang et al., 2014). This would support the view that anxiety is a complex multifactorial construct, comprising domain general and domain-specific aspects that are largely different in origins. On the other hand, as spatial and mathematical abilities correlate substantially phenotypically (Ferguson et al., 2015; Rhode & Thompson, 2007), and have been found to share common neural correlates (Hubbard, Piazza, Pinel, & Dehaene, 2005) and genetic influences (Tosto, Hanscombe, Haworth, Davis, Petrill, Dale, et al., 2014), it is possible that the aetiology of spatial and mathematics anxiety also overlap substantially, above and beyond their relationship with general anxiety.

The aims of the present study

The present study has three main aims: (1) to explore the factor structure of spatial anxiety; (2) to investigate the origins of individual differences in spatial anxiety (or anxieties); and (3) to address whether general anxiety, mathematics anxiety and spatial anxiety are separate constructs phenotypically and aetiologically, using a genetically informative design. Findings from this investigation may inform interventions aimed at alleviating anxiety in both general and specific contexts.

Method

Participants

The sample included 2928 twins (1464 pairs): 586 monozygotic (MZ) and 878 dizygotic (DZ) pairs; 392 pairs were MZ females, 194 pairs were MZ males, 315 pairs were DZ same-sex females, 157 pairs were DZ same-sex males and 406 pairs were DZs of opposite sex. Participants were drawn from the Twins Early Development Study (TEDS), a large-scale multivariate longitudinal twin registry based in the United Kingdom. All families living in England and Wales who had twin-births between 1994 and 1996 were contacted by the office of National Statistics and asked to take part in the study. More than 16,000 families took part at first contact, and more than 10,000 twins are still contributing to the study. TEDS is representative of the population of England and Wales for both socio-economic status and ethnicity (Haworth, Davis, & Plomin, 2013). The current sample was a subsample of 19-21 year old TEDS twins, representative of the larger TEDS sample.

Measures

General Anxiety

The 7-item Generalized Anxiety Disorder Scale (GAD-7; Löwe, Decker, Müller, Brähler, Schellberg, Herzog, & Herzberg, 2008) was used as a measure of general anxiety. The scale asks participants: '*How often in the past month have you been bothered by the following problems?'*. Participants have to rate the 7 items of the GAD-7 on a 4-point scale, from 1 = not at all to 4 = nearly every day. Examples of items are: '*Not being able to control worrying*', '*Have trouble relaxing*', and '*Feeling afraid as if something awful might happen*'. The self-report measure was administered online. The GAD-7 was previously found to be internally valid (α = .89) and reliable (test-retest correlation of.64; Löwe et al., 2008). In our sample the GAD-7 was also found to be internally valid (α = .91).

Mathematics Anxiety

A modified version of the Abbreviated Math Anxiety Scale (AMAS; Hopko, Mahadevan, Bare, & Hunt, 2003) was administered to assess mathematics anxiety. The AMAS asks participants to rate how anxious they would feel when facing several mathematics-related activities. The measure includes 9 items that are rated on a 5-point scale ranging from 'not nervous at all' to 'very nervous'. Examples of items are: '*Reading a maths book*' and '*Listening to a maths lecture*'. We modified some of the existing items slightly in order to make the scale age appropriate for our sample, as all of our participants had left school, and some were no longer in education (please refer to the SOM for additional details on all the items included). The AMAS has been widely used and shows excellent internal validity (α = .90; Hopko et al., 2003).

Our modified version of the AMAS also showed excellent internal validity (α = .94) and showed good test-retest reliability (r = .85).

Spatial Anxiety

In order to assess several aspects of spatial anxiety we developed a 10-item questionnaire. The final 10 items included in the spatial anxiety questionnaire were derived after 2 piloting sessions. The first pilot included 20 items, and the second version included 15 items. Items were deleted from the measures based on three main criteria: (a) showing little variance; (b) low factor loadings; and (c) low test-retest reliability. Those items that showed little variation, low factor loadings and low test-retest reliability were deleted from the scale. Some of the 10 items included in the final measure, are loosely based on the Way-Finding Strategy Scale (Lawton, 1994), whereas other items were created for the purpose of the present investigation. Participants were asked to rate on a scale from 1 to 5 (1 = not at all, and 5 = very much) how anxious they would feel in situations involving spatial skills such as navigation, way-finding, mental rotation and spatial visualization. The items belonging to the spatial anxiety scale were entered into a Principal Component Analysis (PCA) together with the items included in the mathematics anxiety scale and general anxiety scale. This was in order to explore whether spatial anxiety was a separate construct from mathematics and general anxiety, or whether it overlapped with the other anxiety measures. PCA was selected, as it is one of the most widely used data reduction techniques, and therefore appropriate to explore whether different subcomponents existed across all the anxiety-related items. From PCA, taking into consideration both the Scree Plot and Eigen values, four separate factors emerged (see Table 2.1). The first two factors included the items part of the mathematics and general anxiety scales, and were therefore labelled ‘mathematics anxiety’ and ‘general anxiety’, respectively. The other two factors included the items part of the spatial anxiety scale and were clustered as follows: (A) a navigation anxiety factor and (B) a rotation/visualization anxiety factor. The navigation anxiety factor included items such as: ‘Finding your way around an intricate arrangement of streets’, ‘Trying a new shortcut without using a map’, and ‘Following somebody's instructions to get somewhere’. The factor showed very good internal validity (α = .86). The Rotation/Visualization anxiety factor included items such as 'Having to complete a complex jigsaw puzzle', and 'Having to rotate objects in your mind'. This second factor also showed good internal validity (α = .78; see Table 2.1 for more details on the factor structure of spatial anxiety).

Analyses

Phenotypic Analyses

For all phenotypic analyses, one twin out of each pair was included to control for non-independence of observation. Firstly, Principal Component Analysis (PCA) was conducted, using the statistical package SPSS, to explore the factor structure of the newly developed spatial anxiety scale (see Results Table 2.1 and Figure 2.1). Confirmatory factor analysis (CA), using the statistical package MPlus (Muthén & Muthén, 2015) was then conducted, to test whether the factor structure emerging from the exploratory PCA was the solution that best fitted the data. All the details of these analyses are presented in the Results, Table 2.2.

Once the different constructs had been identified and composite scores created, the distribution of the measures and their associations were explored using descriptive statistics and correlation analyses (see Results Table 2.3, and Table 2.4). The possibility that phenotypic sex differences existed for all measures of anxiety was explored conducting univariate analyses of variance (ANOVA; see Results Table 2.5).

Univariate Genetic Analyses

<u>The Univariate ACE/ADE Model</u>

The twin method was applied to investigate the origins of individual differences in general anxiety, mathematics anxiety, navigation anxiety and rotation/visualization anxiety. The twin method capitalises on the fact that monozygotic twins (MZ) share 100% of their genetic makeup and dizygotic twins (DZ) share on average 50% of the genes that differ between individuals, and on the assumption that both types of twins who are raised in the same family share their environments to approximately the same extent (Kendler, Neale, Kessler, & Heath, 1993). Comparing how similar MZ and DZ twins are for a given trait (intraclass correlations), it is possible to estimate the relative contribution of genes and environments to variation in that trait. A stronger intraclass correlation between MZ twins, if compared to that between DZ twins, for a specific trait indicates a degree of genetic influence. Heritability, the amount of variance in a trait that can be attributed to genetic variance, can be calculated as double the difference between the MZ and DZ twin correlations.

The univariate model estimates the proportion of variance that is attributable to additive genetic, non-additive genetic, shared environmental, and non-shared environmental influences by comparing the intraclass correlations for MZ and DZ twins for the trait of interest. Additive genetic factors (A) are the sum of the effects of all alleles at all loci contributing to the variation in a trait or to the co-variation between traits. Non-additive genetic effects (D) describe interactions between alleles at the same locus (dominance) and at different loci (epistasis). Shared environmental factors (C) are environmental factors that contribute to similarities between family members. Nonshared environmental factors (E) are those that do not contribute to similarities between family members. In the model, nonshared environmental variance also includes measurement error. The total phenotypic variance (P) is given by the sum of these variance components (P = A+D+C+E). It is possible to estimate each variance component from twin studies because MZ and DZ twins have different degrees of similarity for A and D, but the same for C (r = 1.00) and E (no correlation). An estimate of E is obtained from the MZ correlation, as the difference between them in a trait can only be due to non-shared environments. For A the correlation between MZ twins is 1.00, as they share 100% of their genes, while for DZ twins is .50, as they share on average 50% of their segregating genes. For D, the correlation between MZ is also 1.00, while the correlation between DZ is .25.

The classic twin design, comparing MZ and DZ twins does not allow to estimate all four sources of influence (A, D, C and E) within one model as they are confounded (Rijsdijk & Sham, 2002). Therefore, with the classic twin design it is possible to partition the variance into three sources of influences: A, E, and either C or D. The decision of including C or D into the model depends on the comparison of the intraclass correlations between MZ pairs and DZ pairs for the same trait. If the intraclass correlation for MZ twins is less than double that of DZ twins, shared environment is likely to have an influence on the trait. Consequently, C would be included in the model – ACE model (Figure 2.1a). On the other hand, if the intraclass correlation for MZ pairs more than doubles that of DZ pairs, non-additive genetic effects are likely to play a role, and therefore D would be included in the model – ADE model (Figure 2.1b).

The proportion of variance that is explained by additive genetic influences (heritability) can be calculated using the following formula, known as Falconer's formula: 2(*r*MZ – *r*DZ), double the difference between the MZ and DZ correlation for a trait. For example, if the correlation between MZ twins for a trait is r = .60 and the correlation between DZ twins for the same measure is r = .40, the heritability (h^2) estimate will be .40. This indicates that 40% of the variance in that trait is explained by genetic differences between individuals. From the h^2 estimate, it possible to derive the estimates for the shared environmental (c^2) and non-shared environmental (e^2) variance components. The formula to calculate c^2 is the following: c^2 = rMZ – h^2, because shared environment contributes to the similarities between MZ twins in addition o their genetic similarity. It is possible to calculate non-shared environmental estimates using the following formula: e^2 = 1– rMZ, as non-shared environment is the only source of difference between MZ twins who grow up together.

As well as using the formulae previously presented, a more comprehensive way of calculating ACE/ADE estimates is to use structural equation modelling (SEM). SEM presents several advantages over simply comparing intraclass correlations to calculate Falconer's formula. Firstly, applying SEM allows for the assessment of the goodness of fit of the model by comparing it to the saturated model (the model based on the observed data). Open Mx, the programme that was used to estimate goodness of fit in all twin analyses presented in this thesis, derives model fit indices using maximum likelihood (see Rijsdijk & Sham, 2002 for additional information on the maximum likelihood estimation). Secondly, SEM allows to compare the ACE/ADE model to more parsimonious models (nested models), which partition the variance into two (AE, CE/DE) or one (E) sources of influence, using goodness of fit indices. Thirdly, SEM allows for the estimation of confidence intervals for all parameters (Neale, Boker, Bergeman, & Meas, 2005).

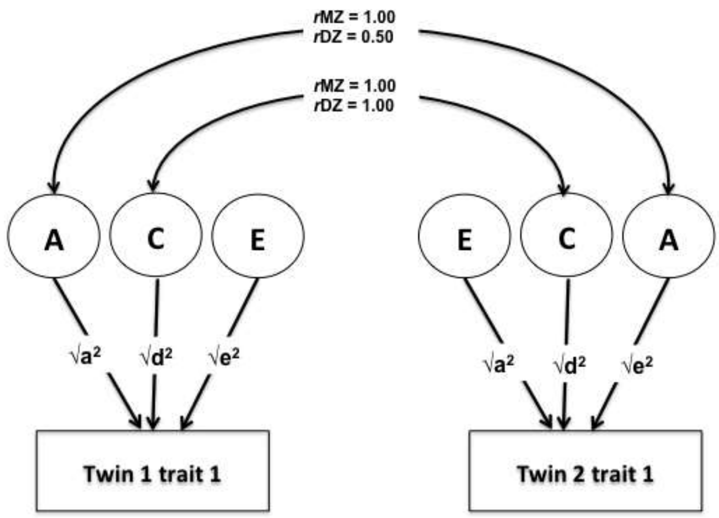

Figure 2.1.a. The univariate ACE model; A= additive genetic, C = shared environmental, E = nonshared environmental variance components. $\sqrt{a^2}$, $\sqrt{c^2}$, $\sqrt{e^2}$ = standardized and squared path estimates for the A, C and E variance components. In this model additive genetic similarity is set to 1 for MZ twins and ½ for DZ twins, as they share on average 50% of their segregating genes. The shared environmental estimates are set to be the same for MZ and DZ twins, as both types of twins are raised together. The degree of similarity for E is not set as E indicates environmental differences between twins raised in the same family.

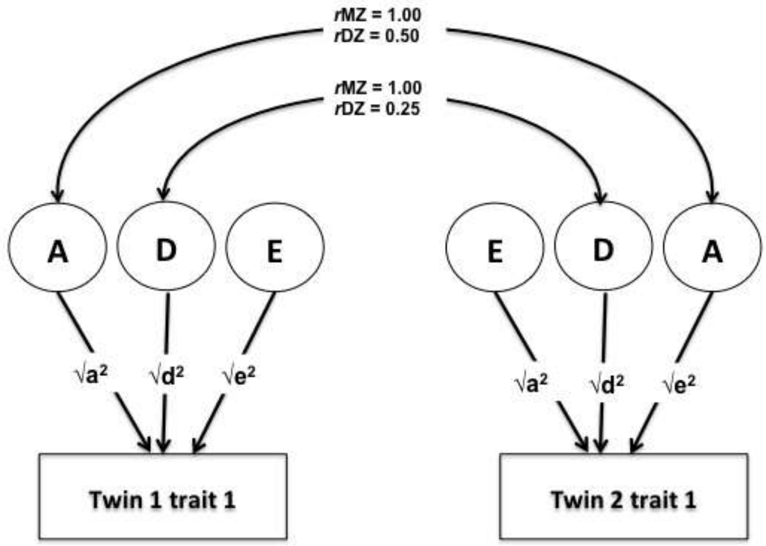

Figure 2.1.b. The univariate ADE model; A= additive genetic, D = non-additive genetic, E = nonshared environmental variance components. $\sqrt{a^2}$, $\sqrt{d^2}$, $\sqrt{e^2}$ = standardized and squared path estimates for the A, D and E variance components. In this model additive genetic similarity is set to be 1 for MZ twins and ½ for DZ twins, as they share on average 50% of their segregating genes. The non-additive genetic similarity is set of be 1 (or 100%) for MZ twins, as they share their entire genetic make up, and .25 (25%) for DZ twins. This is because their genetic differences contribute to make them less than 50% similar if compared to MZ twins. This model is chosen if the correlation between MZ twins is more than double that observed between DZ twins. The degree of similarity for E is not set as E indicates environmental differences between twins growing up in the same family.

The present study uses univariate models to investigate the origins of individual differences in general, mathematics and spatial (navigation and rotation/visualization) anxiety in a large representative sample of young adults from the UK (see Results Table 2.6).

<u>Full Sex Limitation Model</u>

The univariate model can be extended to the full sex limitation model in order to explore whether sex differences characterise the aetiology of individual differences in a trait. The full sex limitation model (see Results Table 2.7 and Table 2.8) allows for the investigation of both qualitative and quantitative sex differences, which are not mutually exclusive. This model allows qualitative sex differences in that the genetic and shared environmental correlations between opposite-sex twins are allowed to be less than 0.5 and 1.0, respectively. The model also allows quantitative sex differences in that the ACE parameters for males and females can differ. Variance differences between the sexes are also allowed.

Qualitative sex differences are observed if different genetic and/or environmental factors are implicated in the aetiology of individual differences in a given trait in males and females. Quantitative sex differences are observed when the factors influencing the variation in a given trait are the same (i.e. same genes and same environments) for males and females, but the magnitude of their effects differs across sexes. The full sex limitation model allows to explore qualitative sex differences derived from the differences in the correlation between same and opposite sex DZ twin pairs, as well as quantitative sex differences, derived comparing the A, C and E estimates obtained for males and females separately. Qualitative differences at the aetiological level are suggested when the correlation between opposite sex DZ pairs is significantly lower than the correlation between same sex DZ pairs. The difference in the correlations between DZ same sex and DZ opposite sex pairs suggests that quantitative sex differences are operating at the level of the aetiology of individual differences in the variables. On the other hand, quantitative sex differences are observed when the estimates for A, C and E (or A, D and E) are different between males and females, which is indicated by non-overlapping confidence intervals around the estimates (Medland, 2004; Kovas, Haworth, Dale, & Plomin, 2007)

Multivariate Genetic Analyses

The Cholesky Decompsition

The univariate model can be extended to multivariate models to investigate the origins of the association between variables. The Cholesky decomposition allows to examine the common and independent genetic and environmental effects on the variance in two or more traits. The Cholesky decomposition partitions the phenotypic variance and covariance between traits into common and independent genetic (A), shared environmental (C) and non-shared environmental (E) sources of variance and covariance (Neale, Boker, Xie, & Maes, 2002). The model works similarly to a hierarchical regression analysis, as the independent contribution of a predictor variable to the dependent variable is estimated after accounting for the variance it shares with other predictors previously entered in the model (Luo, Kovas, Haworth, & Plomin, 2011). Figure 2.2 shows an example of a multivariate Cholesky decomposition including three variables (trivariate Cholesky decomposition).

The first set of A, C and E factors (A1, C1, and E1) assesses genetic, shared and non-shared environmental influences on variable 1, some of which also influence individual differences in variable 2 and variable 3. The second set of A, C and E factors (A2, C2 and E2) assesses the residual genetic, shared and non-shared environmental influences on variable 2 (after accounting for the influences shared with variable 1), some of which also influence individual differences in variable 3. The third set of A, C and E factors (A3, C3 and E3) assess the residual genetic, shared and non-shared environmental influences on the third variable, which are not shared with variable 1 and variable 2.

A Cholesky decomposition was conducted in order to explore the origins of the covariation between anxiety measures. The model was used as a baseline comparison for the Independent and Common Pathway model described below. Results of this Cholesky decomposition are not resented in the present chapter. The results of another Cholesky decomposition, exploring the origins of the covariation between mathematics anxiety and other mathematics-related outcomes are presented in Chapter 3 of the present thesis.

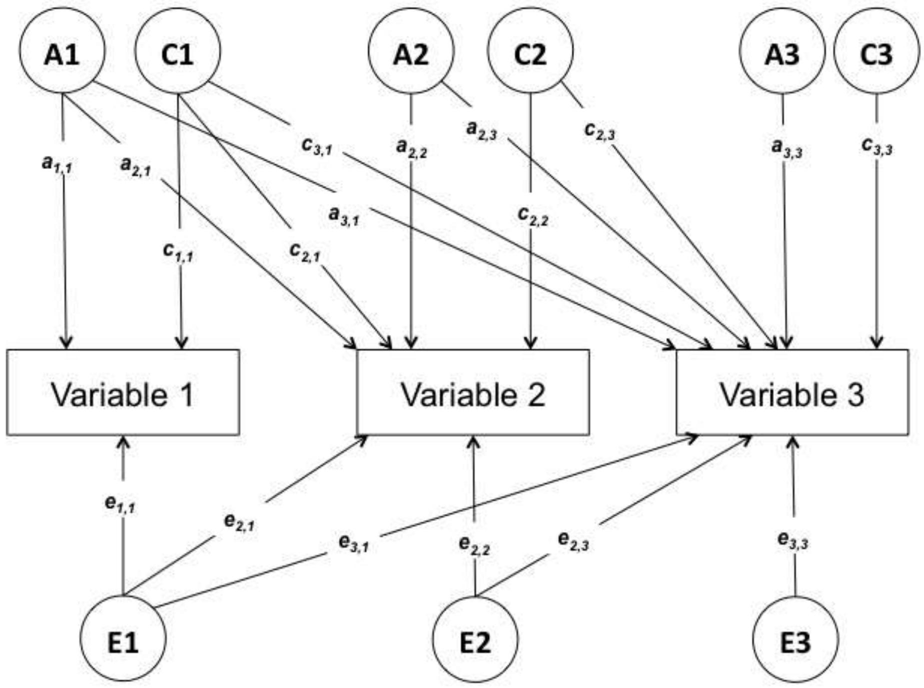

Figure 2.2. Multivariate Cholesky decomposition; A1 = additive genetic effects common to variable 1, variable 2 and variable 3; A2 = additive genetic effects common to variable 2 and variable 3; A3 = additive genetic effects specific to variable 3; C1= shared environmental effects common to variables 1, 2 and 3; C2 = shared environmental effects common to variables 2 and 3; C3 = shared environmental effects specific to variable 3; E1 = non-shared environmental effects common to variable 1, 2 and 3; E2 = non-shared environmental effects common to variable 2 and 3; E3 = non-shared environmental effects specific to variable 3.

Correlated Factors Model

Another way of exploring the origins of the association between several traits is by exploring the origins of the correlations between pairs of variables. In order to investigate the origins of the link between the different anxiety measures we fitted a multivariate correlated factors model. The correlated factors model (Figure 2.3; Plomin & DeFries, 1979) allows for the decomposition of the covariance between two traits into genetic, shared and non-shared environmental sources of variance, which are derived from the comparison of the cross-twin cross-trait correlations, obtained for MZ and DZ twin pairs. Cross-twin cross-trait correlations describe the association between two variables, with twin 1 score on variable 1 correlated with twin 2 score on variable 2. Cross-twin cross-trait correlations are calculated separately for MZ and DZ twins. A higher cross-twin cross-trait correlation for MZ than for DZ twins indicates that genetic factors have a degree of influence on the phenotypic relationship between the two traits. For example, the fact that the correlation between general anxiety for twin 1 and mathematics anxiety for twin 2 is higher for MZ than for DZ twins indicates a degree of genetic influence on the co-variance between general and mathematics anxiety. Comparing the cross-twin cross-trait correlations for pairs of variables, the correlated factors model calculates the genetic, shared environmental and non-shared environmental correlations between variables.

From these estimates it is possible to derive the percentage of the phenotypic correlation between variables that can be attributed to genetic, shared and non-shared environmental influences using the following three formulae: (1) $(\sqrt{h^2}\ (var1) \times \sqrt{h^2}\ (var2) \times r_G)/r_P$; (2) $(\sqrt{c^2}\ (var1) \times \sqrt{c^2}\ (var2) \times r_C)/r_P$; and (3) $(\sqrt{e^2}\ (var1) \times \sqrt{e^2}\ (var2) \times r_E)/r_P$. For example, the first formula derives the percentage of the phenotypic correlation that is explained by the genetic correlation between two traits by multiplying the squared root of the heritability estimates (h^2 –or a^2 as indicated in Figure 2.3*)* for variable 1 and variable 2 and their genetic correlation (r_G), and by then dividing the product by their phenotypic correlation (r_P). The same percentage can be calculated for the shared (r_C) *and* nonshared environmental correlation (r_E)*.* These estimates are known as bivariate heritability and enviromentalities. The formulae described above are applied in order to obtain the estimates presented in Table 2.11, which reports the proportion of phenotypic correlation explained respectively by genetic and environmental variance. For example, taking the association between mathematics and general anxiety, their phenotypic correlation is .32 and their genetic correlation .47, h^2 for mathematics anxiety is .37 and for general anxiety .41. By applying the following formula $(\sqrt{.41} \times \sqrt{.37} \times .47)/.32$ it is possible to obtain the percentage of their phenotypic correlation that is explained by genetic factors common to both variables (58%).

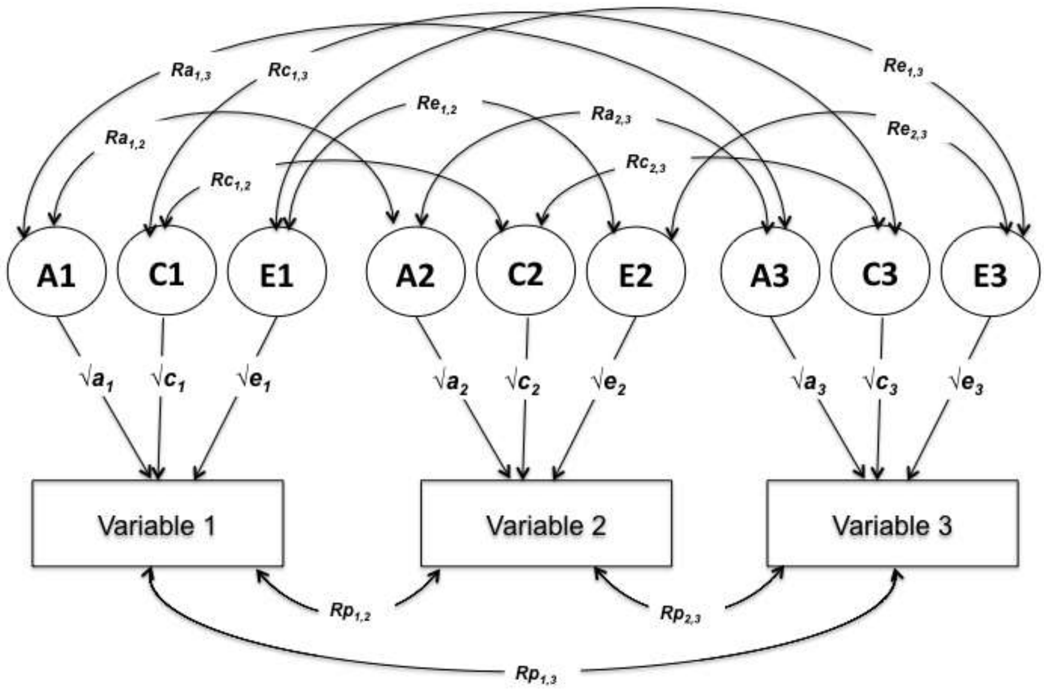

Figure 2.3. The correlated factors model; A = additive genetics; C = shared environment; E = non-shared environment; *Ra* = genetic correlation; *Rc* = shared environmental correlation; *Re* = non-shared environmental correlation; *Rp* = phenotypic correlation, √a √c, √e = standardized and squared path estimates for additive genetic, shared and nonshared environmental variance components.

<u>The Independent Pathway Model</u>

While the correlated factors model allows for the investigation of the aetiology of the co-variation between pairs of variables, multivariate models allow for the exploration of the common aetiology across multiple variables. Another extension of the Cholesky Decomposition is the Independent Pathway model. The independent pathway model (Figure 2.4; McArdle & Goldsmith, 1990) allows for the investigation of the common aetiology between all variables entered in the model. The model decomposes the common variance between traits into: common and specific genetic (A), shared environmental (C) and nonshared environmental (E) influences. The common A, C and E paths (a_C, c_C, e_C in Figure 2.4) indicate the extent to which the same genetic, shared and non-shared environmental variances are shared between all the measures entered in the model. This allows for the investigation of the extent to which the same genes and same environments are implicated in the origins of the co-variation between all traits included in the model. On the other hand, the specific A, C, and E paths (a_S, c_S, e_S in Figure 2.4) represent the genetic, shared and noshared environmental influences that are specific to each measure, indicating specificity in the aetiology of each variable. For example, the present chapter applied the independent pathway model to test the aetiology of the covariation between general, mathematics and spatial anxiety, in order to test whether all anxiety measures are influenced by the same genetic and/or environmental factors.

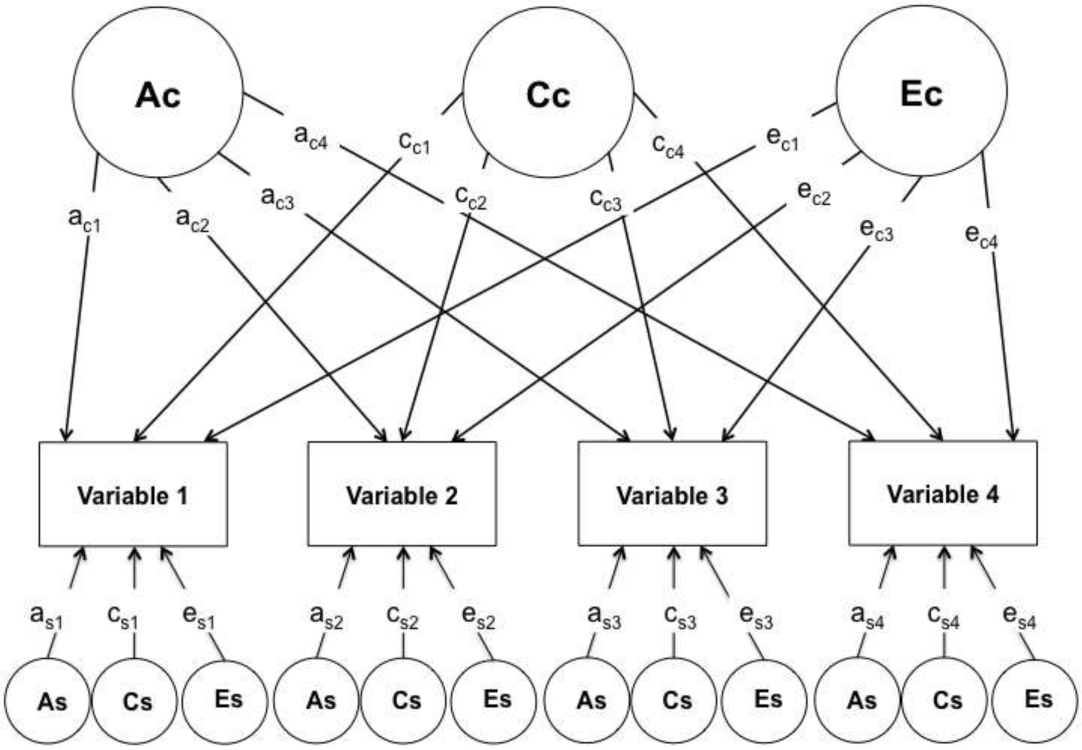

Figure 2.4. Independent pathway model; Ac = common A variance; Cc = common C variance; Ec = common E variance; As = specific A variance; Cs = specific C variance; Es = specific E variance. a_c = common additive genetic paths; c_c = common shared environmental paths; e_c = common non-shared environmental paths; a_s = additive genetic paths specific to each measure; c_s = specific shared environmental paths; e_s = specific non-shared environmental paths.

<u>The Common Pathway Model</u>

The Common Pathway Model (McArdle & Goldsmith, 1990) is a more parsimonious model than the independent pathway model, testing whether all the A, C, and E influences on the covariation between all variables are mediated by a latent variable (see Figure 2.5). In the common pathway models, the latent factor acts as a mediator of the genetic and environmental effects. Therefore, the model tests whether all common influences on the variables can be best summarized by a common aetiological source that includes all common A, common C and common E paths (a_l, c_l, and e_l). Similar to the independent pathway model, the common pathway model calculates the residual variance that is specific to each construct (As, Cs, and Es). The common pathway model is nested within the independent pathway model, so that their goodness of fit can be compared. A correlated factors model was adopted in the present chapter to test whether common genetic and environmental influences on all anxiety measures could be mediated by a common latent factor including all aetiological influences common to all variables.

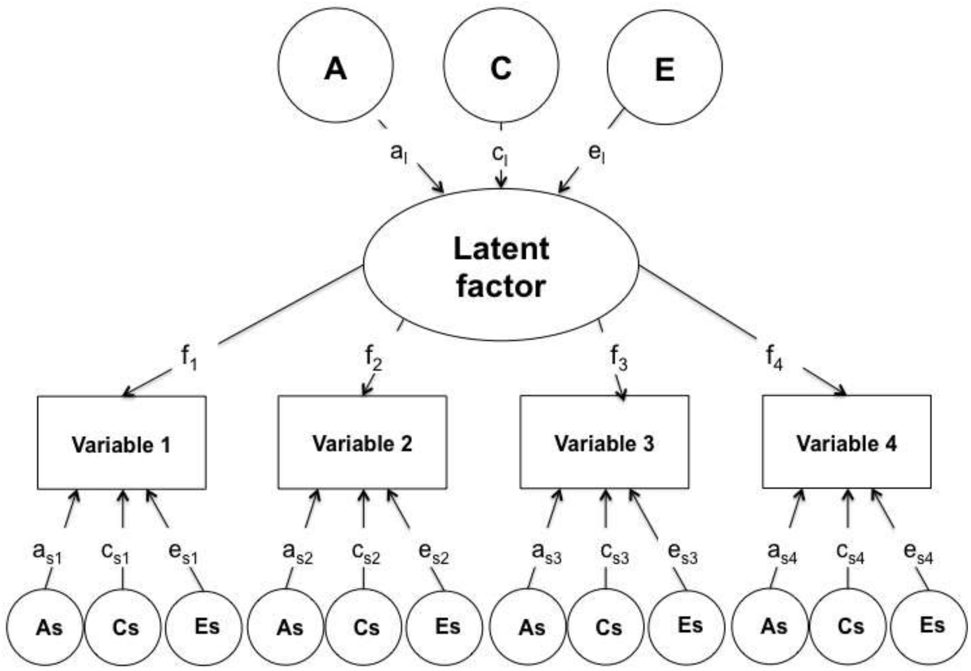

Figure 2.5. Common pathway model; a_l, c_l, e_l = path coefficients for A, C and E common influences on the common latent factor; f_1, f_2, f_3, f_4 = path coefficients for the influence of the common aetiological factor on each construct; a_s, c_s, e_s, = path coefficients for specific sources of A, C and E variance on each construct.

Results

Factor Structure of Spatial Anxiety

To create a fully independent sample, all phenotypic analyses were conducted using data from one randomly selected member of each twin pair. Similar results were obtained when the same analyses were performed on the other half of the sample – providing an in-built replication.

Principal Component Analysis (PCA) was used to explore the factor structure of anxiety. All the items included in the three anxiety measures (general anxiety, mathematics anxiety and spatial anxiety) were included in the analyses. Four clear factors emerged from PCA (see Figure 2.6 and Table 2.1).

The first factor included all the items in the mathematics anxiety scale and explained 35.8% of the total variance. The second factor included all the items in the general anxiety scale and explained 13.2% of the total variance. Six out of the ten items included in the spatial anxiety questionnaire loaded onto a third factor. All these items were related to navigation and way finding, therefore, we named this component navigation anxiety. The third factor explained 9.3% of the total variance. Three of the remaining four items in the spatial anxiety scale loaded onto a fourth factor. All of these described anxiety while performing spatial tasks relevant to mental rotation and visualization, and was therefore named rotation/visualization anxiety. The fourth factor explained 6% of the total variance.

Only one item in the spatial anxiety questionnaire ('*Finding a product in the local supermarket if the shelves have been rearranged'*) loaded similarly on both the navigation anxiety and rotation/visualization anxiety components, and was therefore excluded from composite creation and further analyses.

Confirmatory factor analysis (FA) corroborated the factor structure observed from PCA. The four-factor model was the best fit for the data if compared to more parsimonious models (see Table 2.2).

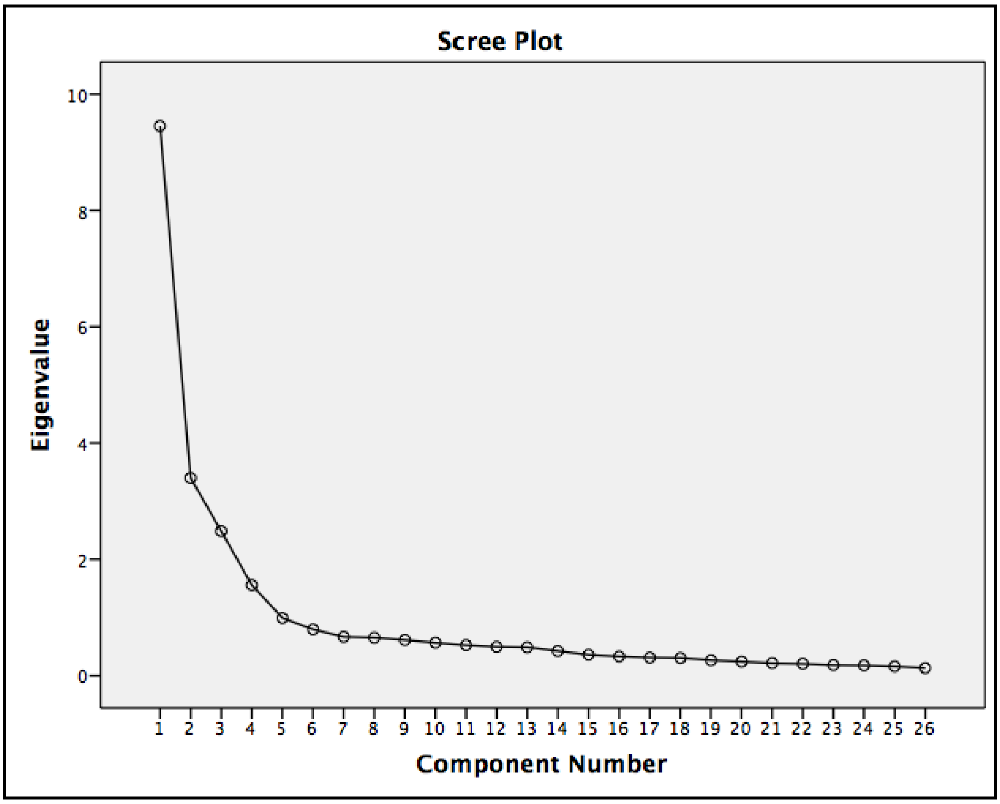

Figure 2.6. Scree plot illustrating the factor structure of anxiety measures

Table 2.1. Factor loadings for the four anxiety measures

	1	**2**	**3**	**4**
1. Finding your way around an intricate arrangement of streets	0.11	0.22	**0.76**	0.11
2. Directing somebody to a place of interest when standing in a windowless room	0.16	0.15	**0.64**	0.25
3. Locating a vehicle in a very large car park or garage	0.12	0.18	**0.57**	0.29
4. Having to complete a complex jigsaw puzzle	0.17	0.07	0.20	**0.61**
5. Finding your way around an unfamiliar place	0.17	0.19	**0.81**	0.04
6. Trying a new shortcut without using a map	0.16	0.10	**0.76**	0.14
7. Following somebody's instructions to get somewhere	0.16	0.17	**0.65**	0.24
8. Having to visualise a 3D object from a 2D drawing	0.12	0.09	0.21	**0.81**
9. Having to rotate objects in your mind	0.15	0.10	0.18	**0.79**

10. Finding a product in the local supermarket if the shelves have been rearranged	0.13	0.13	0.36	0.49
11. Using maths tables in the back of a maths text book	**0.62**	0.18	0.10	0.30
12. Thinking about an upcoming maths test	**0.78**	0.15	0.26	-0.08
13. Watching teacher working out an algebraic equation	**0.80**	0.13	0.06	0.24
14. Taking an exam in a maths course	**0.80**	0.11	0.25	-0.13
15. Being given an assignment of difficult maths problems	**0.86**	0.10	0.21	0.04
16. Listening to a maths lecture	**0.82**	0.14	0.05	0.25
17. Listening to someone explaining a maths formula	**0.83**	0.16	0.07	0.26
18. Being given a surprise quiz	**0.80**	0.10	0.24	-0.01
19. Reading a maths book	**0.78**	0.12	0.01	0.29
20. Feeling nervous anxious or on edge	0.15	**0.77**	0.25	0.01
21. Cannot stop or control worrying	0.16	**0.84**	0.20	0.06
22. Worrying too much about different things	0.19	**0.82**	0.21	0.03
23. Having trouble relaxing	0.10	**0.83**	0.14	0.07
24. Being so restless it is hard to sit still	0.07	**0.72**	0.07	0.14
25. Becoming easily annoyed or irritable	0.09	**0.67**	0.07	0.08
26. Feeling afraid as something awful might happen	0.15	**0.75**	0.15	0.13

Table 2.2. Model fit indices for confirmatory factor analysis

	AIC	BIC	RMSEA	CFI	TLI	SRMR
4 factors	**87988.78**	**88419.74**	**0.08**	**0.88**	**0.86**	**0.05**
3 factors	93012.99	93443.95	0.10	0.82	0.80	0.06
2 factors	96481.61	96901.93	0.13	0.69	0.66	0.12
1 factor	101577.17	101992.17	0.17	0.49	0.45	0.15

Note: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit

Index; TLI = Tucker-Lewis Index, SRMR = Standardized Root Mean Square Residuals.

Descriptive Statistics and Correlations

Descriptive statistics for all anxiety measures are reported in Table 2.3. All variables were widely distributed. Distributions looked very similar when the other twin in the pair was randomly selected to control for the non-independence of observations (i.e. the fact tat the children were twins).

Table 2.3. Descriptive statistics for all variables

	General anxiety	Mathematics anxiety	Navigation anxiety	Rotation/Visualization anxiety
N	1511	1511	1511	1511
Mean	1.97	2.30	2.29	1.64
Std. Deviation	0.74	1.01	0.82	0.77
Skewness	0.87	0.72	0.64	1.37
Kurtosis	0.12	-0.28	0.06	1.69
Minimum	1.00	1.00	1.00	1.00
Maximum	4.00	5.00	5.00	5.00

Note: *N* = one twin out of each pair randomly selected to control for non-independence of observation.

Pairwise associations between all variables are reported in Table 2.4. Correlations between all anxiety measures were moderate, with *r* coefficients ranging from .24 to .42.

Table 2.4. Correlations between measures of general, mathematics, navigation and rotation/visualization anxiety

	G anxiety	M anxiety	N anxiety	R/V anxiety
General anxiety	1	.32**	.44**	.24**
Mathematics anxiety		1	.41**	.32**
Navigation anxiety			1	.42**
Rotation/Vis anxiety				1

Note: *N* = 1464, one twin per pair was randomly selected; **= $p< .001$

Sex differences

Table 2.5 presents the results of four univariate analyses of variance (ANOVA), performed to explore sex differences in all anxiety measures. Significant sex differences were observed for all measures, with females showing higher anxiety scores than males. However, at the phenotypic level, sex differences only accounted for between 1.3% and 5.5% of the variance in anxiety. For the subsequent analyses the measures were corrected for the small age and sex differences using the regression method.

Table 2.5. Univariate analyses of variance (ANOVA) examining sex differences in all variables

	Female	*Male*	*F*	*Partial η2*
	M (SD), N	*M (SD), N*		
General Anxiety	2.07 (.77)	1.78 (.64)	58.71**	0.037
	N = 965	*N* = 546		
Mathematics Anxiety	2.45 (1.03)	2.03 (.88)	64.95**	0.041
	N = 965	*N* = 546		
Navigation Anxiety	2.43 (.83)	2.02 (.72)	88.27**	0.055
	N = 965	*N* = 546		
Rotation/Visualization	1.70 (.78)	1.52 (.72)	20.38**	0.013
Anxiety	*N* = 965	*N* = 546		

Note: One twin per pair was randomly selected; **= *p*< .001

Full Univariate Sex Limitation Models

Because significant, although small, phenotypic sex differences were found for all measures, additional analyses were performed to investigate whether sex differences existed at the aetiological level. The full sex limitation model (see Methods for more details) allows to answer the question of whether the origins of individual differences in a trait are qualitatively and quantitatively the same across sexes. Four univariate sex limitation models were conducted in order to assess whether the origins of individual differences in general, mathematics, navigation and rotation/visualization anxiety were the same or different for males and females. Qualitative sex differences were not found, indicating that the same factors contributed to individual differences in all measures of anxiety for males and females. Although the results indicated some significant quantitative sex differences in the aetiology of all anxiety measures, the confidence intervals around A, C ad E estimates for boys and girls were largely overlapping (see Table 2.6 for ACE estimates for males and females separately).

Table 2.6. Twin correlations across sex and zygosity groups.

	***r*MZm**	***r*MZf**	***r*DZm**	***r*DZf**	***r*DZos**
General anxiety	.51**	.42**	.24**	.22**	-0.01
Maths anxiety	.30**	.45**	.30**	0.05	0.01
Navigation anxiety	.42**	.40**	.20*	.14*	-.00
Rot/Vis anxiety	.30**	.33**	.31**	0.01	.00
N	194	392	157	315	406

Note: *r*MZm = correlation between monozygotic males; *r*MZf = correlation between monozygotic females; *r*DZm = correlation between dizygotic males; *r*DZf = correlation between dizygotic females; rDZos = correlation between dizygotic opposite sex twins; N = number of twin pairs in each group; ** = p< .01; * = p< .05.

Table 2.7 reports the estimates for additive genetic, shared environmental and nonshared environmental influences for each anxiety measure for boys and girls separately. Sex limitation models fitting suggested differences in the estimates of the contribution of genetic and environmental factors to variation in all anxiety measures for males and females (p< .01). However, the confidence intervals around the estimates for males and females were largely overlapping. The overlap in confidence interval suggests two things: (1) our analysis could not differentiate between genetic and environmental estimates for boys and girls with adequate power; and (2) the estimates for boys and girls were comparable (Neale & Cardon, 2004). Consequently, all MZ and DZ pairs, including the opposite sex DZ twin pairs, were included in our analyses in order to maximise power.

Table 2.7. Univariate additive genetic (A), shared environmental (C) and nonshared environmental (E) estimates for males and females separately.

	Am	Cm	Em	Af	Cf	Ef
G anx	.27 (.00, .51)	.23 (.03, .49)	.50 (.40, .61)	.32 (.10, .46)	.08 (00, .26)	.59 (.51, .68)
M anx	.06 (.00, .33)	.35 (.18, .45)	.65 (.55, .77)	.41 (.32, 48)	.02 (.00, .20)	.59 (.51, .67)
N anx	.02 (.00, .33)	.37 (.11, .48)	.61 (.49, .72)	.40 (.23, .49)	.01 (.00, .14)	.59 (.51, .67)
R/V anx	.00 (.00, .20)	.30 (.12, .40)	.70 (.60, .81)	.28 (.18, .37)	.00 (.00, .18)	.71 (.63, .80)

Note: The numbers in bracket rare 95% confidence intervals; Am = additive genetic estimates for males only; Cm = shared environmental estimates for males; E = nonshared environmental estimates for males; Af = additive genetic variance for females only; Cf = shared environmental estimates for females; E = nonshared environmental estimates for females.

The Aetiology of Individual Differences in Anxieties

Univariate genetic analyses (see Methods) were used to explore the origins of individual differences in the four anxiety variables. Based on the observed intraclass correlations (see Table 2.8), four univariate ADE models were conducted to investigate the origins of individual differences in general, mathematics, navigation and rotation/visualization anxiety. By comparing model fit indices it is possible to compare the univariate model with the saturated model, which is which is the baseline model obtained from the descriptive properties of the data, and to evaluate the fit of the ADE model. Additionally, model fitting allows to compare the ADE model with more parsimonious models, which partition the variance into two or one components. After comparing model fit indices (see Table 2.8), the AE model was found to be the best model to fit the data for all variables, indicating that non-additive genetic influences (D) significantly contributed to explaining variation in anxieties.

Results showed that additive genetic factors contributed moderately to variation in all anxiety measures, with heritability estimates ranging between 30-

41%. Non-shared environmental factors, which include measurement error, were found to explain the remaining variance in all anxiety measures (56-70%).

Table 2.8. Intraclass correlations, heritability, shared and nonshared environmental estimates for all anxiety measures with 95% confidence intervals.

	rMZ	rDZ	A	D	E
Gen Anxiety	.44**	.17**	.41 (.34, .48)	-	.59 (.52, .64)
Maths Anxiety	.43**	.09**	.37 (.19, .45)	-	.63 (.62, .69)
Nav Anxiety	.40**	.14**	.37 (.29, .44)	-	.63 (.57, .70)
Rot/Vis Anxiety	.35**	.07**	.30 (.22, .36)	-	.70 (.63, .77)

Note: ** = p< .01; 95% confidence intervals in parentheses, A = additive genetic influences; D = non-additive genetic influences; E = nonshared environmental influences.

Table 2.9. Model fit indices for all univariate models and nested models

	Baseline	Comparison	-2LL	df	AIC	*p*
(a) General Anxiety						
1	Saturated	-	7458.778	2675	2108.778	-
2	Saturated	ADE	7462.354	2681	2100.354	0.73
3	**ADE**	**AE**	**7463.351**	**2682**	**2099.351**	**0.32**
4	ACE	E	7594.550	2683	2228.550	0.00
(b) Mathematics Anxiety						
1	Saturated	-	7488.693	2675	2138.693	-
2	Saturated	ADE	7492.368	2681	2130.368	0.72
3	**ADE**	**AE**	**7501.925**	**2682**	**2137.925**	**0.03**
4	ADE	E	7594.550	2683	2228.550	0.00
(c) Navigation Anxiety						
1	Saturated	-	7494.874	2675	2144.874	-
2	Saturated	ADE	7497.674	2681	2135.674	0.83

3	**ADE**	**AE**	**7499.062**	**2682**	**2135.062**	**0.24**
5	ADE	E	7594.550	2683	2228.550	0.000

(d) Rotation/Visualization Anxiety

1	Saturated	-	7517.452	2675	2167.452	-
2	Saturated	ADE	7526.233	2681	2164.233	0.19
3	**ADE**	**AE**	**7531.338**	**2682**	**2167.338**	**0.04**
4	ADE	E	7594.550	2683	2228.550	0.00

Note: ep = estimated parameters; -2L = negative 2 times log likelihood; df = degrees of freedom; AIC = Akaike Information Criterion.

The Origins of the Co-variation between Anxiety Measures: Multivariate Genetic Analyses

The multivariate ACE correlated factors model allows for the exploration of the origins of the co-variation between pairs of traits (see Methods). The model allows to quantify the genetic and environmental correlations between pairs of variables, as well as the proportion of the phenotypic correlations that can be attributed to genetic and environmental influences. Figure 2.6 and Table 2.11 present the results obtained from the correlated factors model. Phenotypic correlations were generally moderate between all anxiety measures. The AE model best fitted the data (see Supplementary Table 2.10), as dropping shared environmental influences did not significantly decrease the goodness of fit of the model. Genetic correlations for all pairwise associations were strong, ranging from .38 to .63. Nonshared environmental correlations were weak to moderate, ranging from .13 to .38. Shared environmental influences did not play a significant role in explaining the association between anxiety variables.

The correlated factors model also allows to calculate the percentage of the phenotypic correlation that is explained by genetic and nonshared environmental influences (see Methods). As shown in Table 4, genetic factors explained about half or more of the moderate correlations between variables (between 38% and 65%). Non-shared environmental influences, which also encompass measurement error, explained between 35% and 62% of the phenotypic correlations.

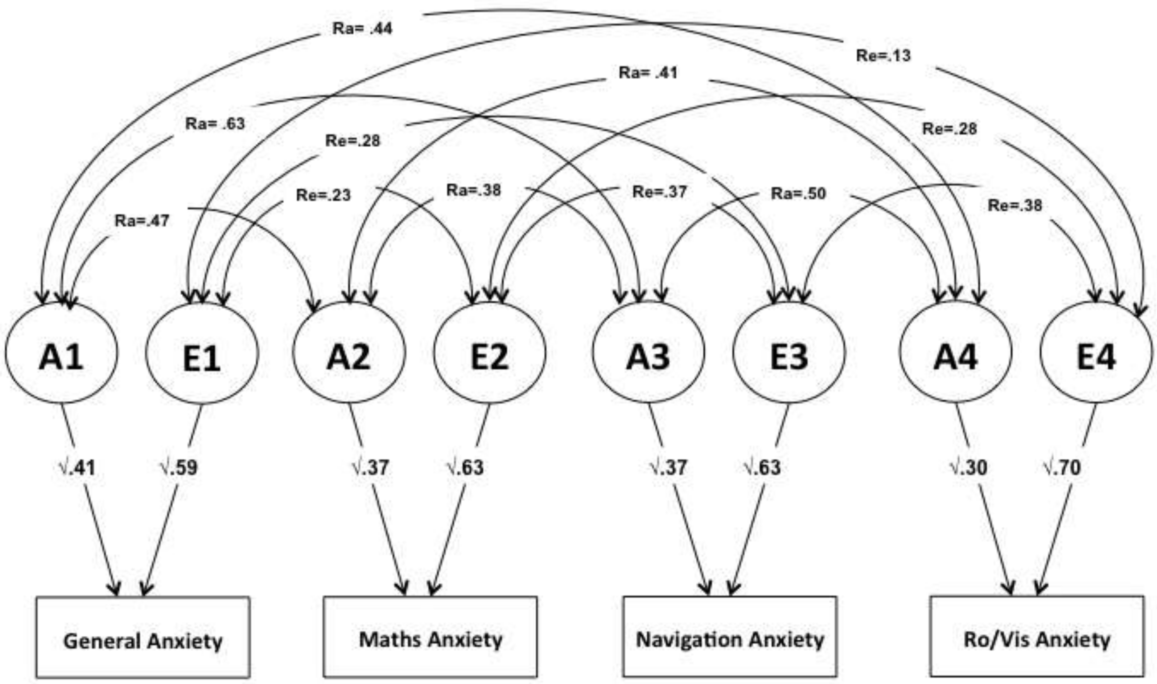

Figure 2.7. Correlated Factors Model for the association between general anxiety, mathematics anxiety, navigation anxiety and rotation and visualization anxiety. Ra = genetic correlation, Re = nonshared environmental correlation.

Table 2.10. Model fit indices for the Correlated Factors Model

Baseline model	Comparison	ep	- 2LL	df	AIC	*p*
Saturated	-	88	18615.90	8376	1863.9056	-
Saturated	Full ACE	34	18702.76	8430	1842.7607	0.003
Saturated	AE Model	24	18704.32	8440	1824.3212	0.023
Full ACE	**AE Model**	**24**	**18704.32**	**8440**	**1824.3212**	**0.999**
Full ACE	CE Model	24	18759.56	8440	1879.5669	0.000
Full AE	E Model	14	19085.38	8450	2185.3879	0.000

Note: ep = estimated parameters;-2L = negative 2 times log likelihood; df = degrees of freedom; AIC = Akaike Information Criterion.

Table 2.11. Phenotypic (r_P), genetic (r_A) and non-shared environmental (r_E) correlations for pairwise associations

Pairs of variables	**r_P (95% CI)**	**r_A (95% CI)** *Proportion of r_P*	**r_E (95% CI)** *Proportion of r_P*
G anxiety & M anxiety	.32 (.29 - .34)	.47 (.44 - .61)	.23 (.16 - .25)
		58%	*42%*
G anxiety & N anxiety	.42 (.39 - .43)	.63 (.55 - .90)	.28 (.21 - .34)
		59%	*41%*
G anxiety & R/V anxiety	.24 (.21 - .27)	.44 (.32 - .72)	.13 (.06 - .18)
		65%	*35%*
M anxiety & N anxiety	.38 (.35 - 40)	.38 (.20 - .52)	.37 (.30 - .41)
		38%	*62%*
M anxiety & R/V anxiety	.32 (.28 - .34)	.41 (.26 - .62)	.28 (.23 - .34)
		43%	*57%*
N anxiety & R/V anxiety	.42 (.41 - .44)	.50 (.32 - .69)	.38 (.32 - .43)
		40%	*60%*

Note: G anxiety = general anxiety; M anxiety = maths anxiety; N anxiety = navigation anxiety; R/V anxiety = rotation/visualization anxiety; 95% CI = 95% confidence intervals; r_A= genetic correlation; r_E = nonshared environmental correlation; r_P = phenotypic correlation.

Common Sources of Genetic and Environmental Variance across Anxiety Measures: the Independent Pathway Model

As well as exploring the origins of the association between pairs of variables, the aim of present Chapter was that of investigating the extent to which all anxiety measures shared a common aetiology. In order to explore whether the data could be best summarised by a common genetic and a common non-shared environmental source of variance across all anxiety measures, an independent pathway model was ran (see Methods). Specifically, the model estimated the extent to which common aetiological influences are shared between general, mathematics, navigation and rotation/visualization anxiety. The independent pathway model also explores the aetiology of the residual variance that is not shared between variables.

Figure 2.8 and Table 2.12 report the results of the independent pathway model. Table 2.12 presents the standardized paths estimates for the model and includes confidence intervals. Figure 2.7 presents the standardized squared paths estimates. The independent pathway model showed that, although some genetic and nonshared environmental influences were shared across the four anxiety measures, the aetiology of each anxiety construct was largely specific; this was evidenced by the significant and substantial residual paths in A and E estimates.

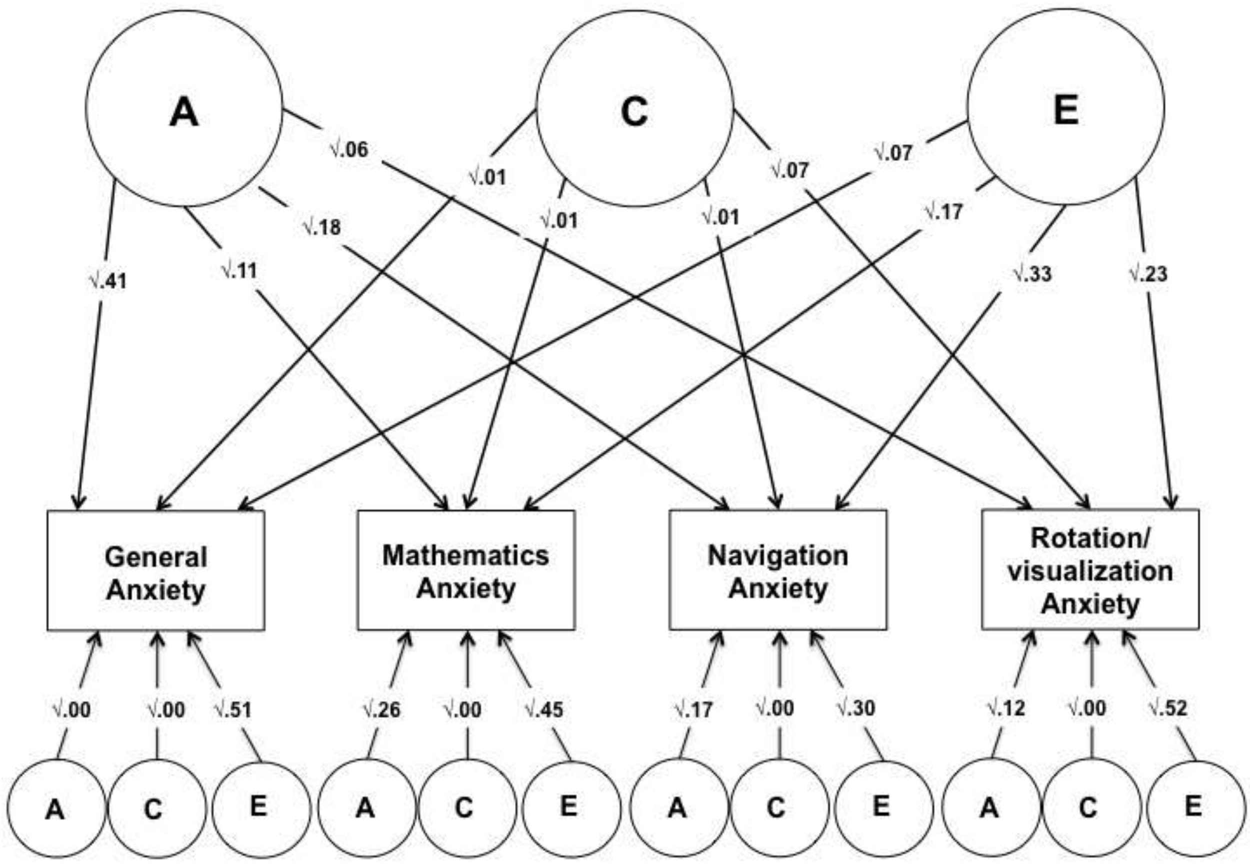

Figure 2.8. Independent Pathway Model looking at the origins of the association between general, mathematics, navigation and rotation/visualization anxiety. All paths are standardized and squared.

Table 2.12. Standardized paths for the Independent Pathway Model.

Common Paths			
AC1	AC2	AC3	AC4
0.64 (.50, .69)	.33 (.24, .42)	.43 (.31, .51)	.25 (.08, .39)
CC1	CC2	CC3	CC4

-.11 (-.33, .14)	.08 (-.04, .21)	.11 (.-63, .21)	.26 (.09, .40)
EC1	EC2	EC3	EC4
.26 (.20, .29)	.42 (.34, .49)	.57 (.50, .65)	.48 (.41, .55)
Specific Paths			
AS1	AS2	AS3	AS4
-.00 (-.34, .34)	.51 (.43, .56)	.42 (.25, .48)	.35 (.12, .54)
CS1	CS2	CS3	CS4
.00 (-.24, .24)	.00 (-.21, .21)	.00 (-.28, .28)	.00 (-.23, .23)
ES1	ES2	ES3	ES4
.71 (.67, .75)	.67 (.62, .72)	.55 (.47, .61)	.72 (.67, .78)

Note: AC1, AC2, AC3, AC4 = Genetic variance common to all anxiety measures; CC1, CC2, CC3, CC4 = shared environmental variance common to al anxiety measures; EC1, EC2, EC3, EC4 = nonshared environmental variance common to all anxiety measures; AS1 = genetic variance specific to general anxiety that is not shared with the other anxiety measures; AS2 = genetic variance specific to mathematics anxiety that is not shared with the other anxiety variables; AS3 = genetic variance specific to navigation anxiety that is not shared with the other anxiety variables; AS4 = genetic variance specific to rotation/visualization anxiety that is not shared with the other anxiety variables; CS1, CS2, C3, CS4 = specific shared environmental variance; ES1, ES2, ES3, ES4 = specific nonshared environmental variance; (95% confidence intervals).

In order to try and explore whether the association between anxiety measures could be better described by one common aetiological factor including all three variance components, a common pathway model (see Chapter 2 Methods, Figure 2.5) was ran. The model tests whether the common aetiology across the four anxiety measures could be best described by one common latent factor encompassing genetic and environmental sources of influence. The common pathway model was significantly lower in fit than the independent pathway model, indicating that one latent factor encompassing all the common A, C and E influences could not best summarise the aetiology of the co-variation between the four anxiety measures (see Table 2.13 for model fit statistics).

Table 2.13. Model fit indices for Cholesky Decomposition, Independent Pathway Model and Common Pathway Model.

Baseline	Comparison	ep	-2LL	df	AIC	*p*
Saturated	-	88	28310.89	10652	7006.897	-
Saturated	Cholesky ACE	34	28388.47	10706	6976.469	.014
Cholesky ACE	Indep. Pathway	28	28407.37	10712	6983.369	.004
Cholesky ACE	Comm. Pathway	23	28439.44	10718	7003.436	.000
Indep. Pathway	Comm. Pathway	23	28439.44	10718	7003.436	.000

Note: ep = number of parameters estimated by the model; -2LL = negative log likelihood, df = degrees of freedom; AIC = Akaike Information Criterion

Discussion

The present study had three main aims: (1) to explore the factor structure of spatial anxiety; (2) to investigate the origins of individual differences in spatial anxiety; and (3) to explore the origins of the association between general anxiety, mathematics anxiety and spatial. Spatial anxiety was found to include two distinct constructs: navigation anxiety –experienced in situations involving navigation and way-finding activities– and rotation/visualization anxiety –relevant to smaller-scale spatial activities such as mental rotation, visualization and object manipulation. Navigation and rotation/visualization anxiety were also partly independent from mathematics anxiety and general anxiety.

The factor structure of spatial anxiety as well as the association between its components and mathematics anxiety and general anxiety had not been previously investigated. The majority of previous research has explored the association between spatial anxiety and performance relevant only to navigation and way finding activities. The results highlight the importance of considering another aspect of spatial anxiety, experienced when performing tasks such as mental rotation, visualization and object manipulation. This is consistent with studies that did not find an association between self-reported navigation ability and mental rotation (Hegarty, Richardson, Montello, & Lovelace, 2002). These findings led to the speculation that navigation ability is mostly independent from smaller scale spatial abilities such as mental rotation (Hegarty, Montello, Richardson, Ishikawa, & Lovelace, 2006). Future investigations exploring the association between navigation anxiety, rotation/visualization anxiety and spatial abilities are needed in order to shed some light not only on the factor structure of spatial abilities, but also on the specificity of the association between anxiety and performance in the domain of spatial skills. Furthermore, the results showed that the domain-specific constructs of navigation anxiety, rotation/visualization anxiety and mathematics anxiety are largely separate form general anxiety. This is the first study to address this research question, and points towards the importance of exploring how emotion regulation relates to performance from a domain-specific perspective.

Females showed significantly higher levels of anxiety than males did. This pattern of results was consistent across all anxiety variables. However, effect sizes were weak, as sex explained between 1% and 5% of the variance in all anxiety constructs. Several previous investigations have reported sex differences in general and mathematics anxiety, usually finding that females experienced higher levels of anxiety (Goetz, Bieg, Lüdtke, Pekrun, & Hall, 2013; McLean & Anderson, 2009; Ferguson et al., 2015). The results are also consistent with one study that found that females experienced higher levels of way-finding anxiety than males (Hund & Minarik, 2006). However, little evidence was found for sex differences in the genetic and environmental architecture of anxiety between males and females; suggesting that the same factors are implicated in the aetiology of individual differences in anxiety to a similar extent in males and females.

All anxiety constructs were moderately heritable, with additive genetic factors explaining 30-41 % of the variance. Nonshared environmental factors, which are the factors that do not contribute to similarities between twins raised in the same family, explained the remaining variance in all anxiety measures. Although it is reasonable to assume that shared environmental factors, such as shared family environment, substantially influence anxiety levels, the present study did not find any significant variance explained by these factors.

The results are in line with those presented in the Wang et al. study in a younger sample of 12-year-old students. As heritability estimates are specific to the population for which they are calculated at a particular time (Plomin, DeFries, Knopik, & Neiderhiser, 2013) it was important to explore whether genetic factors played a similar role in explaining individual differences in a sample of older participants from the UK. Moreover, the present investigation was the first to explore the origins of variation in spatial anxiety. Navigation anxiety was found to be moderately heritable, with genetic factors explaining 37% of individual differences in the trait. Rotation/visualization anxiety was found to be less heritable, with genetic factors explaining 30% of its variance.

Although all anxiety constructs were found to constitute independent factors, all measures correlated moderately with each other. Genetic factors were found to explain about half or more of the phenotypic associations between all measures of anxiety. For example, we found a strong genetic correlation between navigation and rotation/visualization anxiety, indicating that many of the same genes are implicated in individual differences in both measures. The strong genetic correlation between navigation and rotation/visualization anxiety explained nearly half of their moderate phenotypic correlation, and nonshared environmental factors explained the remaining portion of variance. These findings are in line with previous research exploring the origins of the association between mathematics and spatial abilities. In fact, genetic influences were found to explain the largest portion of the covariance between mathematics and spatial abilities in a sample of 16 year-old TEDS twins (Tosto et al., 2014).

Due to the overlapping aetiologies between pairs of anxiety variables, the present investigation explored whether the same aetiological influences underlined all anxiety constructs. The results showed that some genetic and nonshared environmental influences were common to all anxiety measures. This indicates that some of the same genes and same nonshared environments are implicated in individual differences in all anxiety constructs. However, significant specific genetic and non-shared environmental influences were also observed.

The aetiological overlap between anxiety variables is consistent with research suggesting that partly the same physiological (Adams, 2001), cognitive (Ashcraft et al., 2007a) and brain (Suárez-Pellicioni et al., 2013) processes are implicated in both general and mathematics anxiety. At the same time, the specificity observed in the aetiology of each measure is consistent with studies suggesting that mathematics and spatial anxiety manifest themselves independently from general anxiety (Haase et al., 2012; Ramirez et al., 2012). The specific cognitive and neural processes characterising mathematics and spatial anxiety remain mostly unexplored, as research looking into the brain correlates of mathematics anxiety has mainly focused on exploring the process shared with general anxiety. However, the present results indicate a large degree of specificity in the aetiology of general, mathematics and spatial anxiety, which is likely to translate to specific neuronal and cognitive processes characterising these constructs. This is in line with evidence suggesting that mathematics anxiety is associated with a disruption in the subsystem of visual working memory, while general anxiety interferes with the verbal working memory system (Miller & Bichsel, 2004). An interesting development for future research would be to identify the common and specific processes at the heart of different anxiety constructs, including specific genes and environments influencing the development of general and domain-specific anxieties.

The specificity of the association between navigation and rotation/visualization anxiety and spatial abilities remains unexplored. It is possible that domain-specific anxieties would share a specific association with performance in that domain, above and beyond other anxiety measures. Moreover, the origins of these associations have not been investigated, and it is unclear whether specific genetic and environmental influences underlie the association between anxiety and performance in domain-specific contexts. It is part of the author's plans to explore these issues further in future research. New insights in this area are likely to have important implications not only for research, but also for interventions aimed at alleviating anxiety in domain-specific contexts.

It remains unclear whether mathematics anxiety relates differentially to different aspects of mathematics performance, such as understanding numbers, problem solving, mathematics achievement in school and number sense. Furthermore, the origins of the associations between mathematics anxiety and these different components of mathematics remain unexplored. Chapter 3 of the present thesis explores these outstanding research questions.

Limitations

The current study presents some of the limitations common to twin studies. One assumption of the twin method is the equal environments assumption, idea that MZ and DZ twin pairs growing up in the same family share the same degree of environmental similarity. Although there is evidence suggesting that MZ twins are more likely to experience similar environments than DZ twins, for example being treated more similarly, studies have shown that sharing more environmental experiences did not impact on the degree of their phenotypic concordance (Kendler, Neale, Kessler, Heath & Eaves, 1993). A further limitation is that the twin method does not take into account genotype-environment effects such as assortative mating, genotype-environment correlation and gene-environment interaction. These limitations of the methodology are discussed in detail elsewhere (see the Discussion section of Chapter 6 for an overview of how these concepts cannot be disentangled within the classical twin design). Additionally, only self-reported measures of anxiety were used in this study. Combining self-reports with other types of assessment, such as for example measuring physiological symptoms, skin conductance reactivity (Heeren, Lievens, & Philippot, 2011) or cortisol levels (Doane, Mineka, Zinbarg, Craske, Griffith, et al., 2013) would likely provide more in depth phenotypic information on all anxiety measures, the way they are manifested and their unfavourable consequences.

Conclusions

To conclude, the results of the present investigation support a multifactorial view of anxiety, both at the phenotypic and aetiological level. The findings point to the importance of studying anxiety for specific domains. Although specific anxiety constructs show an association with the broader general anxiety domain, considering general anxiety alone is likely to provide only a partial picture of the apprehension experienced by individuals struggling with anxiety in specific fields. The study found that genetic factors played a significant role in explaining variation in anxiety measures and their co-occurrence. Future genetic studies are likely to be able to identify the polygenic bases of anxiety constructs. Identifying the genetic bases of anxiety and of domain specific anxiety constructs is a priority as they have severe consequences for those affected both in terms of emotional wellbeing and performance. The present study provides useful knowledge for future research aimed at exploring the association between emotion regulation and performance in domain-specific contexts, and for the development of interventions aimed at reducing anxiety and alleviating its impact on performance. The specificity of the associations between mathematics anxiety, motivation and performance and their aetiologies are explored in the next Chapter of the present thesis.

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Chapter 3

Mathematics anxiety, motivation and performance: the origins of the association

Abstract

Research has shown that several factors, beyond intelligence, play a role in explaining variation in mathematics performance. Mathematics anxiety, the anxiety experienced in situations involving a mathematical component, has been identified as one of such factors. A moderate negative association between mathematics anxiety and performance has been consistently observed in extant literature, and the same has been found for the relation between mathematics anxiety and mathematics motivation. The current study sets out to investigate the origins of the association between mathematics anxiety, and several aspects of mathematics motivation and performance, which to date remain unexplored. The sample included 3,012, 16-21 year-old twins (1,172 MZ and 1,846 DZ) from the United Kingdom, members of the population-representative Twins Early Development Study (TEDS). Measures of mathematics anxiety, general anxiety, and mathematics motivation were collected using self-reports; mathematics achievement was measured using GCSE exam scores; and mathematical ability (understanding numbers, mathematics problem solving and number sense) was tested administering an online-battery. The results showed that the negative associations between mathematics anxiety and two aspects of mathematics motivation, interest and self-efficacy, were moderate and attributable to both genetic and individual-specific environmental factors. Mathematics anxiety also shared a moderate negative relation with all measures of mathematics performance, with the exception of number sense, which was only weakly correlated with mathematics anxiety. All associations between mathematics anxiety and performance were predominantly genetic in origin. Individual-specific environmental factors explained the remaining part of their co-variance. Results of the multivariate genetic analysis showed that the overlap between mathematics anxiety, and all

measures of motivation and performance was mostly due to genetic influences common to all traits. Family-wide environmental influences contributed only minimally to the overlap between measures, and individual-specific environmental factors were not shared between traits. Although mathematics anxiety shared part of its aetiology with general anxiety, the multivariate association between mathematics anxiety, motivation and performance was not accounted for by general anxiety, phenotypically or aetiologically. This suggests that the association between mathematics anxiety, motivation and performance is domain-specific.

Introduction

Proficiency in Science, Technology, Engineering and Mathematics (STEM) is becoming increasingly essential for contemporary society, which is highly technologically oriented. In fact, mathematics competence, the foundation of all STEM disciplines, is considered an index of a Country's level of international competitiveness (Rubinsten, Bialik & Solar, 2012; OECD, 2013). At the level of individual differences, good mathematical skills have been associated with professional success and higher earnings, and they have even been linked to health and wellbeing (Parsons & Bynner, 2005). Research has shown that several factors beyond intelligence play a role in explaining variation in mathematics performance (Krapohl, Rimfeld et al., 2014). Extant literature has identified anxiety as one of these factors contributing to variation in mathematics performance independently of general intelligence (Ashcraft & Moore, 2009). Recent evidence from the Program for International Student Assessment (OECD, 2013) showed that the incidence of mathematics anxiety has increased in recent years. An alarming 30% of a large cross-cultural 15-year-old student sample reported feeling anxious or incapable when solving a mathematics problem (Suárez-Pellicioni, Núñez-Peña & Colomé, 2016).

The negative association between mathematics anxiety and achievement

A negative moderate relation is consistently observed between mathematics anxiety and mathematics achievement, with correlation coefficients of around .30 (e.g. Hembree, 1990; Ashcraft & Krause, 2007; Eden, 2013; Devine, Fawcett, Szűcs, & Dowker, 2012; Ma, 1999). This negative association between anxiety and performance is observed across the entire distribution of ability. Students who are high achievers in mathematics can experience mathematics anxiety in the same way as low achievers can (Ashcraft & Krause, 2007). One of the earliest investigations into the association between mathematics anxiety and performance showed that high scores in mathematics anxiety corresponded to college students' lower expectation for their performance in a statistics exam as well as to lower statistics grades at the end of the academic year (Hunsley, 1987). Subsequent studies exploring the association between mathematics anxiety and performance in statistics supported these early results, finding modest negative correlations (average $r = -.22$; Nunez-Pena, Suarez-Pellicioni & Bono, 2013; Lalonde and Gardner 1993).

Several studies have investigated the association between mathematics anxiety and mathematics performance in school, consistently observing negative correlations between them. Results replicated across different populations of students of different ages (Ashcraft and Kirk, 2001; Ashcraft, Krause, & Hopko, 2007). However, findings in the literature are mixed with respect to the age of onset of mathematics anxiety and to at what point in development its negative relation with mathematics achievement emerges. One study (Dowker, Bennett & Smith, 2012) failed to observe an association between mathematics anxiety and performance in the primary school years, finding that mathematics self-evaluation was the only reliable predictor of individual differences in basic numerical skills ($r = .25$) in a group of 8-10 year-old students (Dowker et al., 2012).

On the other hand, a significant negative association was observed between mathematics anxiety and basic computational skills and mathematical reasoning in another sample of 8-year-old primary school students (Wu, Barth, Amin, Malcarne & Menon, 2013). The Wu et al. study found that the relationship was stronger between mathematics anxiety and reasoning ($r = -.48$) than between anxiety and basic computational skills ($r = -.26$; difference of slopes test: $z = -3.65$, $p < .001$), suggesting that mathematics anxiety may be associated with greater impairments when facing mathematics tasks that are more cognitively demanding. Importantly, the association between mathematics anxiety and performance was found to be independent from individual differences in general anxiety, finding evidence for the specificity of the association between mathematics anxiety and achievement in the early years of education (Wu et al., 2013).

Another study found that, in a sample of 6-7 year-olds, the negative relationship between mathematics anxiety and achievement was entirely mediated by working memory (Ramirez, Gunderson, Levine & Beilock, 2013). In fact, mathematics anxiety was negatively associated with mathematics performance, measured as mathematics problem solving ability, only in a subsample of primary school students characterised by high working memory capacity. The authors speculated that mathematics anxiety has a greater negative impact on performance for those children who, because of their greater capacity, rely more heavily on working memory when solving a mathematical task (Ramirez et al., 2013). This is in line with the *"Chocking Under Pressure"* cognitive theory of mathematics anxiety (Beilock & Carr, 2005; Maloney, Sattizahn, & Beilock, 2014; described in more details in Chapter 1 and Chapter 2 of the present thesis), proposing that performance would be most disrupted for those with higher working memory capacity, as they would rely on it more when solving a complex mathematics task.

Therefore, although evidence is mixed with regards to the age of onset of mathematics anxiety and of its association with performance, the majority of studies found that a relation between them had already developed in the early years of primary school. Inconsistencies in the literature may stem from difficulties in measuring mathematics anxiety in young samples by only relying on self-reports (Jamenson, 2013; Jansen, 2013). Longitudinal investigations into the relation between mathematics anxiety and mathematic performance have focused on exploring how their association emerges and develops over time. In fact, contrary to the cross-sectional investigations previously described, longitudinal studies allow to establish the growth and directionality of the associations between variables, measured over time.

Longitudinal investigations of the relation between mathematics anxiety and achievement

One longitudinal study investigated the developmental directionality of the relation between mathematics anxiety and achievement using a cross-lagged design, in a large sample of students followed from age 12 to 17 (grade 7 to grade 12; Ma & Xu, 2004). The investigation found that mathematics achievement, measured as a composite of basic numerical skills, algebra, geometry and quantitative literacy, was extremely stable over the six years (average β = .94). The stability of mathematics anxiety was moderate from grade 7 to grade 8 (β = .39) and increased from grade 8 to grade 12 (average β = .57). After accounting for the stability of the measures, results showed that mathematics achievement had a greater impact on later anxiety (average β = .13) than previous anxiety had on achievement. Furthermore, the stronger link was observed from achievement in grade 7 to anxiety in grade 8 (β = .20), suggesting that achievement feedback early on may have a greater influence on the development of mathematics anxiety (Ma & Xu, 2004). These results are consistent with several studies and theories suggesting that early failure or poor performance in mathematics leads to the development of mathematics anxiety (Ma & Xu, 2004; Ashcraft at al., 2007; Maloney & Beilock, 2012).

Another longitudinal investigation explored the emergence of the association between mathematics anxiety and achievement in a sample of 7-8 year-old children, attending the first and second year of primary school (Kritzinger, Kauffman & Willmes, 2010). As participants had only started to formally learn mathematics, the sample was ideal for exploring how the association between mathematics anxiety and achievement emerged from the start. Results of the investigation pointed to the absence of a direct longitudinal relationship between mathematics anxiety and achievement in the young sample. However, both constructs were found to be associated with mathematics self-evaluation, cross-sectionally and longitudinally (Kritzinger, Kauffman & Willmes, 2010). Results could indicate that the relationship between mathematics anxiety and performance arises later in development, and it is not yet formed in the early years of primary school. Alternatively, the findings might indicate that self-report measures may be inadequate for capturing individual differences in mathematics anxiety in very young samples (Kritzinger et al., 2010; Jamenson, 2013; Jansen, 2013).

Although the evidence is mixed with regards to the age of onset of mathematics anxiety, longitudinal investigations suggest that levels of mathematics anxiety are moderately stable over time. Lower achievement in mathematics was found to contribute to this stability of mathematics anxiety over time (Ma & Xu, 2004). Several investigations have focused on exploring the factors that may contribute to the development and maintenance of mathematics anxiety over development.

Mathematics anxiety and a lower-level processing deficit

In addition to the possibility that initial low performance in mathematics could play a significant role, recent investigations have explored the possibility that a deficit in lower-level numerical processing might be associated with higher levels of mathematics anxiety through its impact on mathematics achievement (Maloney, Ansari, & Fugelsang, 2011). In fact, as well as impairing performance in more complex mathematics tasks, a study found mathematics anxiety was negatively related to basic numerical processing such as counting. Participants with high levels of mathematics anxiety were found to perform significantly worse than their low anxious counterparts in a visual enumeration task (Maloney, Risko, Ansari & Fugelsang, 2010). However, another study exploring the association between mathematics anxiety and lower level numerical processing found that mathematics anxiety was not associated with the ability to estimate quantities (Maloney et al., 2010).

More recently, a further investigation explored the association between mathematics anxiety, achievement and numerosity in a twin sample from the United States (Hart, Logan, Thompson, Kovas, McLoughlin, & Petrill, 2016). The study did not find an association between numerosity – the ability to discriminate between symbolic and non-symbolic numerical quantities at a first glance (Halberda, Mazzocco and Feignenson, 2008) – and mathematics anxiety and achievement. From this study, five different latent classes emerged, which identified different profiles shown by the children in their anxiety-achievement-numerosity abilities. Three out of the five latent classes described children presenting diverse numerosity deficits, which were not found to be associated with mathematics anxiety. The fourth class included children who were high achievers, and showed high numerosity and low mathematics anxiety. The fifth class included children who were low achievers and showed high levels of anxiety.

The aetiology of the association between mathematics anxiety and achievement

The investigation conducted by Hart et al. also explored whether familial influences played a role in the classification of children into the different groups. Genetic and shared environmental factors were found to play a role in the classification of the fourth class (high achievers low in mathematics anxiety). On the other hand, child-specific environmental influences were implicated in the classes characterised by low achievement and higher anxiety (Hart et al., 2016).

This is in line with previous findings from another genetically informative investigation looking at the association between mathematics anxiety and mathematics problem solving ability (Wang, Hart, Kovas, Lukowski, Soden, Thompson, et al., 2014). This study (described in detail in Chapter 2 of the present thesis) observed a genetic link between mathematics anxiety and problem solving ability, which was not shared with general anxiety; 12% of the heritability of mathematics anxiety was shared with that of mathematics problem solving, independently of general anxiety (Wang et al., 2014). These findings indicate that the association between mathematics anxiety and performance is largely domain-specific both phenotypically and aetiologically.

Mathematics anxiety and mathematics motivation

A study found that participants with high levels of mathematics anxiety were faster than less anxious participants at attempting to solve complex mathematics problems, but made twice as many errors. This behaviour has been interpreted as indicative of their desire to end the experience involving a mathematical content as soon as possible, disregarding performance outcomes (Ashcraft & Faust, 1994; Ashcraft & Kirk, 2001; Ashcraft, 2002).

The tendency to avoid mathematically relevant situations might be related to the fact that mathematics anxious individuals hold negative beliefs about their competence in mathematics, as proposed by the *Feedback Loop Model* (Wu et al., 2013, described in Chapter 1 of the present thesis). This is supported by several investigations that have observed a negative relation between mathematics anxiety, and mathematics self-efficacy and self-concept. Betz & Hackett (1983) investigated the relationship between mathematics anxiety, self-efficacy and achievement in a sample of college students. Using path analysis, they found that mathematics self-efficacy predicted mathematics anxiety to a greater extent than mathematics achievement did (Betz & Hackett, 1983). Another study found that mathematics self-efficacy, but not the value that students assigned to mathematics, mediated the association between mathematics anxiety and performance (Meece, Wigfield & Eccles, 1990).

Self-efficacy was also found to mediate the association between self-regulation – the cognitive and metacognitive capacity to develop strategies in order to achieve a learning outcome – and mathematics anxiety (Jain & Dowson, 2009). The authors suggested that higher self-regulation about numbers would contribute to the development of higher mathematics self-efficacy, which in turn would decrease anxiety towards mathematics (Jain & Dowson, 2009). The association between mathematics anxiety and motivation (measured as mathematics self-efficacy and self-concept) was found to differ cross-culturally. A study using data from the Programme for International Students Assessment (PISA) across 41 countries identified two main patterns of associations between mathematics anxiety and motivation. The first, mostly observed in Asian countries, was characterised by students showing on average lower levels of self-efficacy, lower self-concept and higher levels of mathematics anxiety. The second, mostly observed in Western countries, included students showing higher levels of self-concept and self-efficacy and lower levels of anxiety. These differential associations were observed independently of achievement (Lee, 2009). Findings might be interpreted in light of the cultural differences in how success in mathematics, and academic success more generally, are perceived by society. The emphasis on academic success prevalent in Asian countries might contribute to create comparatively higher levels of anxiety and lower levels of self-efficacy and self-concept, which are observed although on average Asian countries show higher levels of mathematics achievement (Lee, 2009). However, another study exploring cross-cultural variation in the motivation-anxiety relationship did not find support for such differential associations in a sample of university students from Malaysia (Kargar, Tarmizi & Bayat, 2010).

Negative associations between mathematics self-efficacy and self-concept and mathematics anxiety were also observed in restricted samples of pre-service teachers cross culturally, with correlations ranging from −.40 to −.80 (Hoffman, 2010; Isiksal, Curran, Koc & Askun, 2009). Interestingly, one study found that, when dealing with easy mathematics problems, teachers who were high in self-efficacy and high in anxiety did better than those with low self-efficacy and high anxiety. Results seemed to indicate that self-efficacy could act as a compensating factor in the negative relation between mathematics anxiety problem-solving efficiency (Isiksal et al., 2009).

In line with this, another study found that mathematics intrinsic motivation moderated the association between mathematics anxiety and performance in several aspects of mathematical cognition, including counting, problem solving and quantitative reasoning (Wang, Lukowski, Hart, Lyons, Thompson, Kovas, et al., 2015). The study explored the association between mathematics anxiety, mathematics intrinsic motivation and achievement in a population representative sample of 12-year-olds. Results showed that, for the group high in intrinsic motivation, the association between anxiety and performance in mathematics had an inverted U shape, suggesting that moderate levels of anxiety were actually beneficial for performance. On the other hand, for the group low in intrinsic motivation, the relation between mathematics anxiety and achievement was linear and negative. These findings suggest that mathematics anxiety has a negative impact on performance mostly when it co-occurs with low intrinsic motivation. On the other hand, students high in mathematics motivation perform at their best when experiencing moderate levels of mathematics anxiety. Performance was impaired in those students who were high in motivation and either very high or very low in mathematics anxiety. The findings were replicated in an adult sample of university students (Wang et al., 2015).

Overall findings point to the importance of motivation in the mathematics anxiety-achievement relationship. Mathematics motivation may in fact play a role in the regulation of the negative effects of mathematics anxiety. However, it is not clear how the association between mathematics anxiety, motivation and performance emerges, and specifically what the origins of their co-occurrence are. To date, no study has explored the association between mathematics anxiety and mathematics motivation using a genetically informative design, and therefore the aetiology of their association remains unknown. As mathematics anxiety and motivation were found to correlate substantially (e.g. Wang et al., 2015), and genetic factors were found to contribute moderately to the aetiology of both mathematics anxiety and mathematics motivation (Wang et al, 2014; Luo, Kovas, Haworth, & Plomin, 2011), it is plausible that common genetic influences underlie their co-occurrence.

Genetic factors were found to be the main aetiological source behind the co-variation between mathematics motivation and achievement in a large sample of twin from the United Kingdom, both when the twins were 9 and 12 years old (Luo et al., 2011). Using a longitudinal, genetically informative design, the study found that genetic factors were largely responsible for the reciprocal relationship observed between mathematics motivation and achievement over time. Shared environmental influences, the experiences shared by siblings raised in the same family, were not found to play a role in explaining the longitudinal relationship between motivation and achievement in mathematics (Luo et al., 2011). The study used a composite measure of mathematics self-efficacy and interest, and it remains unclear how these two aspects of motivation relate independently to mathematics performance. Furthermore, the study included teacher ratings as measure of mathematics achievement, and it is unclear how mathematics motivation relates to different aspects of mathematics performance and ability, such as for example problem solving ability, understanding numbers and number sense (numerosity).

Only one study to date has explored the association between mathematics anxiety and performance, finding a specific link between mathematics anxiety and problem solving ability in a sample of 12 year-old twins from the United States (Wang et al., 2014). Furthermore, the investigation found that the aetiological association between mathematics anxiety and achievement was partly domain-specific, as it was observed after accounting for the aetiology they both shared with general anxiety. However, the Wang et al. study included a small sample, which might not have allowed enough power to detect smaller effect sizes or discriminate between aetiological influences. Additionally, the study focused on exploring the association between mathematics anxiety and mathematics problem solving ability, and it remains unclear how mathematics anxiety relates to other aspects of mathematics performance, phenotypically and aetiologically.

Aims of the present research

Several questions remain unanswered about the reasons behind the co-occurrence of mathematics anxiety, motivation and performance. No study to date has explored the origins of their trivariate association. Studying the association between anxiety, motivation and performance within a multivariate, genetically informative design represents a step towards an enhanced understanding of the origins of their co-occurrence. Consequently, the present study has six main aims:

(1) To explore whether mathematics anxiety similarly relates to two different aspects of mathematics motivation: self-efficacy and interest. A large body of existing research has mostly focused on self-efficacy, and the association between mathematics anxiety and mathematics interest has been mostly neglected.

(2) To examine, for the first time, the aetiology of the co-occurrence of mathematics anxiety and two measures of mathematics motivation: interest and self-efficacy.

(3) To explore whether similar associations can be observed between mathematics anxiety and several aspects of mathematics performance, including measures of achievement (GCSE exam scores) and abilities (understanding numbers, problem solving, and number sense).

(4) To investigate for the first time the origins of the associations between mathematics anxiety and these several aspects of mathematics performance.

(5) To explore origins of the co-variation between mathematics anxiety, motivation and performance within a multivariate, genetically informative design, with the aim of identifying the sources behind the co-occurrence of these traits.

(6) To explore whether the multivariate association between mathematics anxiety, motivation and performance is specific to the domain of mathematics, or whether part of their phenotypic and/or aetiological overlap is also shared with domain-general anxiety.

Methods

Participants

Participants were members of the Twins Early Development Study (TEDS), a population-based longitudinal study of twins from the United Kingdom. Over 15,000 families from England and Wales with twins born between 1994 and 1996 took part in TEDS at first contact, and more than 10,000 twins are still actively participating at the study (Haworth, Davis & Plomin, 2013). The families in TEDS are representative of the British population in their socio-economic distribution, ethnicity and parental occupation (Oliver & Plomin, 2007). The present study focuses on data collected when the twins were 16 and the following collection when the twins were aged 18-21. At age 16, a representative sample of TEDS twins contributed data on mathematics ability (N = 2,681 pairs, 5,362 twins; N MZ = 2080; N DZ = 3,508; 60% females), mathematics achievement (N = 3,410 pairs, 6,820 twins; N MZ = 2,612; N DZ = 4,508; 56% females) and mathematics motivation (N = 2,505 pairs, 5,010 twins; N MZ = 1,954; N DZ = 3,270; 61.2% females). At age 18-21, a representative sample of TEDS twins contributed data on mathematics anxiety and general anxiety (N = 1,506 pairs, 3,012 twins; N MZ = 1,172; N DZ = 1,846; 63.9% females).

Measures

Mathematics Anxiety

A modified version of the Abbreviated Math Anxiety Scale (AMAS; Hopko et al., 2003) was administered to the twins at age 18-21 to assess mathematics anxiety. The AMAS asks participants to rate how anxious they would feel when facing several mathematics-related activities. The measure includes 9 items that are rated on a 5-point scale ranging from 'not nervous at all' to 'very nervous'. Examples of items are: '*Reading a maths book*' and '*Listening to a maths lecture*'. We modified some of the existing items slightly in order to make the scale age appropriate for our sample, as all of our participants had left school, and some were no longer in education (see SOM). The AMAS has been widely used and shows excellent internal validity (α = .90; Hopko et al., 2003). Our modified version of the AMAS also showed excellent internal validity (α = .94) and previously showed good test-retest reliability (r = .85). All items included in the scale are presented in Chapter 2, Table 2.1.

General Anxiety

The Generalized Anxiety Disorder Scale (GAD-7; Löwe et al., 2008) was used to assess general anxiety and administered with the same online battery as the AMAS. The scale includes 7 items and asks participants to rate on a scale from 1 = not at all to 4 = nearly every day: 'How often in the past month have you been bothered by the following problems?' Examples of items are: 'Not being able to control worrying', and 'Feeling afraid as if something awful might happen'. The GAD-7 was previously found to be internally valid (α = .89) and reliable (test-retest correlation of r = .64, Löwe et al., 2008). In our sample the GAD-7 was also found to be internally valid (α = .91). The full scale is presented in Chapter 2, Table 2.1.

Mathematics motivation

Mathematics self-efficacy and interest were measured two scales adapted from the OECD Programme for International Student Assessment (www.pisa.oecd.org). The **mathematics self-efficacy** scale asked participants: '*How confident do you feel about having to do the following mathematics tasks?*' The scale included 8 items that participants had to rate on a 4-point scale from 0 = not at all confident to 3 = very confident, for a maximum total score of 24. Examples of items included are: ‘*Understanding graphs presented in newspapers’*, ‘*Solving an equation like 3x + 5 = 17’*, and ‘*Finding the actual distance between two places on a map with a 1:10,000 scale’*. The **mathematics interest** scale included 3 items that participants had to rate on a 4-point scale, from 0 = strongly disagree to 3 = strongly agree. The three items were: (a) ‘*I look forward to my mathematics lessons*’; (b) ‘*I do mathematics because I enjoy it*’; and (c) ‘*I am interested in the things I learn in mathematics*’. This created a maximum total score of 12 for mathematics interest.

Mathematics achievement and abilities

Mathematics school achievement was measured using General Certificate of Secondary Education (GCSE) grades. The GCSE exams are taken nationwide in the UK at the end of the compulsory education, usually when students are 16-years-old. GCSE courses include several different subjects, with students usually taking 10 GCSE courses. Only three subjects and GCSE exams are compulsory across all schools in the UK: English, mathematics and Science; additionally some schools require one modern foreign language and/or English literature. For the present study mathematics GCSE scores were collected by questionnaires sent to the parents of the twins or to the twins themselves in the post or via email, or through a phone interview. The GCSE grades, which are given in letters from A* to G, were then coded on a scale from 11, corresponding to A*, the highest grade, to 4 corresponding to G, the lowest pass grade; no information about failed results was available.

The **understanding numbers** test consisted of a series of 18 mathematical questions arranged in ascending level of difficulty. The test was administered online as part of a larger battery of cognitive tests (also including the number sense test, and the problem verification test described below). The format in which the questions were presented varied depending on the item. Some items required participants to type a numerical response into a box, whereas other questions asked participants to select one or more correct responses out of a set of possible options. Each correct answer was allocated 1 point, and incorrect answers were awarded 0 points, this creates a maximum total score of 18. An example for the easy items is: ‘*Please type the correct number in each box: 123 + __ =123; 123 - __ = 123; 123 x __ = 123; and 123 ÷*

__ = *123*' with the correct answers being 0,0,1, and 0. An example representing the more difficult items is: '*Denise has thought of two numbers. The numbers added together make 23.The smaller number subtracted from twice the larger number makes 22. What are Denise's numbers?*'; with numbers 8 and 15 being the correct answers.

The **problem verification test** (PVT, Murphy & Mazzocco, 2008) presented participants with a series of mathematics equations appearing for 10 seconds on a computer screen. Participants were asked to judge whether each equation was correct, incorrect, or whether they did not know, by pressing the corresponding key on the computer keyboard. Once the 10 seconds ran out, participants were automatically redirected to the following equation. The PVT included 48 items. Each correct response was allocated the score of 1 and other responses the score of 0, for a maximum score of 48. Examples of items are: (a) *'32 – 16 = 14'*; (b) *'2/6 = 3/9'*; and (c) '*28 ÷ 16 = 32*'.

The **number sense** test (Halbeda, Mazzocco, & Feigenson, 2008) was administered online as part of a larger cognitive battery. The test included 150 trials displaying arrays of yellow and blue dots, varying in size. Each trial was presented for 400 ms and included a different number of blue and yellow dots presented on the screen. Participants were required to judge whether there were more yellow or blue dots on the screen for each trial, and each correct answer was allocated the score of 1. Additional information on this task is reported in Tosto et al., 2014.

Analyses

Phenotypic Analyses

All phenotypic analyses were conducted randomly selecting one twin out of each pair in order to control for non-independence of observation (i.e. the fact that the children in the study were twins). The results were replicated when the other twin in the pair was selected. Distributions of the measures and their associations were examined using descriptive statistics and correlation analyses. Univariate analyses of variance (ANOVAs) were carried out to explore phenotypic sex differences in all measures.

Genetic Analyses

Using univariate genetic analysis, it is possible to explore the origins of individual differences in a trait. The univariate model decomposes the variance of a single trait into genetic and environmental sources of variance based on the comparison of intraclass correlations for MZ and DZ twin pairs (Martin & Eaves, 1977). The univariate ACE/ADE model (described in Chapter 2, Methods) was employed to explore the origins of individual differences in mathematics anxiety, general anxiety, and mathematics motivation and performance. After examining intraclass correlations (see Chapter 2 Methods) for MZ and DZ twin pairs, three univariate ACE models were conducted to explore the aetiology of individual differences in: (1) mathematics GCSE, (2) understanding numbers, and (3) mathematics PVT. The univariate ACE model allows for the decomposition of the variance of a trait into additive genetic (A), shared environmental (C) and non-shared environmental (E) influences; and it was selected because the intraclass correlations for DZ twins were more than half than those observed for MZ twins. In addition, five univariate ADE models were carried out to examine the origins of individual differences in: (1) mathematics anxiety, (2) general anxiety, (3) mathematics interest, (4) mathematics self-efficacy, and (5) number sense. The ADE decomposes the variance in a trait into additive genetic (A), non-additive genetic (D) and non-shared environmental (E) sources of influences; and was selected because the intraclass correlations observed for DZ twins were less than half those for MZ twins (please refer to Chapter 2 Methods section for more details on the ACE and ADE models).

The logic of the twin method, explained in the Methods section of Chapter 2, can be extended to examine the aetiology of the covariance between two or more traits (multivariate genetic analysis). Multivariate genetic analysis allows for the decomposition of the correlation between two traits into genetic and environmental sources of variance. Therefore, the method estimates the extent to which the same genes and the same environments are implicated in the correlation between traits.

Multivariate genetic analysis estimates the aetiology of the covariance between traits by comparing the cross-trait twin correlations for those traits (described in Chapter 2, Methods). To the extent that the cross-twin cross-trait correlation of MZ twin pairs is larger than that of DZ pairs, the phenotypic covariance between two traits will be partly, or entirely, attributable to genetic factors common to both traits. The fact that the same genes can influence several traits is a concept known as pleiotropy (Lynch & Walsh, 1998), and is indexed by the genetic correlation between traits. Chapter 2 of the present thesis describes in detail the multivariate correlated factors model, which allows for the exploration of the aetiology of the correlation between pairs of variables.

The study described in this chapter applied the correlated factors model to the exploration of the origins of the correlation between mathematics anxiety, mathematics motivation and mathematics achievement and abilities.

<u>Multivariate Cholesky Decomposition</u>

A Cholesky decomposition (see Chapter 2 of the present thesis – Methods) was conducted in order to explore the origins of the covariation between mathematics anxiety and all mathematics-related measures. A further Cholesky decomposition was carried out explore the domain-specificity of the common aetiology between mathematics anxiety, motivation and performance, after accounting for the aetiology that all measures shared with general anxiety.

Results

Phenotypic analyses

Descriptive statistics and correlations

Descriptive statistics are reported in Table 3.1. All variables met the criteria for normal distribution. Descriptive statistics for monozygotic (MZ), same-sex dizygotic (DZ SS) and opposite-sex dizygotic (DZ OS) twins separately are presented in Table 3.2.

Table 3.1. Descriptive statistics for all the variables included in the study

	Maths Anxiety	General Anxiety	Maths Interest	Maths Self-Eff	Maths GCSE grade	Underst. numbers	Maths PVT	Number sense
N*	1457	1457	2506	2505	3410	2237	2345	2602
Mean	2.27	1.97	2.54	17.71	8.91	11.55	36.08	24.21
St Dev	1.00	0.74	0.94	5.47	1.46	4.33	6.69	3.18
Skew	0.79	0.84	-0.07	-0.90	-0.55	-0.77	-0.58	-0.77
SE Skew	0.06	0.06	0.05	0.05	0.04	0.05	0.05	0.05
Kurtosis	-0.16	0.03	-0.99	0.28	0.29	0.15	-0.21	1.10
SE Kurt	0.13	0.13	0.10	0.10	0.08	0.10	0.10	0.10
Minimum	1	1	1	0	4	0	15	8
Maximum	5	4	4	24	11	18	48	31

Note: St Dev = standard deviation; SE = standard error; * one twin out of each pair was randomly selected.

Correlations between variables are reported in Table 3.3, and the number of participants included in all pairwise associations in Table 3.4. Mathematics anxiety was found to share a moderate positive correlation with general anxiety (*r* = .36), and was negatively associated with all mathematics achievement and abilities (*r* = -.35). Mathematics anxiety also shared a moderate negative association with measures of mathematics motivation (average *r* = -.46). The correlation between general anxiety and mathematics performance was weak (average *r* = -.10), as was the correlation between general anxiety and mathematics motivation (average *r* = -.13).

Table 3.3. Phenotypic correlations between variables

	1	2	3	4	5	6	7	8
1. Maths anxiety	1	.36**	-.45**	-.48**	-.37**	-.33**	-.37**	-.10**
2. General anxiety		1	-.10**	-.16**	-.13**	-.10**	-.12**	-0.03
3. Maths interest			1	.54**	.46**	.38**	.39**	.12**
4. Maths self-efficacy				1	.66**	.59**	.57**	.19**
5. Maths GCSE					1	.72**	.64**	.22**
6. Understand Numbers						1	.64**	.26**
7. Maths PVT							1	.28**
8. Number Sense								1

Note: ** p< .01.

Table 3.4. Number of participants for pairwise phenotypic associations

	1	2	3	4	5	6	7	8
1. Maths anxiety	1457	1457	1448	1447	1335	1402	1411	1378
2. General anxiety		1457	1448	1447	1335	1402	1411	1378
3. Maths interest			2506	2504	2192	2223	2332	2371
4. Maths self-efficacy				2505	2191	2222	2331	2370
5. Maths GCSE					3410	1985	2083	2249
6. Und. Numbers						2237	2168	2117
7. Maths PVT							2345	2219
8. Number Sense								2602

Note: one twin out of each pair was selected to control for non-independence of observation.

In order to explore whether general anxiety contributed to the phenotypic associations between mathematics anxiety and mathematics outcomes, a series of partial correlations were carried out. Partial correlation analyses controlling for general anxiety (see Table 3.5), showed that most correlation estimates remained largely unchanged. This indicates that general anxiety does not account for a portion of the moderate phenotypic associations between mathematics anxiety and mathematics motivation and performance.

Table 3.5. Partial correlations accounting for general anxiety

	1	2	3	4	5	6	7
1. Maths anxiety	1.00	-.44**	-.46**	-.33**	-.34**	-.37**	-.11**
2. Maths interest		1.00	.53**	.45**	.37**	.41**	.15**
3. Maths self-efficacy			1.00	.62**	.56**	.56**	.19**
4. Maths GCSE				1.00	.71**	.64**	.19**
5. Understand Numbers					1.00	.62**	.24**
6. Maths PVT						1.00	.29**
7. Number sense							1.00

Note: control variable = general anxiety; ** = p< .01 level; N = 1179 (one twin out of each pair was randomly selected)

Table 3.2. Descriptive statistics for MZ, DZ SS and DZ OS twins separately

	Mathematics anxiety			General anxiety			Mathematics interest		
	MZ	**DZ SS**	**DZ OS**	**MZ**	**DZ SS**	**DZ OS**	**MZ**	**DZ SS**	**DZ OS**
N*	586	479	444	586	479	444	977	840	796
Mean	2.27	2.28	2.27	1.95	1.93	2.02	2.54	2.54	2.51
St Deviation	0.99	1.01	1.01	0.73	0.73	0.76	0.94	0.93	0.95
Skewness	0.76	0.81	0.78	0.87	0.87	0.77	-0.06	-0.09	-0.06
Kurtosis	-0.17	-0.19	-0.21	0.23	0.06	-0.25	-1.00	-0.96	-1.05
	Mathematics self-efficacy			Mathematics GCSE grade			Understanding numbers		
	MZ	**DZ SS**	**DZ OS**	**MZ**	**DZ SS**	**DZ OS**	**MZ**	**DZ SS**	**DZ OS**
N*	977	840	795	1306	1122	1132	881	752	695
Mean	17.55	17.55	17.87	8.87	8.90	8.91	11.30	11.48	11.84
St Deviation	5.37	5.73	5.42	1.46	1.47	1.46	4.33	4.53	4.17
Skewness (St error)	-0.80	-0.94	-0.95	-0.51	-0.53	-0.60	-0.74	-0.74	-0.84
Kurtosis (St error)	0.02	0.33	0.43	0.26	0.22	0.47	0.09	-0.08	0.43
	Mathematics Problem Verification Test (PVT)			Number Sense					
	MZ	**MZ**	**MZ**	**MZ**	**MZ**	**DZ SS**			
N*	913	1009	1009	1009	913	773			
Mean	35.73	24.07	24.07	24.07	35.73	36.08			
St Deviation	6.57	3.15	3.15	3.15	6.57	6.61			
Skewness (St error)	-0.53	-0.79	-0.79	-0.79	-0.53	-0.55			
Kurtosis (St error)	-0.11	1.25	1.25	1.25	-0.11	-0.32			

Sex differences in anxiety, motivation and performance

Eight univariate ANOVAs were performed to explore sex differences in all variables (see Table 3.6). Levene's test showed that variances were comparable across males and females. Significant sex differences were observed; however, sex explained a relatively small portion of the variance in all measures. Sex differences were found to explain 7% of the variance in mathematics anxiety and 5% of the variance in general anxiety, with females showing higher levels of anxiety than males. Males showed higher levels of mathematics interest and self-efficacy, with sex explaining 2% and 7% of the variance, respectively. Males also showed higher levels of mathematics performance in all the tasks, with sex explaining 1-6% of the variance.

Table 3.6. Univariate analyses of variance (ANOVAs) examining sex differences in all variables

	Female *M (SD), N*	*Male* *M (SD), N*	*F*	*Partial η2*
General Anxiety	2.09 (.77) *N* = 938	1.74 (.62) *N* = 519	77.15**	0.05
Mathematics Anxiety	2.45 (1.04) *N* = 938	1.91 (.79) *N* = 519	101.58**	0.07
Mathematics interest	2.42(.95) *N* = 1474	2.69(.89) *N* = 1032	48.37**	0.02
Mathematics self-efficacy	16.51(5.60) *N* = 1473	19.40(4.78) *N* = 1032	181.65**	0.07
Maths GCSE grade	8.80 (1.48) *N* = 1812	9.03 (1.41) *N* = 1598	20.48**	0.06
Understanding numbers	11.00 (4.40) *N* = 1317	12.35(4.08) *N* = 920	54.13**	0.02
Maths PVT	34.81(6.46) *N* = 1364	37.85(6.58) *N* = 981	124.700**	0.05
Number sense (dot task)	24.05(3.14) *N* = 1510	24.44(3.21) *N* = 1092	9.21**	0.01

Note: one twin out of each pair was selected to control for non-independence of observation; ** = $p < .01$.

Genetic analyses

Full Sex limitation model

As significant, albeit small, phenotypic sex differences were observed in all measures, the full sex limitation model was applied to the investigation of whether sex differences existed in their aetiologies. The full sex limitation model allows to examine the possibility that qualitative and/or quantitative sex differences characterise the aetiology of a trait (see Chapter 2 for a description of the method). After conducting model fitting, qualitative sex differences were not found for any of the measures, indicating that the same factors are implicated in the aetiology of the traits for males and females.

Some quantitative sex differences were observed for all measures, with two exceptions: mathematics PVT and number sense. Quantitative sex differences suggest that the heritability, shared and nonshared environmental estimates are different for males and females. Although the *p* value derived from model fitting indicated that the aetiology of mathematics, anxiety, general anxiety, interest, self-efficacy, GCSE score, and understanding numbers was different for males and females, confidence intervals around the A, C and E estimates were largely overlapping between males and females. Table 3.7 reports univariate estimates and 95% confidence intervals around the estimates for males and females separately. As confidence intervals overlapped between the estimates obtained for males and females for all the measures, all twin pairs (also opposite sex DZ twins) were included in the following analyses, in order to maximise power.

Table 3.7. Univariate additive genetic (A), shared environmental (C) and nonshared environmental (E) estimates for males and females separately (95% confidence intervals).

	Am	Af	Cm	Cf	Em	Ef
MA	.06 (.00, .33)	.41 (.32, 48)	.35 (.18, .45)	.02 (.00, .20)	.65 (.55, .77)	.59 (.51, .67)
GA	.35 (.00, .54)	.32 (.08, .46)	.12 (.00, .45)	.08 (.00, .29)	.53 (.43, .65)	.60 (.53, .68)
M int	.32 (.04, .48)	.41 (.22, .52)	.18 (.00, .30)	.05 (.00, .23)	.60 (.52, .70)	.54 (.48, .60)
M self-eff	.38 (.18, .57)	.56 (.47, .61)	.26 (.08, .43)	.01 (.00, .09)	.36 (.41, .43)	.43 (.38, .48)

M GCSE	.76 (.60, .82)	.47 (.36, .60)	.05 (.00, .19)	.35 (.19, .45)	.19 (.16, .22)	.18 (.16, .22)
UN	.38 (.16, .66)	.63 (.42, .68)	.23 (.00, .41)	.01 (.00, .21)	.39 (.33, .46)	.36 (.31, .41)
PVT	.61 (.42, .67)	.57 (.43, .62)	.00 (.00, .17)	.00 (.00, .12)	.39 (.33, .46)	.43 (.38, .48)
NS	.34 (.12, .44)	.33 (.13, .42)	.02 (.00, .19)	.02 (.00, .18)	.64 (.56, .73)	.65 (.58, .73)

Note: Am = estimate of genetic effects for males; Cm = estimates of shared environmental effects for males; Em = estimates of nonshared environmental effects for males; Af = estimate of genetic effects for females; Cf = estimates of shared environmental effects for females; Ef = estimates of nonshared environmental effects for females; MA = mathematics anxiety; GA =general anxiety; M int = mathematics interest; M self-eff = mathematics self-efficacy; M GCSE = mathematics GCSE; UN = understanding numbers; PVT = mathematics problem verification test; NS = number sense.

The origins of variation in mathematics related traits: Univariate Genetic Analyses

Consequently eight univariate models were conducted on the entire sample in order to explore the origins of individual differences in all mathematics-related traits. Based on intraclass correlations (described in Chapter 2), three ACE models were conducted to explore the origins of individual differences in mathematics GCSE results, understanding numbers, and number sense. The ACE model was chosen, as the correlation between MZ twins for those measures was less than double that of DZ twins, indicating the potential shared environmental influences in the aetiology of the measures. Additionally, five ADE models were carried out to explore the origins of individual differences in mathematics anxiety, general anxiety, mathematics interest, mathematics self-efficacy, and mathematics PVT. The ADE model was selected, as the MZ twin correlation for all measures was more than double that of DZ twins, consequently indicating non-additive genetic influence. Table 3.8 reports intraclass correlations and univariate A, C (D) and E estimates for all the measures included in the present study. As described in more detail in Chapter 2, structural equation model fitting allows to compare the ACE/ADE full model to more parsimonious models, including two (AE, CE, DE) or one (E) sources of variance. Table 3.9 presents model fit indices for all the univariate models and nested models.

Table 3.8. Intraclass correlations, heritability, shared and nonshared environmental estimates for all measures with 95% confidence intervals.

	rMZ	rDZ	A	C	D	E
Maths Anxiety	.43**	.09**	.37 (.29, .43)	-	-	.63 (.57, .70)
Gen Anxiety	.44**	.17**	.41 (.34, .48)	-	-	.59 (.52, .64)
Maths interest	.43**	.18**	.43 (.37, .48)	-	-	.57 (.53, .62)
Maths self-eff	.59**	.25**	.58 (.52, .63)	-	-	.42 (.42, .46)
Maths GCSE	.82**	.49**	.62 (.54, .71)	.19 (.11, .26)	-	.19 (.18, .20)
Und numbers	.61**	.34**	.63 (.58, .68)	-	-	.36 (.33, .40)
Maths PVT	.56**	.23**	.59 (.47, .64)	-	-	.41 (.38, .45)
Number sense	.33**	.19**	.36 (.29, .42)	-	-	.64 (.59, .69)

Note: ** = p< .01; 95% confidence intervals in parentheses, A = additive genetic influences; D = non-additive genetic influences; C= shared environmental influences; E = nonshared environmental influences.

With the exception of mathematics GCSE scores, the AE model was found to be the best fit for the data for all mathematics-related traits. In fact, dropping the C or D paths did not significantly decrease the goodness of fit of the univariate models. The only exception was observed for the aetiology of mathematics GCSE, for which dropping the C variance component resulted in a significant decrease in goodness of fit of the model (see Table 3.9). This indicates that environmental factors shared between family members significantly contribute to individual differences in mathematics GCSE scores. Estimates of heritability were moderate for mathematics and general anxiety, mathematics interest and number sense (36-43%) and strong for all other mathematics variables (58-63%). The remaining variance was mostly explained by non-shared environmental factors, which also include measurement error. Shared environmental factors, those that contribute to similarities between twins raised in the same family, explained 18% of the variance in mathematics GCSE scores.

Table 3.9. Model fit indices for all univariate models and nested models

	Baseline	Comparison	-2LL	df	AIC	*p*
(a) Mathematics Anxiety						
1	Saturated	-	8173.964	2919	2335.964	NA
2	Saturated	ADE	8180.603	2925	2330.603	0.356
3	**ADE**	**AE**	**8191.810**	**2926**	**2339.810**	**0.028**
4	ACE	E	8286.672	2927	2432.672	0.000
(b) General Anxiety						
1	Saturated	-	8150.253	2919	2312.253	NA
2	Saturated	ADE	8154.761	2925	2304.761	0.608
3	**ADE**	**AE**	**8155.145**	**2926**	**2303.145**	**0.535**
4	ADE	E	8286.672	2927	2432.672	0.00
(c) Mathematics interest						
1	Saturated	-	14008.597	5019	3970.60	NA
2	Saturated	ADE	14013.891	5025	3963.89	0.507
3	**ADE**	**AE**	**14015.521**	**5026**	**3963.52**	**0.202**
5	ADE	E	14244.217	5027	4190.22	0.000
(d) Mathematics self-efficacy						
1	Saturated	-	13795.712	5020	3755.712	NA
2	Saturated	ADE	13796.995	5026	3744.995	0.973
3	**ADE**	**AE**	**13798.807**	**5027**	**3744.807**	**0.178**
4	ADE	E	14247.055	5028	4191.055	0.000
(e) Mathematics GCSE grade						
1	Saturated	-	12219.407	4767	2685.407	NA
2	**Saturated**	**ACE**	**12220.770**	**4773**	**2674.770**	**0.968**
3	ACE	AE	12240.237	4774	2692.238	0.000
4	ACE	CE	12458.058	4774	2910.058	0.000
5	ACE	E	13529.263	4775	3979.263	0.000
(f) Understanding numbers						
1	Saturated	-	12161.345	4473	3215.345	NA
2	Saturated	ACE	12166.992	4479	3208.992	0.464
3	**ACE**	**AE**	**12168.361**	**4480**	**3208.362**	**0.242**
4	ACE	CE	12246.462	4480	3286.462	0.000
5	ACE	E	12695.163	4481	3733.163	0.000
(g) Mathematics Problem Verification Test						
1	Saturated	-	12845.662	4677	3491.662	NA
2	Saturated	ACE	12848.623	4683	3482.623	0.814

3	**ACE**	**AE**	**12848.623**	**4684**	**3480.623**	**1.000**
4	ACE	CE	12927.622	4684	3559.622	0.000
5	ACE	E	13273.925	4685	3903.925	0.000
(h) Number sense						
1	Saturated	-	13358.946	4761	3836.946	NA
2	Saturated	ADE	13370.762	4767	3836.762	0.066
3	**ADE**	**AE**	**13370.762**	**4768**	**3834.762**	**1.000**
4	ADE	E	13512.241	4769	3974.241	0.000

Note: ep = estimated parameters; -2LL = negative 2 times log likelihood; df = degrees of freedom; AIC = Akaike Information Criterion.

The origins of the correlations between mathematics anxiety, motivation, achievement and abilities: Bivariate Genetic Analyses

Cross-twin cross-trait correlations between all measures are reported in Table 3.10. Cross-twin cross-trait correlations for MZ twin (reported above the diagonal) were generally larger than those observed for DZ twin pairs (reported below the diagonal in Table 3.10), indicating genetic contribution to the covariance between pairs of variables.

Six bivariate ACE models were conducted in order to explore the origins of the correlations between mathematics anxiety and mathematics motivation and performance. Strong genetic correlations were observed between mathematics anxiety and all other traits. In fact, genetic factors were found to explain more than half (52-88%) of the moderate phenotypic correlations between mathematics anxiety and all other measures (see Table 3.11). This indicates that the moderate negative correlations between mathematics anxiety and mathematics motivation and performance are mostly explained by their genetic overlap. The fact that the same genes can influence several traits is described as pleiotropy. Pleiotropic effects were observed between mathematics anxiety and each one of the other mathematics-related measures. Nonshared environmental factors explained the remaining proportions of the phenotypic associations between mathematics anxiety and all other mathematics-related outcomes. Shared environmental influences did not to contribute to the phenotypic associations between mathematics anxiety, motivation and performance. The correlation between mathematics anxiety and number sense was significantly weaker if compared to all other associations (*r* = -.09; CIs = -.13; -.03), suggesting a differential relationship between mathematics anxiety and the ability to discriminate numerosity if compared to all other mathematics outcomes. Comparatively weaker correlations were also observed between mathematics interest and self-efficacy and number sense (*r* = .12; CIs = .08; .15; and *r* = .18; CIs = .15; .20, respectively; see Table 3.13 and Table 3.15). Nevertheless, to the extent that mathematics anxiety and motivation correlated with number sense ability, this was mostly explained by shared genetic influences (61-81%). Table 3.12 reports model fit indices for the bivariate models between mathematics anxiety and all other mathematics-related outcomes.

Table 3.11. Phenotypic (r_P), genetic (r_A), shared environmental (r_C) and non-shared environmental (r_E) correlations for pairwise associations between mathematics anxiety and mathematics-related outcomes.

Pairs of variables	r_P (95% CI)	r_A (95% CI) *Proportion of r_P*	r_C (95% CI) *Proportion of r_P*	r_E (95% CI) *Proportion of r_P*
M anxiety & M INT	-.42 (-.46; -.39)	-.56 (-.76; -.46)	-.00 (-.00; .00)	-.34 (-.40; -.27)
		52%	*0%*	*48%*
M anxiety & M S-E	-.44 (-.47; -.41)	-.56 (-.72; -.47)	-.00 (-.00; .00)	-.35 (-.41; -.28)
		59%	*0%*	*41%*
M anxiety & M GCSE	-.34 (-.38; -.31)	-.73 (-.95; -.56)	-.00 (-.00; .00)	-.24 (-.32; -.16)
		75%	*0%*	*25%*
M anxiety & UN	-.30 (-.33; -.26)	-.61 (-.88; -.41)	-1.00(-.100; .00)	-.16 (-.24; -.08)
		88%	*0%*	*22%*
M anxiety & M PVT	-.34 (-.37; -.31)	-.65 (-.93; -.46)	-1.00(-.100; .00)	-.18 (-.25; -.10)
		72%	*-.09%*	*28%*
M anxiety & NS	-.09 (-.13; -.03)	-.17 (-.47; -.04)	-.00 (-.00; .00)	-.52 (-.13; -.02)
		63%	*0%*	*37%*

Note: M anxiety = maths anxiety; M INT = mathematics interest; M S-E = mathematics self-efficacy; M GCSE = mathematics GCSE score; UN =

understanding numbers; M PVT = mathematics problem verification test; NS = number sense; 95% CI = 95% confidence intervals; r_A= genetic correlation; r_C = shared environmental correlation; r_E = nonshared environmental correlation; r_P = phenotypic correlation.

Table 3.10. Cross-twin cross-trait association between mathematics anxiety, motivation and performance for MZ and DZ twin pairs.

	MA 1	INT 1	S-EFF 1	GCSE 1	UN 1	PVT 1	NS 1	MA 2	INT 2	S-EFF 2	GCSE 2	UN 2	PVT 2	NS 2
MA 1	--	-.42	-.44	-.30	-.29	-.34	-.12	.44	**-.28**	**-.29**	**-.21**	**-.21**	**-.27**	**-.07**
INT 1	-.41	--	.51	.44	.38	.38	.08	**-.29**	.47	**.37**	**.34**	**.29**	**.31**	**.04**
S-EFF 1	-.44	.51	--	.58	.58	.55	.14	**-.29**	**.32**	.62	**.51**	**.41**	**.40**	**.02**
GCSE 1	-.40	.46	.59	--	.64	.58	.16	**-.25**	**.27**	**.55**	.81	**.58**	**.55**	**.09**
UN 1	-.35	.39	.52	.67	--	.59	.21	**-.23**	**.25**	**.50**	**.59**	.55	**.48**	**.15**
PVT 1	-.37	.41	.50	.64	.59	--	.17	**-.23**	**.20**	**.42**	**.49**	**.46**	.53	**.14**
NS 1	-.13	.19	.16	.16	.20	.28	--	**.02**	**.00**	**.03**	**.13**	**.18**	**.12**	.38
MA 2	.08	***-.06***	***-.04***	***.00***	***.01***	***-.01***	***.02***	--	-.46	-.44	-.31	-.26	-.35	-.03
INT 2	***-.04***	.18	***.12***	***.08***	***.04***	***.11***	***-.01***	-.42	--	.49	.38	.30	.33	.00
S-EFF 2	***-.10***	***.17***	.22	***.28***	***.20***	***.20***	***.03***	-.39	.46	--	.61	.50	.52	.10
GCSE 2	***-.10***	***.23***	***.27***	.49	***.34***	***.29***	***.01***	-.31	.35	.56	--	.64	.62	.14
UN 2	***-.05***	***.14***	***.17***	***.32***	.30	***.28***	***.07***	-.27	.30	.46	.62	--	.55	.21
PVT 2	***-.11***	***.13***	***.18***	***.28***	***.29***	.29	***.06***	-.31	.37	.47	.57	.59	--	.25
NS 2	***-.10***	***.08***	***.11***	***.13***	***.15***	***.15***	.14	-.08	.06	.15	.22	.28	.28	--

Note: MZ twin correlations are shown above the diagonal and DZ twin correlations are shown below the diagonal. Cross-twin cross-trait correlations are shown in the upper right quadrant for MZ twin pairs (**bolded and underlined**) and lower left quadrants for DZ twin pairs (***bolded and in Italic***); age and sex were regressed out from all variables; ^{ns} p > .05; MA = mathematics anxiety; INT = mathematics interest; S-EFF = mathematics self-efficacy; GCSE = mathematics GCSE score; UN = understanding numbers; PVT = mathematics problem verification test; NS = number sense; 1 = twin 1; 2 = twin 2.

Table 3.12. Model fit indices for bivariate correlated factors ACE models exploring the origins of the correlations between mathematics anxiety and all other mathematics-related measures.

	Baseline	Comparison	-2LL	df	AIC	*p*
(a) Mathematics anxiety & interest						
1	Saturated	-	21646.92	7930	5786.92	NA
2	Saturated	ACE	21671.96	7947	5777.96	0.09
(b) Mathematics anxiety & self-efficacy						
1	Saturated	-	21404.26	7931	5542.26	NA
2	Saturated	ACE	21428.11	7948	5532.11	0.12
(c) Mathematics anxiety & GCSE score						
1	Saturated	-	20041.41	7678	4685.41	NA
2	Saturated	ACE	20070.76	7695	4680.76	0.03
(d) Mathematics anxiety & understanding numbers						
1	Saturated	-	20087.96	7384	5319.96	NA
2	Saturated	ADE	20118.98	7401	5316.98	0.02
(e) Mathematics anxiety & PVT						
1	Saturated	-	20686.14	7588	5510.14	NA
2	**Saturated**	**ACE**	20719.12	7605	5509.12	0.01
(f) Mathematics anxiety & number sense						
1	Saturated	-	21502.88	7672	6158.88	NA
2	Saturated	ACE	21541.68	7689	6163.68	0.00

Note: ep = estimated parameters; -2LL = negative 2 times log likelihood; df = degrees of freedom; AIC = Akaike Information Criterion.

Five additional bivariate models were conducted to investigate the aetiology of the correlations between mathematics interest, mathematics self-efficacy and performance. Strong genetic correlations were observed between mathematics interest and all other mathematics-related outcomes. Similar to their associations with mathematics anxiety, genetic factors accounted for the largest portions (64-81%) of the moderate phenotypic correlations between traits (see Table 3.13 and Table 3.14 for model fit indices).

Table 3.13. Phenotypic (r_P), genetic (r_A), shared environmental (r_C), non-shared environmental (r_E) correlations for pairwise associations between mathematics interest, self-efficacy, achievement and ability.

Pairs of variables	**r_P (95% CI)**	**r_A (95% CI)**	**r_C (95% CI)**	**r_E (95% CI)**
		Proportion of r_P	***Proportion of r_P***	***Proportion of r_P***
M INT & M S-E	.53 (.51; .55)	.68 (.62; .75)	.00. (-.00; .00)	.39 (.34; .44)
		64%	*0%*	*36%*
M INT & M GCSE	.44 (.41; .45)	.59 (.48; .70)	1.00 (-1.00; .00)	.34 (.27; .39)
		75%	*0%*	*25%*
M INT & UN	.37 (.34; .41)	.62 (.48; .79)	1.00 (.00; 1.00)	.19 (.13; .26)
		76%	*0%*	*24%*
M INT & M PVT	.38 (.36; .41)	.55 (.46; .70)	.00 (-.00; .00)	.23 (.17; .28)
		71%	*0%*	*29%*
M INT & NS	.12 (.09; .15)	.24 (.13; .43)	.00 (-.00; .00)	.04 (-.21 - .10)
		81%	*0%*	*19%*

Note: M INT = mathematics interest; M S-E = mathematics self-efficacy; M GCSE = mathematics GCSE score; UN = understanding numbers; M PVT = mathematics problem verification test; NS = number sense; 95% CI = 95% confidence intervals; r_A= genetic correlation; r_C = shared environmental; r_E = nonshared environmental correlation; r_P = phenotypic correlation.

Table 3.14. Model fit indices for bivariate correlated factors ACE models exploring the origins of the correlations between mathematics interest and all other mathematics-related measures.

	Baseline	Comparison	-2LL	df	AIC	*p*
(a) Mathematics interest & self-efficacy						
1	Saturated	-	26248.73	10031	6186.73	NA
2	Saturated	ACE	26267.44	10048	6171.44	0.35
(b) Mathematics interest & GCSE score						
1	Saturated	-	95882.01	9778	76326.01	NA
2	Saturated	ACE	25319.94	9795	5729.94	1.00
(c) Mathematics interest & understanding numbers						
1	Saturated	-	25574.21	9484	6606.21	NA
2	Saturated	ADE	25595.27	9501	6593.27	0.22

(d) Mathematics interest & PVT						
1	Saturated	-	26167.40	9688	6791.40	NA
2	**Saturated**	**ACE**	26190.40	9705	6780.40	0.15
(e) Mathematics interest & number sense						
1	Saturated	-	27289.33	9772	7745.33	NA
2	Saturated	ACE	27321.10	9789	7743.10	0.02

Note: ep = estimated parameters; -2LL = negative 2 times log likelihood; df = degrees of freedom; AIC = Akaike Information Criterion.

Four additional bivariate models were run to explore the aetiology of the association between mathematics self-efficacy and performance. As previously observed for mathematics anxiety and motivation, genetic factors were found to explain 51-82% of the phenotypic associations between mathematics self-efficacy and mathematics performance (see Table 3.13).

Table 3.15. Phenotypic (r_P), genetic (r_A) and non-shared environmental (r_E) correlations for pairwise associations between mathematics self-efficacy and mathematics-related outcomes.

Pairs of variables	**r_P (95% CI)**	**r_A (95% CI) *Proportion of r_P***	**r_C (95% CI) *Proportion of r_P***	**r_E (95% CI) *Proportion of r_P***
M S-E & M GCSE	.64 (.62; .65)	.81 (.75; .89)	1.00. (.89; 1.00)	.31 (.25; .37)
		73%	*13%*	*14%*
M S-E & UN	.57 (.55; .59)	.82 (.75; .92)	1.00 (-1.00; .00)	.21 (.15; .28)
		80%	*5%*	*15%*
M S-E & M PVT	.55 (.52; .58)	.76 (.70; .85)	1.00 (-1.00; .00)	.24 (.18; .30)
		80%	*2%*	*18%*
M S-E & NS	.18 (.15; .20)	.22 (.12; .36)	1.00 (-1.00; .00)	.12 (.06; .18)
		51%	*14%*	*35%*

Note: M S-E = mathematics self-efficacy; M GCSE = mathematics GCSE score; UN = understanding numbers; M PVT = mathematics problem verification test; NS = number sense; 95% CI = 95% confidence intervals; r_A= genetic correlation; r_C = shared environmental; r_E = nonshared environmental correlation; r_P = phenotypic correlation.

Table 3.16. Model fit indices for bivariate correlated factors ACE models exploring the origins of the correlations between mathematics self-efficacy and all other mathematics-related measures.

	Baseline	Comparison	-2LL	df	AIC	*p*
(a) Mathematics self-efficacy & GCSE score						
1	Saturated	-	24047.80	9779	4489.80	NA
2	Saturated	ACE	24061.16	9796	4469.16	0.71
(b) Mathematics self-efficacy & understanding numbers						
1	Saturated	-	24453.78	9485	5483.78	NA
2	Saturated	ACE	24470.01	9502	5466.01	0.51
(c) Mathematics self-efficacy & PVT						
1	Saturated	-	25226.77	9689	5848.77	NA
2	Saturated	ACE	25235.29	9706	5823.29	0.95
(d) Mathematics self-efficacy & number sense						
1	Saturated	-	27005.96	9773	7459.96	NA
2	Saturated	ACE	27035.39	9790	7455.40	0.03

Note: ep = estimated parameters; -2LL = negative 2 times log likelihood; df = degrees of freedom; AIC = Akaike Information Criterion.

Finally, six bivariate models were fitted to explore the aetiology of the association between the mathematics variables (GCSE scores, understanding numbers, mathematics problem solving and number sense). Results, reported in Table 3.17 shows strong genetic correlations between all mathematics performance variables. In line with what observed for the other bivariate models, genetic factors explained the largest proportion of the association between all mathematics variables (63-78%). Table 3.18 reports model fit indices for all bivariate models.

Table 3.17. Phenotypic (r_P), genetic (r_A), shared environmental (r_C); and non-shared environmental (r_E) correlations for pairwise associations between mathematics achievement and abilities.

Pairs of variables	r_P (95% CI)	r_A (95% CI)	r_C (95% CI)	r_E (95% CI)
		Proportion of r_P	***Proportion of r_P***	***Proportion of r_P***
M GCSE & UN	.70 (.68 - .71)	.91 (.85 - 1.00)	.87 (.87; 1.00)	.24 (.18; .30)
		77%	*14%*	*9%*
M GCSE & PVT	.65 (.63; .67)	.84 (.77; .92)	.28 (-1.00; 1.00)	.29 (.23; .36)
		77%	*11%*	*12%*
M GCSE & NS	.25 (.21; .28)	.33 (.24; .52)	1.00 (-.47; 1.00)	.11 (.04; .18)
		62%	*22%*	*16%*
M UN & PVT	.64 (.63; .66)	.91 (.87; .98)	1.00 (-1.00; .00)	.23 (.17; .28)
		78%	*8%*	*14%*
M UN & NS	.30 (.27; .33)	.46 (.40; .59)	1.00 (-1.00; .00)	.12 (.05; .19)
		63%	*17%*	*20%*
M PVT &NS	.30 (.27; .33)	.46 (.38; .66)	1.00 (.00; 1.00)	.17 (.10; .23)
		67%	*4%*	*29%*

Note: GCSE = mathematics GCSE score; UN = understanding numbers; PVT = mathematics problem verification test; NS = number sense; 95% CI = 95% confidence intervals; r_A= genetic correlation; r_C = shared environmental; r_E = nonshared environmental correlation; r_P = phenotypic correlation.

Table 3.18. Model fit indices for bivariate correlated factors ACE models exploring the origins of the correlations between measures of mathematics performance.

	Baseline	Comparison	-2LL	df	AIC	*p*
(a) Mathematics GCSE score & understanding numbers						
1	Saturated	-	22088.58	9232	3624.58	NA
2	Saturated	ACE	22105.96	9249	3607.96	0.43
(b) Mathematics GCSE score & PVT						
1	Saturated	-	23119.09	9436	4247.09	NA
2	Saturated	ACE	23131.70	9453	4225.70	0.76

(c) Mathematics GCSE score & number sense						
1	Saturated	-	25333.74	9520	6293.74	NA
2	Saturated	ACE	25357.73	9537	6283.73	0.12
(d) Understanding numbers & PVT						
1	Saturated	-	22935.60	9142	4651.60	NA
2	Saturated	ADE	22946.90	9159	4628.90	0.84
(e) Understanding numbers & number sense						
1	Saturated	-	25158.89	9226	6706.89	NA
2	Saturated	ACE	25177.75	9243	6691.75	0.34
(f) Mathematics PVT & number sense						
1	Saturated	-	25828.87	9430	6968.87	NA
2	Saturated	ACE	25848.28	9447	6954.28	0.31

Note: ep = estimated parameters; -2LL = negative 2 times log likelihood; df = degrees of freedom; AIC = Akaike Information Criterion

The Multivariate association between mathematics anxiety, motivation and performance: Multivariate Cholesky Decomposition

A multivariate Cholesky decomposition (see Methods) was conducted to explore the origins of the multivariate association between all mathematics-related traits. As the main aim of the analysis was that of exploring the association between mathematics anxiety and all other traits, mathematics anxiety was entered first in the Cholesky decomposition. Variables were entered in the model in the following order: (1) mathematics anxiety; (2) mathematics interest; (3) mathematics self-efficacy; (4) mathematics GCSE grades; (5) understanding numbers; (6) mathematics PVT; and (7) number sense. As described in the Methods section of this chapter of the present thesis, the Cholesky decomposition works similarly to a hierarchical regression, so that the aetiology shared between a pair of variables is calculated after accounting for the aetiology they share with the other variables that were previously entered in the model. For example, in this case, the latent factors A2, C2, and E2 indicate the aetiological variance that mathematics interest and mathematics self-efficacy share, after having accounted for the variance that they both shared with mathematics anxiety. Figure 3.1.a presents the standardized squared path estimated for all the genetic associations; Figure 3.1.b reports all standardized path estimated for all shared environmental associations; and Figure 3.1.c reports all the standardized squared path estimates for all non-shared environmental associations. Standardized path estimates for all associations and 95% confidence intervals are reported in Table 3.19.

The Cholesky decomposition showed that mathematics anxiety shared a substantial part of its genetic aetiology with all other mathematics-related traits (Figure 3.1.a). For example, nearly half of the genetic aetiology of mathematics interest was shared with that of mathematics anxiety (path $a_{2,1}$). Similarly, about half of the genetic aetiology of mathematics self-efficacy was shared with that of mathematics anxiety (path $a_{3,1}$), and the same was observed for the aetiologies of mathematics GCSE scores (path $a_{4,1}$), understanding numbers (path $a_{5,1}$) and mathematics PVT (path $a_{6,1}$). On the other hand, very little of the aetiology of number sense was shared with mathematics anxiety (path $a_{7,1}$).

About half of the aetiology of mathematics interest was independent from that of mathematics anxiety (path $a_{2,2}$). After accounting for the genetic variance shared with mathematics anxiety, genetic influences on mathematics interest were largely specific. Only very little genetic variance was shared between mathematics interest and all other mathematics related outcomes after accounting for the genetic variance they all shared with mathematics anxiety (path $a_{3,2}$, path $a_{4,2}$, path $a_{5,2}$, path $a_{6,2}$, path $a_{7,2}$).

Nearly half of the aetiology of mathematics self-efficacy was not shared with mathematics anxiety and mathematics interest (path $a_{3,3}$). This residual aetiology of mathematics self-efficacy was partly shared with mathematics performance. In fact, about 15% of the genetic aetiology of mathematics GCSE was shared with mathematics self-efficacy (path $a_{4,3}$), after accounting for the genetic variance they both shared with mathematics anxiety and mathematics interest.

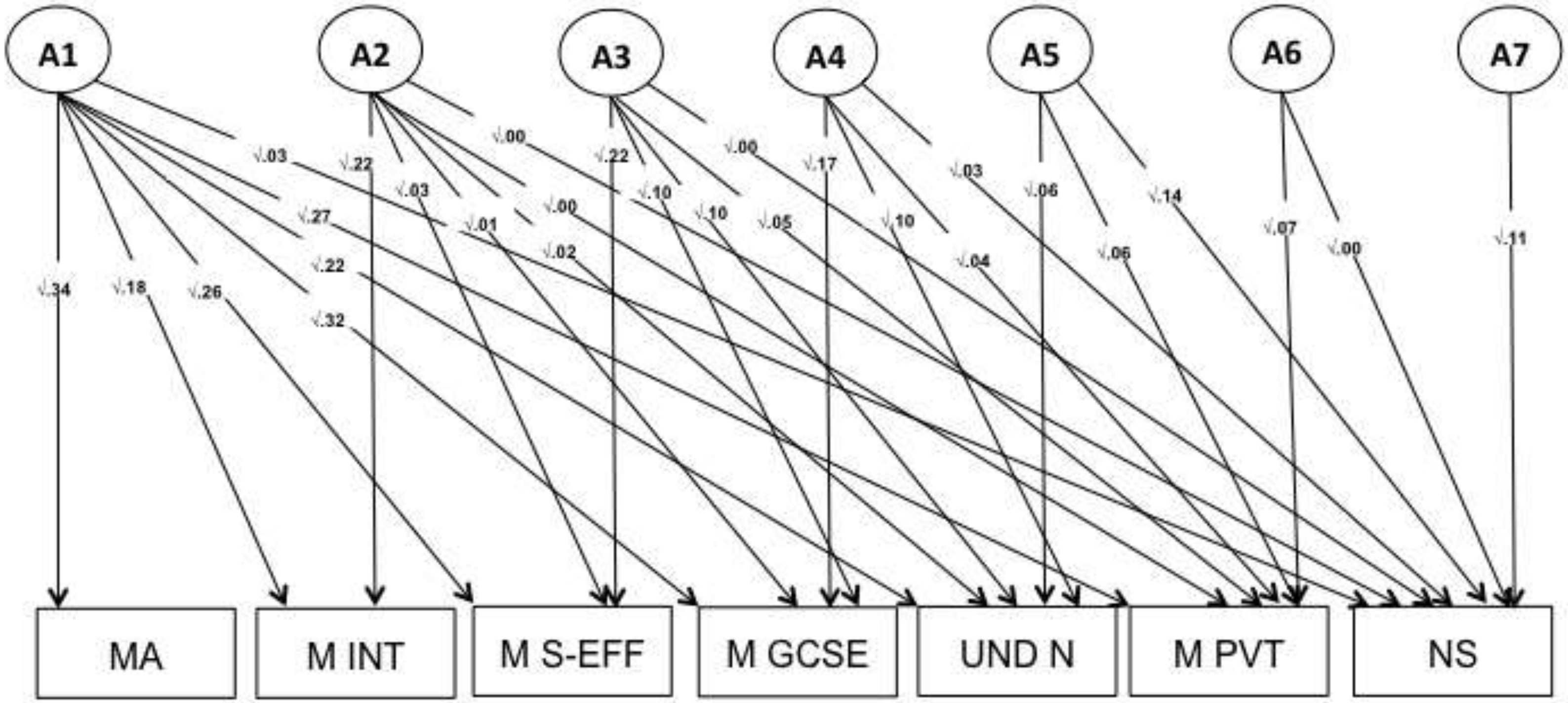

Figure 3.1.a. Standardized squared genetic path estimates for the multivariate Cholesky decomposition exploring the origins of the association between mathematics anxiety, mathematics motivation and mathematics performance.

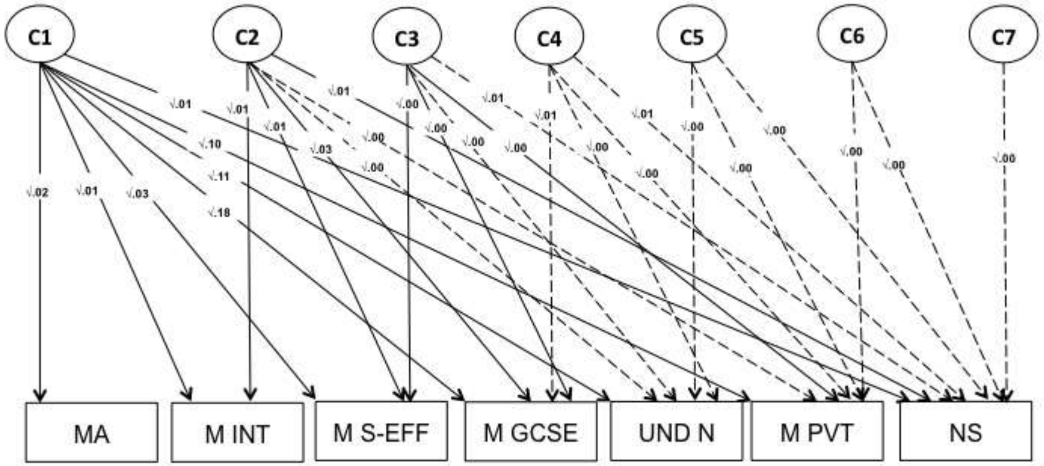

Figure 3.1.b. Standardized squared shared environmental path estimates for the multivariate Cholesky decomposition exploring the origins of the association between mathematics anxiety, mathematics motivation and mathematics performance.

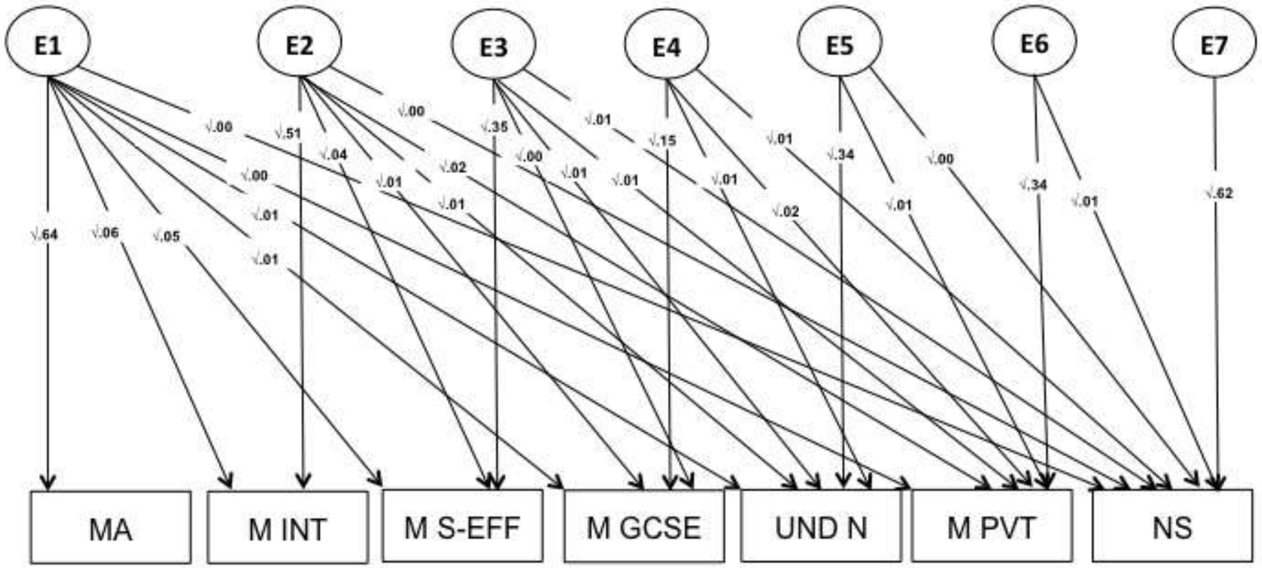

Figure 3.1.c. Standardized squared nonshared environmental path estimates for the multivariate Cholesky decomposition exploring the origins of the association between mathematics anxiety, mathematics motivation and mathematics

Table 3.19 Standardized path estimates for the Cholesky decomposition exploring the origins of the association between mathematics anxiety, motivation and performance

	A1, C1, E1	A2, C2, E2	A3, C3, E3	A4, C4, E4	A5, C5, E5	A6, C6, E6	A7, C7, E7
	A1 (95% CIs)	**A2 (95% CIs)**	**A3 (95% CIs)**	**A4 (95% CIs)**	**A5 (95% CIs)**	**A6 (95% CIs)**	**A7 (95% CIs)**
1. Maths Anxiety	.58 (.58; .61)	-	-	-	-	-	-
2. Maths Interest	-.43 (-.46; -.42)	.47 (.47; .48)	-	-	-	-	-
3. Maths Self-Efficacy	-.51 (-.55; -.46)	.18 (.58; .61)	.47 (.46; .47)	-	-	-	-
4. Maths GCSE	-.56 (-.57; -.56)	.08 (.07; .18)	.31 (.24; .37)	.41 (.41; .42)	-	-	-
5. Understand Numbers	-.47 (-.48; -.43)	.12 (.12; .13)	.32 (.32; .34)	.31 (.21; .32)	.25 (.15; .25)	-	-
6. Maths PVT	-.52 (-.53; -.51)	.06 (.05; .18)	.22 (.22; .23)	.20 (.12; .31)	.24 (.24; .27)	.26 (.25; .26)	-
7. Number Sense	-.17 (-.23; -.16)	.02 (.02; .10)	-.03 (-.03; -.02)	.17 (.04; .34)	.37 (.37; .38)	-.06 (-.07; -.05)	.33 (.33; .47)
	C1 (95% CIs)	**C2 (95% CIs)**	**C3 (95% CIs)**	**C4 (95% CIs)**	**C5 (95% CIs)**	**C6 (95% CIs)**	**C7 (95% CIs)**
1. Maths Anxiety	.15 (.11; .15)	-	-	-	-	-	-
2. Maths Interest	.08 (.00; .09)	.12 (.12; .13)	-	-	-	-	-
3. Maths Self-Efficacy	.18 (.08; .19)	.11 (.10; .11)	.07 (.07; .09)	-	-	-	-
4. Maths GCSE	.42 (.42; .43)	.18 (.18; .21)	.09 (.08; .17)	.10 (.10; .11)	-	-	-
5. Understand Numbers	.34 (.31; .39)	-.06 (-.18; .20)	.07 (.05; .23)	-.02 (-.21; .23)	.00 (.00; .04)	-	-
6. Maths PVT	.32 (.31; .38)	-.02 (-.04; .01)	.01 (.00; .04)	-.02 (-.04; .01)	.00 (-.02; .01)	.00 (.00; .15)	-
7. Number Sense	.10 (.08; .12)	.09 (.09; .32)	.14 (-.17; .16)	-.10 (-.11; -.07)	.00 (.00; .31)	.00 (-.01; .26)	.00 (.01; .08)
	E1 (95% CIs)	**E2 (95% CIs)**	**E3 (95% CIs)**	**E4 (95% CIs)**	**E5 (95% CIs)**	**E6 (95% CIs)**	**E7 (95% CIs)**
1. Maths Anxiety	.80 (.78; .80)						
2. Maths Interest	-.25 (-.25; -.24)	.72 (.70; .72)					
3. Maths Self-Efficacy	-.22(-.22; -.21)	.20 (.18; .22)	.59 (.58; .60)				
4. Maths GCSE	-.11(-.25; -.24)	.11 (.11; .12)	.07 (.07; .08)	.39 (.38; .40)			
5. Understand Numbers	-.10(-.14; -.07)	.10 (.07; .10)	.08 (.08; .10)	.10 (.09; .10)	.59 (.58; .60)		
6. Maths PVT	-.11(-.12; -.10)	.13 (.11; .13)	.10 (.10; .13)	.13 (.12; .15)	.09 (.08; .09)	.59 (.57; .60)	
7. Number Sense	-.02(-.03; -.01)	.02 (.02; .04)	.09 (.05; .13)	.07 (.07; .12)	.05 (.05; .06)	.10 (.10; .11)	.79 (.78; .80)

Note: A =additive genetic; C = shared environment; E = nonshared environment; (95% confidence intervals)

Similarly, about 20% of the aetiology of understanding numbers was shared with the aetiology of self-efficacy, after accounting for the variance they both shared with mathematics anxiety and interest (path $a_{5,3}$). About 10% of the genetic aetiology of mathematics PVT was shared with the residual genetic aetiology of mathematics self efficacy (path $a_{6,3}$), whereas none of the genetic aetiology of self-efficacy was shared with number sense (path $a_{7,3}$), after accounting for the genetic influences they both shared with mathematics anxiety and mathematics interest.

About 20% of the aetiology of mathematics GCSE scores was found to be independent from that of mathematics anxiety, interest and self-efficacy (path $a_{4,4}$). More than half of this residual variance in the genetic aetiology of mathematics GCSE scores was shared with the aetiology of understanding numbers (path $a_{5,4}$), and about 25% of this residual variance was shared with mathematics PVT (path $a_{6,4}$). About 15% of the residual variance in the genetic aetiology of GCSE scores was shared with the aetiology of number sense (path $a_{7,4}$).

About 15% of the genetic aetiology of understanding numbers was found to be independent form the aetiology of mathematics anxiety, interest, self-efficacy, and GCSE scores (path $a_{5,5}$). About 15% of the genetic aetiology of mathematics PVT was shared with understanding numbers independently of mathematics anxiety, interest, self-efficacy and GCSE scores (path $a_{6,5}$). About 45% of the genetic aetiology of number sense was shared with the aetiology of understanding numbers (path $a_{7,5}$). In fact, understanding numbers was found to be the only mathematical skill showing substantial genetic overlap with number sense ability. All the other measures of mathematics ability and related non-cognitive traits showed very little or no genetic overlap with number sense.

Around 15% of the genetic variance in the mathematics PVT was found to be independent from mathematics anxiety, interest, self-efficacy, GCSE and understanding numbers (path $a_{6,6}$). None of the genetic aetiology of number sense was shared with the aetiology of mathematics PVT, after accounting for the genetic variance shared with all the measures that were previously entered in the Cholesky decomposition. This indicates that there is no specific genetic overlap between mathematics problem solving and number sense after accounting for the genetic variance they share with mathematics anxiety, interest, self-efficacy, GCSE, and understanding numbers. About 1/3 of the genetic aetiology of number sense was found to be independent of all other mathematics and mathematics-related measures (path $a_{7,7}$).

Figure 3.1.b and Table 3.19 show the shared environmental overlap between all measures entered in the model. Shared environmental variance mostly did not overlap between variables. However, to the extent that shared environmental influences overlapped, these were shared across all measures. This is suggested by factor C1 in Table 3.19 and paths $c_{1,1}$ to $c_{1,7}$ in Figure 3.1.b, which constitute the main shared environmental overlap across measures of anxiety, motivation and performance. In fact, residual shared environmental variance was not found for all measures entered in the model.

Figure 3.1.c and Table 3.19 show the nonshared environmental overlap across all measures entered in the Cholesky decomposition. Contrary to what observed for shared environmental influences, nonshared environmental factors were found to be largely specific to each measure. Nonshared environmental influences, which in the model cannot be separated from measurement error, explained a significant portion of the aetiology of all measures. However, nonshared environmental influences mostly did not overlap across measures of mathematics anxiety, motivation and performance. A small, yet significant, overlap was observed between mathematics anxiety and interest and self-efficacy. Mathematics interest shared 10% of its nonshared environmental aetiology with mathematics anxiety. Mathematics self-efficacy also shared around 10% of its nonshared environmental aetiology with mathematics anxiety. Additionally, an additional 8% of the nonshared environmental aetiology of self-efficacy was shared with mathematics interest after accounting for the nonshared environmental variance they both shared with mathematics anxiety. Nonshared environmental overlap was not observed for all other measures.

Overall, the Cholesky decomposition showed substantial overlap in the aetiology of mathematics-related measures. This overlap was mostly due to shared genetic influences on all traits. Nevertheless, although some of the genetic aetiology was shared across all traits, a substantial part of the genetic aetiology of mathematics motivation and performance was also found to be independent from mathematics anxiety. Furthermore, measures of mathematics performance were found to share additional genetic variance after accounting for the genetic variance they shared with mathematics anxiety and motivation. The overlap in shared environmental aetiology was found to be minimal and common to all measures. On the other hand, nonshared environmental influences were found to be largely specific to each variable.

The domain-specificity of association between mathematics anxiety, motivation and performance: A multivariate Cholesky decomposition including general anxiety

An additional Cholesky decomposition was carried out in order to assess whether the aetiological association between mathematics anxiety, motivation and performance was domain specific, or whether the majority of the aetiological overlap was shared with general anxiety. In order to test this hypothesis, general anxiety was entered first in the Cholesky model. Consequently, it was possible to examine the aetiology that general anxiety shared with all mathematics related measures. Results of this second Cholesy decomposition are reported in Figure 3.2 and Table 3.20 and. Figure 3.2 shows the standardized squared paths for the genetic overlap between general anxiety, mathematics anxiety and all other mathematics-related constructs. Table 3.20 reports the standardized paths estimates for the genetic, shared environmental and nonshared environmental overlap between general anxiety and all other measures, including 95% confidence intervals.

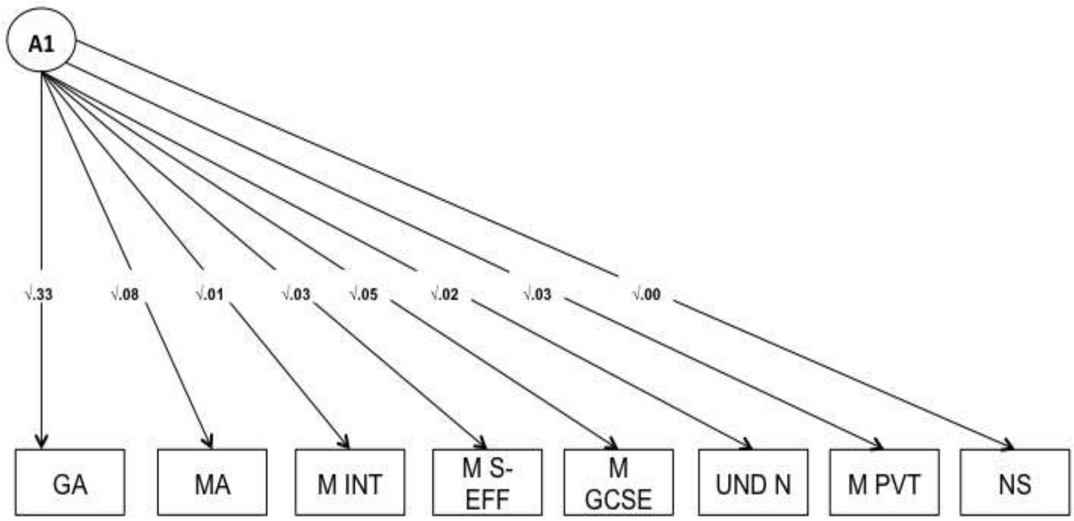

Figure 3.2. Standardized squared paths estimates for the genetic overlap between general anxiety and mathematics-related measures.

General anxiety was found to share part of its aetiology with mathematics anxiety, and their correlation was found to be largely due to shared genetic influences. Although mathematics and general anxiety partly overlapped, the same genes implicated in their association were not found to influence mathematics motivation and mathematics performance. In fact, general anxiety shared very little of genetic and environmental aetiology with mathematics motivation and mathematics performance.

After accounting for general anxiety, the aetiological links between mathematics anxiety, motivation and performance remained largely unchanged (see Table 3.20). Results indicate that the association between mathematics anxiety, motivation and performance is specific to mathematics anxiety, not only at the phenotypic, but also at the aetiological level. This corroborates the idea that mathematics anxiety is a specific construct that shares a specific association with mathematics motivation and mathematics performance.

Table 3.20. Standardised paths for the Cholesky decomposition exploring the origins of the association between general anxiety, mathematics anxiety, mathematics motivation and mathematics performance.

	A1, C1, E1	**A2, C2, E2**	**A3, C3, E3**	**A4, C4, E4**	**A5, C5, E5**	**A6, C6, E6**	**A7, C7, E7**	**A8, C8, E8**
	A1 (95% CIs)	**A2 (95% CIs)**	**A3 (95% CIs)**	**A4 (95% CIs)**	**A5 (95% CIs)**	**A6 (95% CIs)**	**A7 (95% CIs)**	**A8 (95% CIs)**
1. General Anxiety	.58 (.57; .58)	-	-	-	-	-	-	-
2. Maths Anxiety	.29 (.28; .29)	.51 (.50; .53)	-	-	-	-	-	-
3. Maths Interest	-.08 (-.09; -.07)	-.45 (-.45; -.44)	.44 (.43; .44)	-	-	-	-	-
4. Maths Self-Efficacy	-.17 (-.17; -.17)	-.49 (-.49; -.48)	.14 (.12; .15)	.46 (.45; .47)	-	-	-	-
5. Maths GCSE	-.21 (-.22; -.16)	-.53 (-.53; -.52)	.05 (.04; .07)	.32 (.31; .32)	.41 (.41; .41)	-	-	-
6. Understand Numbers	-.14 (-.14; -.12)	-.47 (-.47; -.47)	.09 (.08; .09)	.32 (.32; .32)	.29 (.28; .37)	.24 (.24; .26)	-	-
7. Maths PVT	-.17 (-.18; -.17)	-.51 (-.52; -.49)	.01 (-.07; .12)	.21 (.20; .22)	.20 (.20; .20)	.24 (.23; .24)	.24 (.23; .24)	
8. Number Sense	.03 (-.06; .03)	-.22 (-.22; -.15)	-.05 (-.09; -.04)	-.07 (-.08; -.01)	.19 (.18; .19)	.39 (.28; .40)	-.19 (-.19; -	.00 (-.00; .01)
	C1 (95% CIs)	**C2 (95% CIs)**	**C3 (95% CIs)**	**C4 (95% CIs)**	**C5 (95% CIs)**	**C6 (95% CIs)**	**C7 (95% CIs)**	**C8 (95% CIs)**
1. General Anxiety	.25 (.25; .34)	-	-	-	-	-	-	-
2. Maths Anxiety	.04 (.04; .06)	.15 (.14; .15)	-	-	-	-	-	-
3. Maths Interest	-.05 (-.06; -.03)	.11 (.10; .11)	.10 (.10; .11)	-	-	-	-	-
4. Maths Self-Efficacy	-.05 (-.05; -.04)	.20 (.16; .21)	.08 (.05; .10)	.07 (.00; .09)	-	-	-	-
5. Maths GCSE	.12 (.12; .12)	.39 (.39; .46)	.19 (.18; .30)	.14 (-.08; .16)	.10 (.08; .11)	-	-	-
6. Understand Numbers	.13 (.12; .13)	.31 (.30; .36)	-.06 (-.11; .09)	.07 (.06; .08)	.00 (.00; .04)	.00 (-.23; .05)	-	-
7. Maths PVT	.06 (.06; .07)	.32 (.26; .32)	-.03 (-.03; -.01)	.07 (.06; .08)	.00 (-.18; .03)	.00 (.00; .01)	.00 (.00; .01)	
8. Number Sense	-.17 (-.18; .08)	.17 (.16; .18)	.00 (-.01; .01)	.00 (-.05; .17)	.00 (-.19; .19)	.00 (-.07; .13)	.00 (-.03; .03)	.00 (.00; .23)
	E1 (95% CIs)	**E2 (95% CIs)**	**E3 (95% CIs)**	**E4 (95% CIs)**	**E5 (95% CIs)**	**E6 (95% CIs)**	**E7 (95% CIs)**	**E8 (95% CIs)**
1. General Anxiety	.78 (.77; .78)	-	-	-	-	-	-	-
2. Maths Anxiety	.18 (-17; .19)	.78 (.77; .78)	-	-	-	-	-	-
3. Maths Interest	-.03(-.03; -.01)	-.25 (-.26; -.23)	.72 (.71; .72)	-	-	-	-	-
4. Maths Self-Efficacy	-.02(-.03; -.01)	-.22 (-.25; -.22)	.20 (.20; .22)	.59 (.59; .61)	-	-	-	-
5. Maths GCSE	-.01(-.01; .01)	-.11 (-.12; -.11)	.11 (.11; .13)	.07 (.07; .07)	.39 (.39; .39)	-	-	-
6. Understand Numbers	-.02(-.03; .01)	-.10 (-.10; -.09)	.10 (.10; .13)	08 (.08; .09)	.10 (.09; .10)	.59 (.58; .59)	-	-
7. Maths PVT	.00 (.00; .01)	-.12 (-.12; -.11)	.13 (.12; .13)	.10 (.10; .10)	.12 (.12; .15)	.09 (.08; .09)	.59 (.58; .60)	-
8. Number Sense	.00 (-.01; .01)	-.02 (-.02; .02)	.03 (.01; .04)	.10 (.10; .12)	.07 (.07; .07)	.05 (.01; .06)	.11 (.10; .12)	.79 (.79; .80)

Note: A =additive genetic; C = shared environment; E = nonshared environment; (95% confidence intervals)

Discussion

The present investigation was the first to explore the origins of the co-variation between mathematics anxiety, motivation and performance in a genetically informative sample of 16-21-year-old twins. The results showed that their multivariate association was mostly due to genetic influences common to all traits, indexing pleiotropic effects. In fact, part of the genes implicated in variation in mathematics anxiety were also found to be implicated in variation in mathematics motivation and several aspects of mathematics performance. Additionally, pleiotropic effects were found to be specific to the domain of mathematics, as genetic influences were mostly not shared with domain-general anxiety.

The present study had six main aims. The first aim was to explore how mathematics anxiety related to two different aspects of mathematics motivation: self-efficacy and interest. Extant literature has mostly focused on exploring how mathematics anxiety relates to self-efficacy, consistently finding moderate negative correlations between the two constructs (e.g. Jain & Dowson, 2009; Lee, 2009; Hoffman, 2010). However, few investigations have explored the association between mathematics anxiety and other aspects of motivation, for example interest. The present study found that mathematics interest and self-efficacy shared a strong positive correlation, and that both self-efficacy and interest shared moderate negative correlations with mathematics anxiety. Correlation obtained after controlling for the variance explained by age and sex were highly similar, and confidence intervals around these estimates overlapped, indicating that the associations were comparable. These associations remained unchanged after the variance shared with domain-general anxiety was taken into account. Therefore, results show that mathematics anxiety is similarly associated with two different aspects of mathematics motivation: self-efficacy and interest, and that their association is specific to the domain of mathematics.

Secondly, the present study was the first to explore the origins of the correlations between mathematics anxiety and mathematics interest and self-efficacy. Because previous investigations found that genetic factors were moderately implicated in individual variation in both mathematics anxiety (Wang et al., 2014) and motivation (Luo et al., 2011), it was predicted that genetic influences would have also played a role in the origins of their co-variation. In line with previous investigations, the results of univariate genetic analyses showed that mathematics anxiety and mathematics interest were moderately heritable, with genetic factors explaining 37% and 43% of individual difference in the traits, respectively. Genetic factors were found to explain a larger portion of variance in mathematics self-efficacy, accounting for 58% of individual differences in the trait. The remaining variance in all traits was explained by nonshared environmental factors, which also include measurement error. This is also in line with heritability estimates obtained from other investigations looking at domain-general motivation (Luo et al., 2010; Greven et al., 2009).

The correlations between mathematics anxiety and mathematics interest and self-efficacy were mostly explained by common genetic influences. Results showed strong genetic correlations between mathematics anxiety and mathematics interest and between mathematics anxiety and mathematics self-efficacy. These common genetic influences were found to explain a large proportion of the phenotypic correlations between the traits. In fact, genetic factors accounted for 52% of the correlation between mathematics anxiety and mathematics interest, and for 59% of the correlation between mathematics anxiety and mathematics self-efficacy. The remaining proportions of both phenotypic correlations were attributable to nonshared environmental influences. Results also showed a strong genetic correlation between mathematics interest and self-efficacy, with genetic factors accounting for 64% of their strong phenotypic correlation. Also in this case, the remaining proportion of their covariance was attributable to individual-specific environmental influences.

The strong genetic correlations observed between pairs of variables shows that many of the same genes that are implicated in individual differences in mathematics anxiety are also involved in explaining a moderate portion of individual variation in mathematics interest and self-efficacy. Additionally, the same nonshared environmental influences were modestly implicated in explaining individual variation in mathematics anxiety, interest and self-efficacy, as indicated by the modest nonshared environmental correlations between the traits.

Interestingly, family-wide environments, which are shared between twins raised in the same family, did not play a role in explaining why individuals differ in their mathematics anxiety and motivation. Furthermore, they did not play a role in explaining why they co-occur. Investigations have explored how family environment had a potential impact on experiencing mathematics anxiety, considering factors such as socio-economic status and parental involvement at home. One investigation (Vukovic, Roberts & Wright, 2013) found that parental involvement at home acted as a protective factor for the development of mathematics anxiety in children growing up in families with low socio-economic status, but the effect size was small. Our findings suggest that child-specific, rather than family-wide, environments play a role in explaining why some students experience higher levels of mathematics anxiety, interest and self-efficacy than others. Different environmental experiences such as different classrooms, teachers, peers, life events, and even perception of parental involvement and socio-economic status, could all play a role in explaining variation in mathematics anxiety, interest and self-efficacy, and also in explaining why they co-occur. For example, one study found a small association between classroom-learning environment and mathematics anxiety and self-efficacy (Taylor and Fraser, 2013).

The third aim of the present research was to explore how mathematics anxiety relates to different subcomponents of mathematics performance, including school achievement and abilities. Mathematics achievement was measured via GCSE scores, whereas a battery of tests administer online was used to measure several aspects of mathematics ability: understanding numbers, mathematics problem solving, and number sense. The results showed that mathematics anxiety was negatively associated with all measures of mathematics performance. However, whilst anxiety shared a moderate negative correlation with GCSE scores, understanding numbers and problem solving ability, its correlation with number sense ability was only weak. This is consistent with findings of previous investigations (e.g. Hart et al., 2016;

Maloney et al., 2010), that observed small or no relations between mathematics anxiety and numerosity. All correlations remained highly similar after the variance explained by general anxiety had been accounted for, suggesting that the phenotypic association between mathematics anxiety and several components of mathematics performance is domain specific.

Therefore, mathematics anxiety was found to share a similar association with several different aspects of mathematics performance, including mathematics achievement in GCSE exams, and web-administered tests of understanding numbers and problem solving. This was indicated by the highly overlapping confidence intervals around their correlations. On the other hand, the association between mathematics anxiety and number sense was very small, and confidence interval did not overlapped with those obtained for all other correlation estimates. This shows that the correlation between mathematics anxiety and number sense is significantly smaller than that observed between mathematics anxiety and all other measures of mathematics performance. A small relation was also observed between mathematics motivation (interest and self-efficacy) and number sense.

The observed negligible association between number sense and the non-cognitive and emotional correlates of mathematics is not surprising. It may be that, as observed by Hart et al., the association between number sense and anxiety is distinguishable only in subgroups of children who are highly motivated and achieve highly in mathematics (Hart et al., 2016). As the present study focused on exploring their associations and corresponding aetiology across the entire distribution, it may have failed to detect stronger effects that may characterize restricted subsamples of high achievers. However, this may also reflect the nature of the association between number sense and mathematics performance. In fact, extant literature has suggested that number sense plays a role only in very early mathematical learning, and not in later mathematical development. This is supported by longitudinal evidence showing that number sense was associated with mathematics achievement only in the first year of primary school, but not in the second year (Desoete, Ceulemans, De Weerdt, & Pieters, 2010). As mathematics anxiety was found to emerge as a consequence of achievement feedback (Ma & Xu, 2004) and it is not decisively established in the early years of primary school (Kritzinger et al., 2010; Dowker et al., 2012), it may be that number sense and mathematics anxiety relate to mathematics performance at two different stages in development, and consequently share a very small relationship. Similar speculations could apply to the association between number sense and mathematics motivation.

The fourth aim of the present investigation was to explore the origins of the co-variation between mathematics anxiety and several different aspects of mathematics performance. Measures of mathematics performance were all substantially heritable, with genetic factors explaining 59-63% of individual differences. The only exception was number sense ability, which was found to be substantially less heritable than the other performance measures, with heritability estimated at 36%. These estimates are in line with those obtained in previous studies of mathematical ability (Kovas, Petrill, & Plomin, 2007) and number sense (Tosto, Petrill, Halberda, Trzaskowski, Tikhomirova, Bogdanova et al., 2014). Heritability estimates were found not to differ significantly between males and females, and the same aetiological influences were implicated in the variation in all traits for males and females. Overall, the results showed strong genetic correlations between mathematics anxiety and all aspects of mathematics performance, showing that a large part of the same genetic influences that are implicated in variation in mathematics anxiety are also implicated in explaining variation in all aspects of mathematics performance. The only exception was the genetic correlation between mathematics anxiety and number sense, which was fund to be weak.

Similar to the association between mathematics anxiety and motivation, genetic influences were found to explain a substantial portion of the moderate phenotypic correlation between mathematics anxiety and performance. In fact, genetic influences explained 72-88% of the moderate correlations between mathematics anxiety and the different mathematics performance measures. Genetic factors were also found to explain the largest portion (63%) of the small phenotypic association between mathematics anxiety and number sense, and similar findings were observed for the small phenotypic associations between number sense and mathematics motivation. This indicates that, largely the same genetic factors are involved in the pairwise associations between all variables.

The fifth aim of the present research was to identify the origins of the co-occurrence of mathematics anxiety, motivation and performance. A multivariate Cholesky decomposition was fitted in order to test whether common aetiological influences characterized all mathematics-related variables. The multivariate Cholesky decomposition showed an overlap in the aetiology of all mathematics-related measures. The observed overlap was mostly attributable genetic influences that were common to all variables. Genetic factors contributing to variation in mathematics anxiety also contributed to individual differences in motivation and performance. In fact, approximately half of the genetic factors influencing variation in mathematics interest, self-efficacy, GCSE scores, understanding numbers, and mathematics problem solving ability, also influenced mathematics anxiety. Overall, the aetiological overlap between mathematics anxiety and mathematics performance was similar across all performance variables. The only exception was number sense, as its aetiology was mostly independent from mathematics anxiety. A significant portion of the genetic aetiology of mathematics motivation and performance was found to be independent from mathematics anxiety. After accounting for the variance they shared with mathematics anxiety and motivation, measures of GCSE scores, understanding numbers, mathematics problem solving, and number sense shared additional performance-specific genetic variance.

The overlap in shared environmental aetiology was found to be minimal and common to all measures. On the other hand, nonshared environmental influences were found to be largely specific to each variable. The results indicate that to the extent that mathematics anxiety, motivation and number sense co-occur, they do so largely because the same genes are implicated in variation in all these traits. This is consistent with what observed by previous research, as genetic factors were found to explain the largest portion of the co-occurrence of low mathematics anxiety, and high number sense and mathematical ability, in a sample of children selected for high intrinsic motivation for mathematics (Hart et al., 2016).

Results of the multivariate analysis are consistent with the 'generalist genes' account of learning abilities and disabilities (Plomin, & Kovas, 2005). The theory proposes that the majority of the genes that are implicated in variation in academic achievement and abilities are shared between traits. The 'generalist genes' account is grounded in the two concepts of pleiotropy (one gene affects many traits) and polygenicity (several genes influence one trait) and proposes that genetic influences on different abilities, as well as disabilities, overlap. Studies using multivariate genetic analyses, molecular genetics, and bioinformatics techniques, such as genome-wide complex trait analysis (GCTA; Yang, Benyamin, McEvoy, Gordon, Henders et al., 2010), have found support for the 'generalist genes' theory (e.g. Plomin & Kovas 2005; Kovas, Harlaar, Petrill, & Plomin, 2005; Haworth, Meaburn, Harlaar, & Plomin, 2007; Trzaskowski, Davis, DeGries, Yang, Visscher & Plomin, 2013). The current study found support for the pleiotropic effects of genes working not only between measures of cognitive abilities and achievement, but also across the non-cognitive and emotion regulation correlates of cognitive performance within the domain of mathematics.

The sixth aim of the present study was to explore whether the multivariate association between mathematics anxiety, motivation and performance could be conceived as domain-specific, or whether general anxiety could account for part of the aetiology shared between traits. At the phenotypic level, general anxiety was found to share a very small relationship with mathematics motivation and performance. The same domain-specificity was observed at the aetiological level. General anxiety was found to explain around 20% of its genetic aetiology with mathematics anxiety, indicating that, although the two anxiety constructs partly overlap, they are also mostly independent in their origins. This is in line with the results of Chapter 2 of the present thesis. In fact, general anxiety, mathematics anxiety and spatial anxiety were found to be separate constructs both phenotypically and aetiologically.

On the other hand, the overlap between general anxiety and mathematics motivation and performance was minimal, and the aetiological overlap between mathematics anxiety, motivation and performance remained largely unchanged after accounting for the aetiology they all shared with general anxiety. This indicates that the association between mathematics anxiety, motivation and performance is domain-specific, phenotypically and aetiologically, replicating what was observed for mathematics anxiety and problem solving ability in the Wang et al study (Wang et al., 2014). This is in line existing theories that propose that the association between motivation and performance is largely domain-specific (e.g. Möller, Retelsdorf, Köller, & Marsh, 2011). The domain-specificity of the association between motivation and achievement in mathematics and literacy is the topic of the next chapter – Chapter 4 of the present thesis.

Limitations

The current study includes a number of limitations. Firstly, the present data was collected in a twin sample, which resents a number of limitations. Twin studies are based on a number of assumptions. One of these assumptions, the 'equal environments assumption' reflects the idea that in the ACE model environmental similarity is considered to be the same for MZ and DZ twin pairs growing up in the same family. Although existing evidence suggests that MZ twins are more likely to experience similar environments than DZ twins (e.g. they tend to be treated more similarly, to more often share the same playmates etc.), sharing more environmental experiences was not found to impact on the degree of their phenotypic concordance (Kendler, Kessler, Neale, Heath, & Eaves, 1993). A further limitation of the twin method is that it does not allow to account for gene–environment interplay. It is possible that those children with a predisposition towards mathematical difficulties might be more vulnerable to negative social influences, such as negative feedback from teachers or parents' negative attitudes towards mathematics. This increased vulnerability due to the interplay of genetic and environmental influences is likely to lead to greater feelings of anxiety towards mathematics (Maloney & Beilock, 2012). The topic of gene-environment interplay is discussed in greater detail in Chapter 5 of the present thesis (discussion section).

An additional limitation of the present investigation was not including a measure of working memory. All the cognitive theories developed to explain the mechanisms at the hearth of the association between mathematics anxiety and performance have identified a disruption in working memory processing (e.g.

Ashcraft et al., 2001; Maloney et al., 2014). Understanding the aetiology of the association between mathematics anxiety, working memory and performance would represent a step further in understanding the mechanisms behind the negative relationship between mathematics anxiety and performance. Studies using neuroimaging techniques have attempted to identify the brain network associated with mathematics anxiety and its negative relation with performance. A study using functional magnetic resonance (fMRI) found that participants high in mathematics anxiety who showed increased activity in the inferior fronto-parietal regions when anticipating a mathematics task, showed a lower deficit in mathematics performance, if compared to those showing lower levels o activity (Lyons and Beilock, 2011). These results suggest that the ability to reappraise negative feelings of anxiety and to redirect cognitive resources towards solving the task might protect anxious students from showing deficits in mathematics performance (Lyons & Beilock, 2011). However, investigating the association between mathematics anxiety, performance and working memory within a genetically informative design would shed additional light on the reasons behind their co-variation.

A further limitation of the present investigation is the fact that measures of mathematics anxiety and mathematics motivation and performance were not collected at the same collection wave, However, longitudinal investigations have found mathematics anxiety to be moderately stable over time, and achievement to be highly stable (e.g. Ma & Xu, 2004). This suggests that their association is unlikely to change drastically from one collection wave to the next. Future longitudinal investigations conducted using a genetically sensitive design will be able to investigate the aetiology of the stability and change in mathematics anxiety and its relation with achievement over time.

Conclusions

To conclude, the present investigation set out to explore the origins of the association between mathematics anxiety, and several aspects of mathematics motivation and performance in a sample of 16-21-year-old twins. Results showed that individual differences in all mathematics related traits were partly or mostly attributable to genetic effects. Mathematics anxiety shared a similar association with two different aspects for mathematics motivation: interest and self-efficacy.

The origins of these negative moderate associations were genetic and individual-specific environmental. Mathematics anxiety shared a moderate association with several measures of mathematics performance, including GCSE exam scores, understanding numbers and problem solving ability. All associations were comparable, with the exception of number sense ability, which shared only a weak and negative relation with mathematics anxiety. All correlations between mathematics anxiety and performance were predominantly explained by shared genetic influences, and to a lesser extent by individual-specific environmental influences common to all pairwise associations.

Multivariate genetic analysis including all mathematics-related measures found that mathematics anxiety, motivation and performance in several mathematics all shared part of their aetiology. The overlap between measures was mostly due to shared genetic influences, which were common to all traits. Family-wide environmental influences contributed only minimally to the overlap between measures, and individual-specific environmental factors were largely specific to each trait. Additionally, the present study found that the association between mathematics anxiety, motivation and performance was highly domain-specific, both phenotypically and aetiologically. This is in line with the results of the analyses presented Chapter 2 of the present thesis, exploring the domain-specificity of academic anxiety. Additionally, the issue of domain-specificity in the association between motivation and achievement is central to the study presented in the next chapter of the present thesis.

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Chapter 4

The co-development of self-efficacy, enjoyment and achievement in reading and mathematics across eight school years

Abstract

Studies have demonstrated associations between non-cognitive characteristics, such as self-efficacy and enjoyment with measures of cognitive ability and achievement. Previous research also showed that, although these associations are positive and moderate within academic domains (e.g., mathematics), they can be negative and weak across domains (e.g., mathematics and literacy). The present study applies cross-lagged design to the exploration of the longitudinal relations between self-efficacy, enjoyment and achievement in literacy and mathematics. Participants (N = 5,527) contributed data at ages 9, 12 and 16. The results showed that measures of academic achievement highly correlated across the two domains at all ages (average r = .75). On the other hand, correlations across domains for self-efficacy and enjoyment were only moderate (average r = .33). All variables were moderately stable over the 8-year developmental time (average β = .40). Reciprocal positive associations were observed between motivation (self-efficacy and enjoyment) and achievement within domains over time. However, effect sizes were stronger for the links from previous achievement to later self-efficacy and enjoyment (average β = .26) than from previous self-efficacy and enjoyment to later achievement (average β = .10). Little evidence was found for the existence of negative associations between self-efficacy, enjoyment and achievement across academic domains: most longitudinal cross-domain associations were non-significant. The results highlight the complexity of the developmental relations between achievement, self-efficacy and enjoyment, complexity that may not be captured by existing developmental theories.

Introduction

Academic achievement and motivation within and across academic domains

A wealth of cross-sectional research has explored the association between academic achievement and aspects of academic motivation, such as self-belief and enjoyment. However, the longitudinal relations between these constructs, both within one academic domain and across different academic domains, remain unclear. An interesting pattern of associations has emerged from extant literature. Strong correlations are observed between measures of academic achievement across different domains, such as for example reading and mathematics. In contrast, correlations between measures of academic self-belief for different school subjects are only moderate (e.g. Chamorro-Premuzic, Harlaar, Greven, & Plomin, 2010; Luo, Kovas, Haworth, & Plomin, 2011). This suggests that, to a large extent, the same factors underlie achievement in different academic domains, whereas factors driving academic self-belief and other motivational characteristics may be more subject-specific. This pattern of associations might partly reflect differences in how achievement and motivation are measured (i.e. highly reliable standardized tests vs. less-reliable self-report questionnaires). However, it is consistently observed, also when self-report measures show high reliability (Marsh, Aduljabbar, Abu-Hilal, Morin, Abdelfattah, Leung et al., 2013).

Longitudinal studies have shown that associations between achievement and self-belief and enjoyment are reciprocal and positive within every academic domain. For example, enjoyment of mathematics positively predicts later mathematics achievement, and mathematics achievement predicts later enjoyment of mathematics (Luo et al., 2011). Similarly, Chapter 5 of the present thesis shows a reciprocal association between reading enjoyment and self-belief and reading achievement. Such longitudinal links are sometimes observed to be stronger from previous achievement to later enjoyment and self-belief, than the opposite link from previous enjoyment and self-belief to later achievement (e.g. Retelsdorf et al., 2013).

Contrary to the moderate positive longitudinal links between measures of self-belief and achievement within domains, longitudinal associations between self-belief and achievement across different academic domains have been found to be small and negative (e.g. Martin et al., 2011). This suggests that over development, a higher self-belief in one domain (e.g. reading) may lead to the development of lower subsequent self-belief in another domain (e.g. mathematics). Similarly, higher self-belief, or other aspects of motivation, in one domain may contribute to lower achievement in another domain (e.g. Marsh, 1986; Möller et al., 2009; Marsh, Lüdtke, Nagengast, Trautwein, Abduljabbar, Abdelfattah, & Jansen, 2015).

Several theoretical models have been proposed to account for this observed pattern of results (e.g. Shavelson & Marsh, 1985; Marsh, 1986; Marsh & Craven, 2006), including the *Reciprocal Internal/External Frame of Reference* (rI/E) model (Möller, Retelsdorf, Köller, & Marsh, 2011). The rI/E model has been developed focusing on one specific aspect of academic self-belief: academic self-concept, and its association with achievement.

Academic Self-Belief (Self-Concept and Self-Efficacy) and Achievement

As part of the large construct of academic motivation, self-belief has been studied extensively in relation to school achievement (Marsh, 2007). Two main aspects of academic self-belief have been predominantly investigated: academic self-concept and self-efficacy. Both constructs require students to assess their competence and have been described in the literature as hierarchical and domain-specific (Marsh & Craven, 2006; Huang, 2011).

The main difference between self-concept and self-efficacy lies in the explicit and implicit nature of self-evaluation. Self-efficacy assesses participants' evaluation of their own competence for specific abilities (Pajares & Miller, 1994; Marsh et al., 2015). For example a question such as: 'How good do you think you are at multiplying and dividing?' assesses self-efficacy for one aspect of mathematics. In evaluating their own ability for multiplying and dividing, students are believed to reflect upon their performance in that particular skill, judging whether their ability in such skill (e.g. multiplying) meets their own standard of competence for that academic domain (e.g. mathematics). On the other hand, self-concept is concerned with participants’ judgement of their ability in relation to their general sense of competence, proficiency and worthiness (Bandura, 1986). Self-concept is measured through ratings of more general statements, for example: ‘I am good at mathematics’. The absence of references to specific academic activities when measuring self-concept requires participants to rely on both their internal and external frames of reference when evaluating their abilities (Bong and Skaalvik, 2003; Marsh et al., 2015). The internal frame of reference involves comparing one’s own ability in an academic domain (or skill) to one’s own ability in other domains (or skills). The external frame of reference, on the other hand, entails comparing one’s own ability in a particular academic domain to that of other peers (Marsh et al., 2015).

In other words, for self-efficacy, the model proposes that people would compare their performance with that of other individuals (external) and with their own performance in other aspects of the same domain (internal, within domain). For self-concept, people are thought to compare their performance with that of other people (external) and with their own performance in another academic domain (internal, across domains).

Self-concept and self-efficacy are highly correlated, and they both share a moderate relationship with academic achievement. For example, a strong correlation was observed between science self-concept and science self-efficacy (*r* = .57; Jansen, Scherer, & Schroeders, 2015). Another study (Marsh et al., 2015) found self-concept and self-efficacy for several school subjects to be substantially correlated (with *r* coefficients ranging from .50 to .70).

The Reciprocal Internal/External Frame of Reference Model

Academic self-concept has been widely researched. The interest in self-concept is likely to be due to its association with important life outcomes, including school achievement, academic persistence and long-term professional success (Guay, Larose, & Boivin, 2004; Marsh, & O'Mara, 2010; Chen, Yeh, Hwang, & Lin, 2013). This large body of research has led to the development of several theories aimed at explaining the association between academic self-concept and achievement. One of the most influential theories in this field is the *Reciprocal Internal/External Frame of Reference* (rI/E; Möller et al., 2011) model. The rI/E model integrates two existing models: the Reciprocal Effects model (Marsh & Craven, 2006) and the Internal/External Frame of Reference model (Marsh, 1986). The former suggests that there is a reciprocal influence between self-concept and achievement, whereas the latter proposes that one's self-concept for a specific academic domain develops in relation to both achievement in that same domain and achievement in other academic domains.

The rI/E model argues that self-concepts are based on two main comparisons, or frames of reference: a social (external) comparison –judging one's own performance against that of other peers; and a dimensional (internal) comparison –comparing one's accomplishments in one domain with one's own achievement in another academic subject. This differentiation between frames of references would predict that students who achieve highly in one academic domain would also show high levels of self-concept for the same domain (external frame of reference). On the other hand, the internal frame of reference would lead those students who are high achievers in one academic domain (e.g. mathematics) to develop lower self-concept for another, often contrasting, academic domain (e.g. literacy; Möller et al., 2011). This creates a model in which the links between self-concept and achievement within domains are positive and moderate to strong, and the links between self-concept and achievement across academic domains negative and characterised by smaller effect sizes (Marsh et al., 2015).

The rI/E model has been developed and tested focusing on mathematics and verbal abilities, often perceived by students as opposing school subjects. Evidence supporting the rI/E model comes from several studies that have tested its predictions using multiple research designs: from experimental manipulations of achievement feedback (e.g. Möller & Köller, 2001) to introspective diary studies of academic dimension comparisons (e.g. Möller & Housemann, 2006). A meta-analysis including more than 60 studies (Möller, Pohlmann, Koller, & Marsh, 2009) found that, as predicted by the reciprocal I/E model, the relationship between verbal and mathematics self-concept was small

(.10). Additionally, the links from mathematics achievement to verbal self-concept and the opposite links from verbal achievement to mathematics self-concept were modest and negative: −.21 and −.27, respectively. These associations were observed although the relationships between self-concept and achievement within domains were moderate to strong and positive (Möller et al., 2009).

Longitudinal research exploring the relationship between self-belief constructs and achievement

Longitudinal investigations have consistently found moderate to strong relationships between self-belief and achievement within academic domains. For example, a meta-analysis including 39 independent longitudinal samples (Huang, 2011) found modest to moderate correlations between measures of initial self-concept and later achievement (*r* ranging from .20 to .27) and between initial achievement to later self-concept (*r* ranging from .19 to .25). Several studies using structural equation model found support for a reciprocal modest longitudinal link between measures of self-belief and achievement within numerous academic domains, including literacy, reading and mathematics (Marsh & O'Mara, 2008, Retelsdorf, Köller, & Möller, 2013; Niepel, Brunner, & Preckel, 2014).

Although several studies have assessed the associations between academic self-belief constructs and achievement within domains, only a few longitudinal studies have looked at the relationships both within and across domains, and tested the prediction of the rI/E model with adequate power. One study (Möller & Köller, 2001) examined the longitudinal association between achievement and self-concept in the domains of mathematics and literacy, measured twice during one academic year, finding significant positive links from achievement to self-concept and vice versa within academic domains (ranging from .21 to .63), and negative relationships across the two domains (with effects ranging from -.02 to -.25). Similar results were observed in a sample of secondary school students assessed 3 times over 4 years (Marsh & Köller, 2004). A third study (Möller et al., 2011) observed weak, mostly not significant, negative links from self-concept to later achievement in mathematics and

German, as first language, over three years and six collection waves, partly supporting the rI/E model.

The longitudinal evidence on the relationship between self-belief (and motivation more generally) and achievement across academic domains is limited and presents mixed findings. The aim of the present study is to investigate their association in a very large sample of children tested 3 times over a period of 8 years (from 9 to 16 years-old). The present research explores the relationship between two measures of academic motivation (self-efficacy and enjoyment) and achievement in literacy and mathematics. The current study tests the predictions of the rI/E model extending it beyond self-concept, examining two other components of academic motivation: self-efficacy and enjoyment. Additionally, multiple measures of achievement (teacher rated achievement, achievement measured with standardized tests, and exam grades) are considered within a longitudinal design. In order to control for the possible impact of general intelligence (*g*) on the associations (e.g. Chamorro-Premuzic et al., 2010; Spinath et al., 2006), analyses were repeated before and after controlling for *g* at all collection waves. In fact, as both motivation and achievement are associated with general intelligence, it is plausible to assume that *g* would account, at least in part, for their association.

The present study: Hypotheses

The current investigation presents five main hypotheses: (1) Within academic domains, a positive relationship will be observed between achievement and motivation at all ages; (2) Across domains, correlations will be stronger for measures of achievement than for measures of self-efficacy and enjoyment; (3) Within domains, the links from self-efficacy and enjoyment to later achievement will be weaker than those from achievement to later self-efficacy and enjoyment; (4) Across domains, a weak negative association will be observed between achievement in one domain and later self-efficacy and enjoyment in another domain; and between self-efficacy and enjoyment in one domain and subsequent achievement in the other domain; (5) general cognitive ability will explain a portion of every observed association, but most associations will remain significant even after controlling for *g*.

Methods

Participants

The sample included 5,624 children (55% females), drawn from the Twins Early Development Study (TEDS; Haworth, Davis, & Plomin, 2013). TEDS is a large-scale longitudinal study of twins born in England and Wales between 1994 and 1996. The present study used data collected over 3 waves, when the twins were 9, 12 and 16 years old. At age 9 and 12 data were collected from children and teachers using questionnaires. At age 16 GCSE grades were collected from the children as part of a larger online assessment. Because data were collected in a twin sample, in order to control for non-independence of observations (i.e. the fact that the children in the sample were twins), one twin out of each pair was randomly selected for all the analyses reported in this manuscript.

When the same analyses were conducted on the other half of the sample, very similar results were obtained, showing internal replicability of the findings.

Measures

Self-efficacy and Enjoyment in Literacy and Mathematics

Separate measures of literacy and mathematics self-efficacy and enjoyment were obtained via self-reports when the children were 9 and 12 years old. Children were asked to rate on a 5-point scale how good they thought they were (self-efficacy) and how much they liked (enjoyment) activities related to literacy and mathematics. Examples of items are '*How good do you think you are at reading?*' and '*How much do you like solving number problems?*' Four composite measures were created on the basis of internal validity analyses (Cronbach's alpha): literacy self-efficacy (average α = .65, N of items = 3) and literacy enjoyment (average α = .69, N = 3), and for mathematics self-efficacy (average α = .86, N = 3) and mathematics enjoyment (average α = .85, N = 3) were created at age 9 and age 12.

Achievement in Literacy and Mathematics

Teacher ratings for literacy and mathematics achievement were collected when the children were 9 and 12 years old. At age 9 teachers rated each student on a scale from 1 to 5 on the basis of the expected UK achievement standards for Key Stage 2 (Qualifications and Curriculum Authority, 2003). Teachers assessed students' abilities in three broad areas for each academic domain. For literacy, teachers evaluated each student's abilities in (1) speaking and listening; (2) reading; and (3) writing. For mathematics, teachers rated the following three abilities: (1) using and applying mathematics; (2) numbers and algebra; and (3) shapes, space and measures. Teacher ratings were based on the expected UK standard at Key stage 2. The overall teacher rated achievement score was calculated for each domain as the first unrotated principal component.

At 12 teachers rated each child's literacy and mathematics achievement on the same ability areas that were measured at age 9, on a scale from 1 to 8 (plus a 9th point reserved for exceptional performance) on the basis of the expected UK standards at Key stage 3 (Qualifications and Curriculum Authority, 2003). As for the composite scores at age 9, the overall teacher-rated achievement score at 12 was calculated for each academic domain as the first unrotated principal component.

At age 12, achievement in literacy and mathematics was also measured via online test batteries. The battery assessing literacy ability included 3 tests: the Peabody Individual Achievement test of reading comprehension (PIAT; Markwardt 1997); the GOAL formative assessment in literacy for Key stage 3, assessing reading comprehension (GOAL, plc 2002); and the Woodcock-Johnson III-test of reading fluency (Woodcock, McGrew, and Mather 2001). The total score for the web assessment of literacy at 12 was obtained from factor analysis as the first unrotated component. The online battery assessing mathematics at 12 was composed of three measures assessing: understanding numbers; non-numerical processes; and computation and mathematical knowledge. The total score for mathematics at 12 was also derived from principal component analysis. Further details on the batteries can be found in previous publications (Kovas, Haworth, Petrill, & Plomin, 2007; Haworth, Kovas, Harlaar, Hayiou-Thomas, Petrill, Dale, & Plomin, 2009).

At age 16, achievement in literacy and mathematics was measured via General Certificate for Secondary Education (GCSE) scores for English and Mathematics.

General Cognitive Ability

General cognitive ability (*g*) at 9 was measured with 4 tests: WISC-III-PI Vocabulary Multiple Choice; WISC-III-PI General Knowledge tests (Kaplan et al. 1999); Puzzle and Shapes tests taken from the Cognitive Abilities Test 3 (CAT3; Smith, Fernandes, & Strand, 2001).

At 12 a measure of *g* was obtained from 4 tests: WISC-III-PI Vocabulary Multiple Choice; WISC-III-PI General Knowledge tests (Kaplan et al. 1999); Picture Completion test (Wechsler 1992); and Raven Standard Progressive Matrices (Raven, Court, & Raven, 1996).

At 16 *g* was measured with two tests: Raven Standard Progressive Matrices, and Mill Hill Vocabulary Test (Raven, Raven, & Court 1998).

Analytic Strategies

The cross-lagged cross-domain model

Several cross-lagged, cross-domain models, using the OpenMx package (Boker et al., 2011) for R (Team R, 2012), were fitted to test the hypotheses of the present study. The models included measures of literacy and mathematics self-efficacy and enjoyment obtained over two collection waves (age 9 and 12), and achievement collected over three waves (age 9, 12 and 16). The cross-lagged cross-domain model allows for the exploration of the links from previous self-efficacy (or enjoyment) to subsequent achievement and vice versa (i.e. cross-lagged links) within academic domains (e.g. from literacy self-efficacy at wave 1 to literacy achievement at wave 2) as well as across academic domains (e.g. from literacy self-efficacy at wave1 to mathematics achievement at wave 2). These links are calculated after accounting for the variance explained by the stability of the measures and their contemporaneous correlations at each previous time point. By modeling both literacy and mathematics variables in the same model, the longitudinal links across domains are calculated after accounting for the domain-general aspects of motivation and achievement constructs (i.e. their correlations). Therefore, the cross-lagged cross-domain links reflect the links between domain-specific motivation and achievement in one domain and domain-specific achievement and motivation in another domain.

We ran three alternative models including different measures of achievement, self-efficacy and enjoyment in order to assess whether the relation between motivation and performance was comparable across all measures. **Model 1** (see figure 4.1.a) explored the association between self-efficacy and achievement in literacy and mathematics over time. In this model, achievement was assessed using different measures at every collection wave. Therefore, Model 1 included the following variables: mathematics and literacy self-efficacy (measured at 9 and 12); teacher-rated achievement in literacy and mathematics at age 9; web-based assessments of literacy and mathematics at age 12; and English and Mathematics GCSE scores at age 16.

Model 2 (Figure 4.2.a) also explored the association between self-efficacy and achievement. However, in this second model achievement in literacy and mathematics was measured via teacher ratings both at age 9 and 12. Therefore, Model 2 included the same variables as Model 1, with the exception of the web-assessed literacy and mathematics variables at 12, which were replaced with teacher ratings of literacy and mathematics achievement at 12. By comparing the results of Model 1 and Model 2 it is possible to evaluate whether the association that achievement shares with self-efficacy is consistent irrespectively of how achievement is measured (i.e. teacher ratings and web-based ability tests).

Model 3 (Figure 4.3.a) explored the longitudinal relation between enjoyment of literacy and mathematics and achievement. As well as including measures of mathematics and literacy enjoyment at ages 9 and 12, this third model included teacher ratings at age 9, web-assessed literacy and mathematics ability at 12, and GCSE scores for Mathematics and English at age 16. By comparing results if model 3 with those obtained from the previous two models, it is possible to explore whether different motivational constructs (enjoyment and self-efficacy) share a similar longitudinal relation with measures of achievement. A fourth model including the same variables as those included in Model 3, but replacing web-based assessments at 12 with teacher ratings was also conducted. Because results of the fourth model were practically identical to those obtained from Model 3 and similar to those of Model 1 and Model 2, the fourth model is not presented in the present chapter.

The same models were run once more after controlling for the effect of general intelligence (*g*). **Model 1b, Model 2b, and Model 3b** were fitted in order to observe the impact that general intelligence had on the observed associations between self-efficacy, enjoyment and achievement (see Figure 4.1.b; Figure 4.2.b; and Figure 4.3.b). The variance explained by age and sex was also controlled for in every model by using linear regression.

Results

Descriptive statistics and correlations

Descriptive statistics are presented in Table 4.1. Examination of histograms showed that the data were symmetrically distributed, and only slightly skewed for the self-efficacy and enjoyment variables. The significant values for skewness reported in Table 4.1 are likely due to the very large sample size included in the present study. In fact, given the large sample size, and hence high statistical power, any slight deviation from normality was likely to be detected.

Table 4.1. Descriptive statistics (Mean, Standard Deviation, Skewness, Kurtosis and Standard Error)

Variable	N*	M	SD	Skew[a]	Kurtosis[a]
Literacy SE 9	3116	4.08	0.72	−19.83	9.04
Maths SE 9	3110	3.82	0.98	−16.67	−0.69
Literacy ENJ 9	3103	3.79	0.86	−13.69	2.69

Maths ENJ 9	3102	3.52	1.14	−1.77	−7.53
Literacy TR ach 9	2641	0.00	0.98	−2.84	0.22
Maths TR ach 9	2625	0.00	0.99	−4.31	1.43
Literacy SE 12	5523	3.92	0.73	−21.60	7.71
Maths SE 12	5527	3.81	0.90	−2.38	−0.40
Literacy ENJ 12	5523	3.46	0.82	−1.04	−0.42
Maths ENJ 12	5527	3.29	1.03	−6.66	−7.84
Literacy TR ach 12	3754	0.04	0.97	1.17	35.47
Maths TR ach 12	3688	0.04	0.95	9.68	31.52
Literacy Web ach 12	4980	0.00	0.98	−13.35	1.49
Maths Web ach 12	4857	66.74	14.98	−25.91	11.93
English GCSE 16	5128	9.12	1.28	−17.84	14.93
Maths GCSE 16	5079	8.94	1.46	−16.71	7.92

Note: Literacy SE 9 = Literacy Self-Perceived Ability at 9; Maths SE 9 = Mathematics Self-Perceived Ability at 9; Literacy ENJ 9 = Literacy Enjoyment at 9; Maths ENJ 9 = Mathematics Enjoyment at 9; Literacy TR ach 9 = Teacher-rated literacy achievement at 9; Maths TR ach 9 = Teacher-rated mathematics achievement at 9; Literacy SE 12 = Literacy Self-Perceived Ability at 12; Maths SE 12 = Mathematics Self-Perceived Ability at 12; Literacy ENJ 12 = Literacy Enjoyment at 12; Maths ENJ 12 = Mathematics Enjoyment at 12; Literacy TR ach 12 = Teacher-rated literacy achievement at 12; Maths TR ach 12 = Teacher-rated mathematics achievement at 12; Literacy Web ach 12 = Literacy web test score at 12; Maths Web ach 12 = Mathematics web test score at 12; English GCSE 16 = English GCSE grade at 16; Maths GCSE 16 = Mathematics GCSE grade at 16; a = Skewness and Kurtosis are standardised; * = 1 twin out of each pair was randomly selected.

Correlations between variables are reported in Table 4.2, and the sample size for each pairwise association in Table 4.3. Overall, contemporaneous correlations between measures of achievement across the two academic domains (literacy and mathematics) were strong (average r = .75). Longitudinal correlations between measures of achievement were strong both within and across academic domains. Correlations between contemporaneous measures of self-efficacy across domains were moderate (average r = .35). Longitudinal correlations between measures of self-efficacy within domain were strong (average r = .52), while longitudinal correlations between measures of self-efficacy across academic domains were modest (average r = .20). Correlations between contemporaneous measures of enjoyment were moderate (average r = .32). Longitudinal correlations between measures of enjoyment within academic domains were moderate to strong (average r = .41), whereas they were weak across academic domains (average r = .13). Correlations between measures of self-efficacy and achievement were moderate (average r = .38) both cross-sectionally and longitudinally within academic domains.

Across academic domains, correlations between measures of self-efficacy and achievement were modest to moderate (average r = .27) both cross-sectionally and longitudinally. Correlations between measures of enjoyment and achievement were modest (average r = .21) cross-sectionally within academic domains, and weak across domains (average r = .11). Longitudinal correlations between measures of enjoyment and achievement were moderate (average r = .21) within academic domains, and weak across domains (average r = .09)

The cross-lagged cross-domain model

The present chapter focuses on reporting the results of Model 1 and Model 1b for which the largest sample size was achieved (N = 5622). Model 1 explores the longitudinal association between achievement and self-efficacy in literacy and mathematics over an 8-year developmental time. While measures of self-efficacy are consistent across collection waves, measures of achievement are different at every collection wave. In Model 1 and Model 1b achievement in literacy and mathematics is measures via teacher ratings at age 9, web-based assessments at 12 and GCSE scores at 16. Results were highly consisted across all Models, and therefore only the results of Model 1 are discussed in detail in this Results section.

Table 4.2. Correlational relationships between variables (Ns for all associations are reported in Table 3)

Variable*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. L SE 9	1																
2. M SE 9	.33	1															
3. L ENJ 9	.55	.19	1														
4. M ENJ 9	.19	.72	.30	1													
5. L TR ach 9	.36	.22	.18	.08	1												
6. M TR ach 9	.27	.36	.08	.21	.75	1											
7. L SE 12	.52	.17	.36	.10	.45	.33	1										
8. M SE 12	.24	.51	.09	.42	.30	.43	.36	1									
9. L ENJ 12	.38	.10	.42	.10	.28	.17	.62	.22	1								
10. M ENJ 12	.14	.41	.14	.43	.12	.24	.21	.73	.33	1							
11. LTR ach 12	.31	.26	.14	.12	.59	.51	.37	.31	.21	.13	1						
11. MTR ach 12	.26	.37	.09	.23	.56	.58	.29	.44	.13	.25	.81	1					
13. L Web 12	.30	.17	.16	.06	.58	.50	.39	.24	.28	.10	.53	.47	1				
14. M Web 12	.23	.35	.08	.22	.53	.57	.28	.45	.16	.30	.49	.55	.61	1			
15. E GCSE 16	.27	.22	.14	.10	.59	.54	.40	.34	.28	.16	.58	.53	.55	.53	1		
16. M GCSE 16	.22	.36	.08	.20	.54	.59	.28	.47	.17	.29	.54	.61	.50	.66	.72	1	
17. *g*	.19	.24	.05	.11	.42	.45	.24	.28	.15	.15	.42	.45	.60	.63	.51	.56	1

Note: **L SE 9** = Literacy Self-Efficacy at 9; **M SE 9** = Mathematics Self-Efficacy at 9; **L ENJ 9** = Literacy Enjoyment at 9; **M ENJ 9** = Mathematics Enjoyment at 9; **L TR ach 9** = Teacher-rated literacy achievement at 9; **M TR ach 9** = Teacher-rated mathematics achievement at 9; **L SE 12** = Literacy Self-Efficacy at 12; **M SE 12** = Mathematics Self-Efficacy at 12; **L ENJ 12** = Literacy Enjoyment at 12; **M ENJ 12** = Mathematics Enjoyment at 12; **L TR ach 12** = Teacher-rated literacy achievement at 12; **M TR ach 12** = Teacher-rated mathematics achievement at 12; **L Web 12** = Literacy web test score at 12; **M Web 12** = Mathematics web test score at 12; **E GCSE 16** = English GCSE grade at 16; **M GCSE 16** = Mathematics GCSE grade at 16;

All correlations are significant at the .001 level; *g* = general cognitive ability, correlations between *g* at age 9, 12 and 16 and measures at the respective age are included; *All measures were adjusted for age and sex.

Table 4.3. Sample sizes for the pairwise associations.

Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
L SE 9	3116																
M SE 9	3109	3110															
L ENJ 9	3097	3094	3103														
M ENJ 9	3097	3095	3097	3102													
L TR ach 9	2242	2237	2232	2232	2641												
M TR ach 9	2228	2223	2218	2219	2594	2625											
L SE 12	2523	2520	2517	2515	1960	1942	5523										
M SE 12	2524	2521	2518	2516	1961	1943	5522	5527									
L ENJ 12	2520	2517	2514	2512	1958	1940	5517	5521	5523								
M ENJ 12	2523	2520	2517	2515	1960	1942	5521	5525	5522	5527							
LTR ach 12	1226	1225	1225	1224	983	972	3191	3195	3193	3195	3754						
MTR ach 12	1176	1176	1176	1175	946	934	3126	3130	3128	3130	3598	3688					
L Web 12	2151	2147	2142	2141	1710	1695	4386	4389	4386	4389	2844	2791	4980				
M Web 12	2100	2097	2092	2092	1666	1654	4302	4305	4303	4305	2812	2763	4796	4857			
E GCSE 16	2409	2405	2400	2398	1955	1947	3812	3815	3811	3813	2452	2394	3498	3431	5128		
M GCSE 16	2391	2387	2382	2380	1939	1932	3781	3784	3780	3782	2434	2377	3467	3399	5068	5079	
g	3024	3020	3015	3014	2188	2176	3863	3866	3865	3868	2465	2410	3958	3915	2034	2022	*

Note: **L SE 9** = Literacy Self-Efficacy at 9; **M SE 9** = Mathematics Self-Efficacy at 9; **L ENJ 9** = Literacy Enjoyment at 9; **M ENJ 9** = Mathematics Enjoyment at 9; **L TR ach 9** = Teacher-rated literacy achievement at 9; **M TR ach 9** = Teacher-rated mathematics achievement at 9; **L SE 12** = Literacy Self-Efficacy at 12; **M SE 12** = Mathematics Self-Efficacy at 12; **L ENJ 12** = Literacy Enjoyment at 12; **M ENJ 12** = Mathematics Enjoyment at 12; **L TR ach 12** = Teacher-rated literacy achievement at 12; **M TR ach 12** = Teacher-rated mathematics achievement at 12; **L Web 12** = Literacy web test score at 12; **M Web 12** = Mathematics web test score at 12; **E GCSE 16** = English GCSE grade at 16; **M GCSE 16** = Mathematics GCSE grade at 16; g = general cognitive ability; * the N for *g* varies at the different collection waves.

Parameter estimates for Model 1 are presented in Table 4.5 and Figure 4.1.a. Parameter estimates for Model 1b, including the same measures as Model 1 but after accounting for the variance explained by *g*, are reported in Table 4.6 and Figure 4.1.b. Although not discussed in detail in the Results section of the present chapter, Figure 4.2.a Figure 4.2.b and Table 4.7 report the outcomes for Model 2 and Model 2b, and Results of Model 3 and Model 3b are reported in Figure 4.3.a and Figure 4.3.b and Table 4.8. Model fit indices for all the models are reported in Table 4.4. Overall the three models show acceptable fit. Although the 6 cross-lagged cross-domain models provide a significantly poorer fit to the data then their saturated models, the decrease in fit is likely due to the very large sample size. In fact, CFI, TLI and RMSEA indices show that all the models were a good fit for the data.

Goodness of fit was estimated using Maximum Likelihood, which allows to test the models' goodness of fit by comparing it against the Saturated Model (baseline model), and to obtain confidence intervals for all the parameters within the model (Rijsdijk & Sham, 2002; Neale, 2009). Using Maximum Likelihood also allows to avoid the exclusion of cases due to missing data points, as soon as the likelihood for each data point is computed (Neale, 2009). Significance of each path was estimated using 95% confidence intervals (CIs) for standardized paths, the paths with CIs overlapping zero were not significant.

Table 4.4. Model fit indices for the 3 cross-lagged cross-domain Models and their respective saturated models

Model	**ep**	**−2LL**	**df**	**AIC**	**CFI**	**TLI**	**RMSEA**	**χ^2**	**df**	***p***
Saturated 1	65	128,902.30	42,521	43,860.30	-	-	-	-	-	-
Model 1	57	129,144.04	42,529	44,086.04	.99	.92	.03	241.74	8	.000
Saturated 1b	65	89,167.78	30,001	29,165.78	-	-	-	-	-	-
Model 1b	57	89,268.89	30,009	29,250.89	.98	.92	.03	101.11	8	.000
Saturated 2	65	94,976.55	40,126	14,724.55	-	-	-	-	-	-
Model 2	57	95,248.91	40,134	14,980.91	.99	.94	.03	272.36	8	.000
Saturated 2b	65	60,577.47	27,003	6,571.47	-	-	-	-	-	-

Model 2b	57	60,661.52	27,011	6,639.52	.99	.94	.03	84.05	8	.000
Saturated 3	65	135,630.11	42,500	50,630.11	-	-	-	-	-	-
Model 3	57	135,914.19	42,508	50,898.19	.98	.89	.04	284.08	8	.000
Saturated 3b	65	94,709.19	29,990	34,729.19	-	-	-	-	-	-
Model 3b	57	94,829.36	29,998	34,833.36	.98	.89	.039	12.16	8	.000

Note: ep = number of parameters estimated; -2LL = negative *2 log likelihood; df = degrees of freedom; AIC = Akaike information criterion; CFI = comparative fit index; TLI = Tucker Lewis index; RMSEA = root mean square residual; χ^2 = chi square.

Relationships within academic domains: Correlations

The correlation between literacy self-efficacy and literacy achievement at wave 1, when students were 9, was moderate (r = .37; CIs = .33, .39); and the same was observed for the correlation between mathematics self-efficacy and achievement (r = .37, CIs = .34, .40). Correlations between measures at wave 2 are residual correlations, as the estimates are calculated after accounting for the variance explained by correlations at wave 1, their stability from wave 1 to wave 2, and the cross-lagged links from wave 1 to wave 2. The residual correlation between literacy self-efficacy and literacy achievement at wave 2, when students were 12, was small (r = .09, CIs = .07, .12), and a similar effect was observed for the correlation between mathematics self-efficacy and mathematics achievement (r = .15, CIs = .12, .17). Within academic domains, measures of self-efficacy were moderately stable from wave 1 to wave 2 (with path coefficients for stability of .40 and .42 for literacy and mathematics, respectively). Although different measures of achievement in literacy and mathematics were used (teacher ratings and web tests) at different ages, they were moderately stable from the first to the second collection wave, with path coefficients of .45 and .35, respectively. Stability of achievement was also moderate from wave 2 to wave 3, as path coefficients were .32 (CIs = .28, .35) for literacy, and .49 (CIs = .46, .52) for mathematics, respectively.

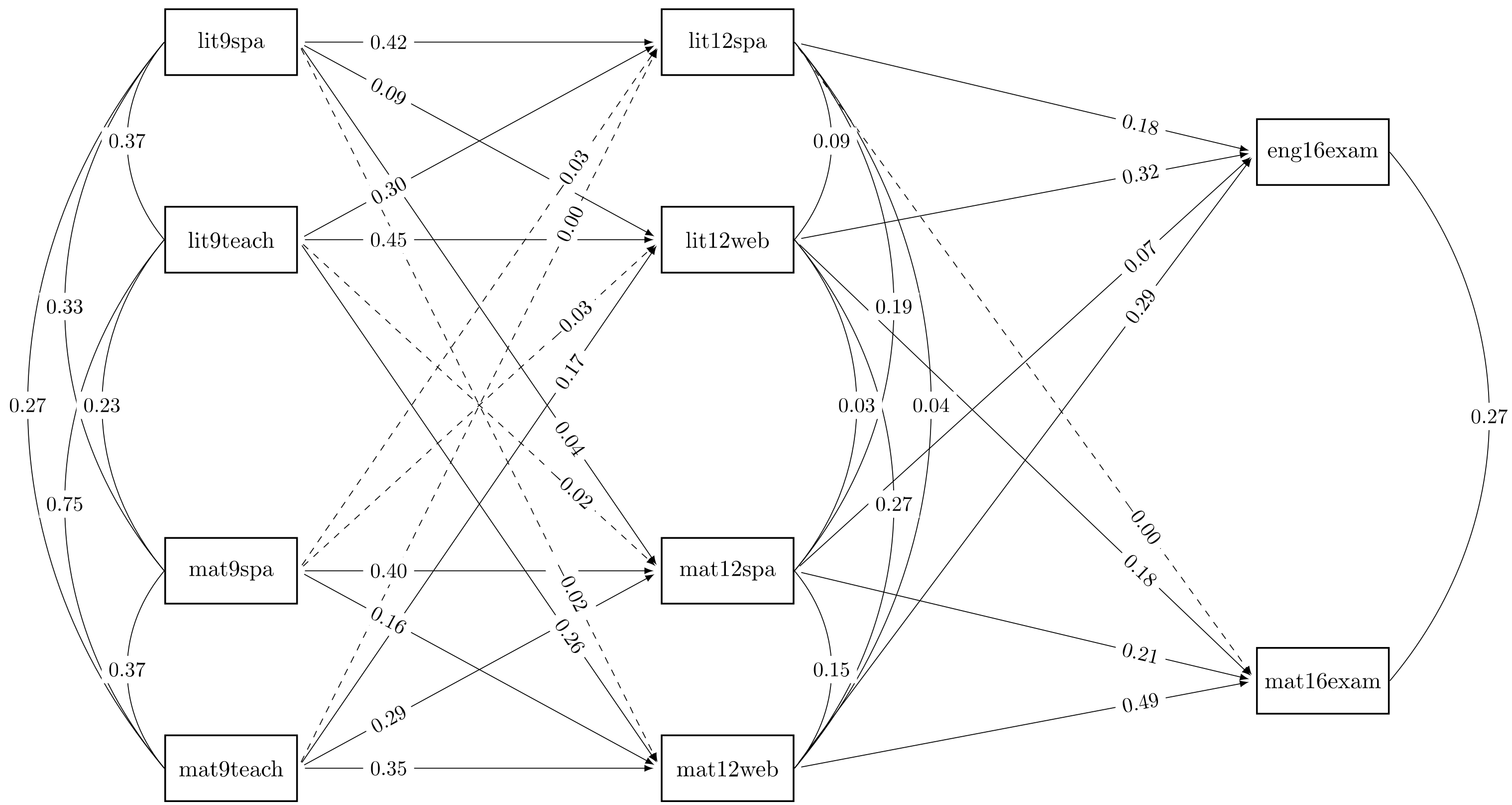

Figure 4.1.a. Path diagram for Model 1 including path estimates for all associations; lit9spa = literacy self-efficacy (or self-perceived ability) at 9; lit9teach = teacher- rated literacy achievement at age 9; mat9spa = mathematics self-efficacy at 9; mat9teach = teacher-rated mathematics achievement at age 9; lit12spa = literacy self-efficacy at 12; lit12web = web-based literacy achievement at age 12; mat12spa = mathematics self-efficacy at 12; mat12web = web-based mathematics achievement at age 12; lit16exam = English GCSE score at 16; mat16exam = Mathematics GCSE score at 16.

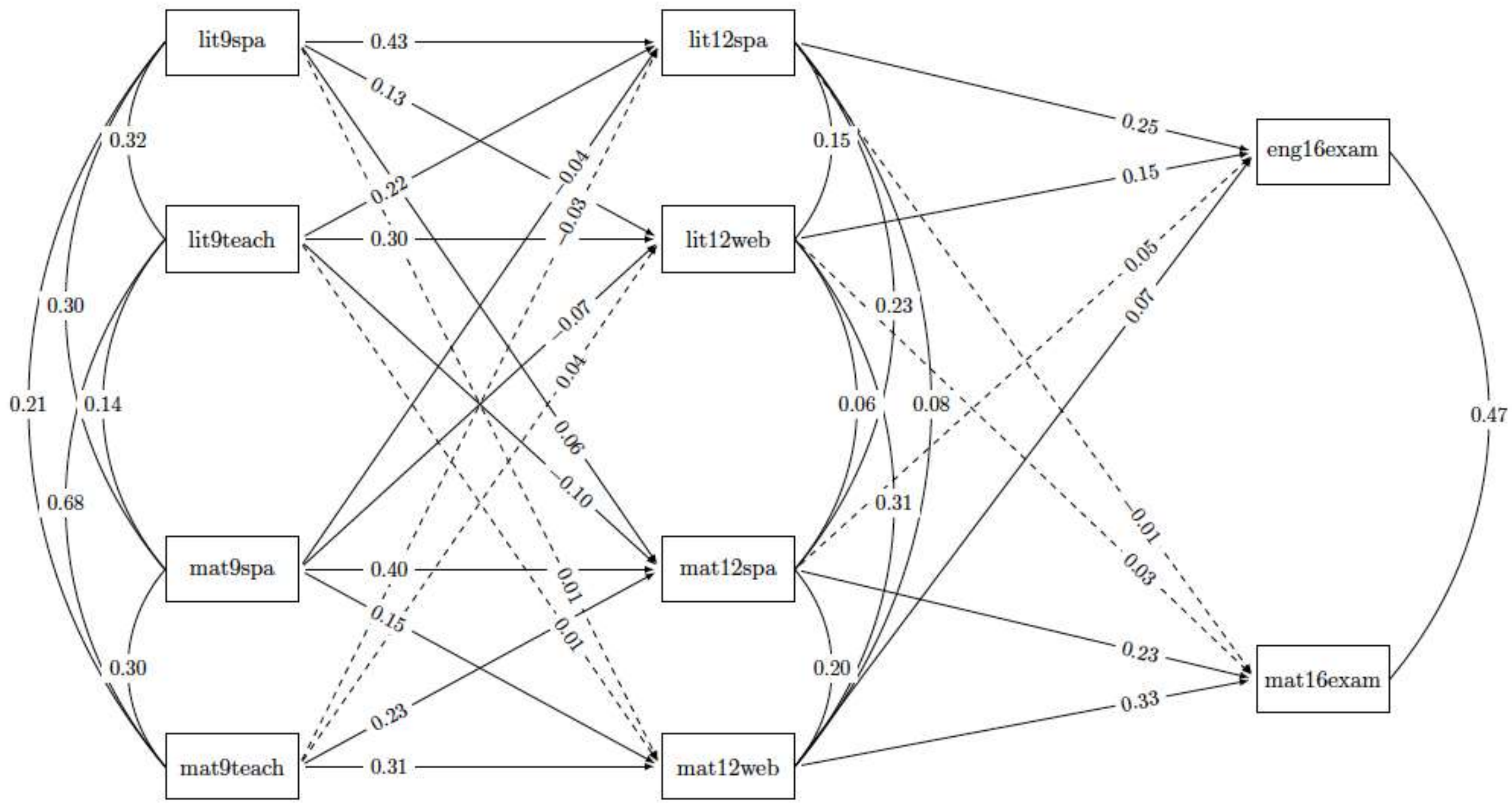

Figure 4.1.b. Path diagram for Model 1(b) after accounting for general cognitive ability (*g*) at all ages; lit9spa = literacy self-efficacy (self-perceived ability) at 9; lit9teach = teacher- rated literacy achievement at age 9; mat9spa = mathematics self-efficacy at 9; mat9teach = teacher-rated mathematics achievement at age 9; lit12spa = literacy self-efficacy at 12; lit12web = web-based literacy achievement at age 12; mat12spa = mathematics self-efficacy at 12; mat12web = web-based mathematics achievement at age 12; lit16exam = English GCSE score at 16; mat16exam = Mathematics GCSE score at 16.

The model presented in Figure 4.1.b, Model 1b, includes the same variables as Model 1, but after accounting for the variance explained by *g*, using linear regression. Overall, *g* accounted for part of the associations between achievement and self-efficacy. However, the majority of the variance in the association between achievement and self-efficacy was not attributable to *g*. The same was observed for Model 2 and Model 3.

Relationships within academic domains: Cross-lagged associations

Within academic domains, the cross-lagged associations (links from achievement at wave 1 to self-efficacy at wave 2 and the opposite link from initial self-efficacy to subsequent achievement) were small to modest. The cross-lagged links from achievement at wave1 to self-efficacy at wave 2 were of larger effect sizes (. 30; CIs = .24, .35 for literacy and .29; CIs = .23, .35 for mathematics) than the opposite links from self-efficacy at wave1 to achievement at wave 2 (.09; CIs = .05, .13 for literacy and .16; CIs = .13, .20 for mathematics). Also in this case, *g* accounted for only part of these associations. In fact, after accounting for *g,* cross-lagged links from achievement at wave 1 to self-efficacy at wave 2 were of weaker effect, but still significant (.22; CIs = .15, .28 for literacy and .23; CIs = .16, .29 for mathematics; see Figure 2). On the other hand, *g* was not found to impact the cross-lagged links from self-efficacy at wave 1 to achievement at wave 2.

Relationships across academic domains: Correlations

The correlation between contemporaneous measures of achievement in literacy and mathematics at wave 1 was strong (r = .75; CIs = .73, .77). The residual correlation between achievement measures at wave 2 was moderate (r = .27; CIs = .24, .29). This shows that the relationship between literacy and mathematics achievement at wave 2 was not entirely explained by the association between measures of achievement at wave 1, the stability of achievement from wave 1 to wave 2, and its cross-lagged relationship with self-efficacy at wave 1. However, it is possible that the residual relationship between literacy and mathematics achievement at wave 2 may be due to the fact that model 1 included different measures of achievement from wave 1 (teacher rating) to wave 2 (web test). We tested this hypothesis with Model 2 (see Appendix B), as this second model included teacher rated achievement scores for both wave 1 and wave 2. We found that the residual correlation between measures of mathematics and literacy achievement at wave 2 in Model 2 (see Figure B1) was significant and of comparable effect (r = .39, CIs = .36, .42) to that observed in Model 1. This indicates that the association between achievement in literacy and mathematics at the end of primary school does not entirely account for their later association in the first years of secondary school. The residual correlation between GCSE grades for mathematics and English at wave 3, at the end of secondary school, was moderate (r = .27). Overall, this suggests the relationship between literacy and mathematics achievement is dynamic over the course of primary and secondary school, with new influences contributing to it at every stage.

Contemporaneous correlations between measures of self-efficacy across domains at wave 1 were modest to moderate (r = .33, CIs = .30, .36). The residual correlation between literacy and mathematics self-efficacy at wave 2 was weak (r = .19, CIs = .17, .22),

Relationships across academic domains: Cross-lagged links

As shown in Figure 1, the strength of cross-lagged links across academic domains was weak or negligible (ranging from -0.10 to 0.07). Results of Model 1 show that none of the cross-lagged cross-domain links were negative and significant. The only significant cross-lagged cross-domain links were positive, weak to modest, and observed between: (1) literacy self-efficacy at 9 and mathematics self-efficacy at 12 (β = .04); (2) mathematics achievement at 9 and literacy achievement at 12 (β = .17); (3) literacy achievement at 9 and mathematics achievement at 12 (β = .26); (4) mathematics achievement at 12 and English GCSE grade at 16 (β = .29); and (5) mathematics self-efficacy at 12 and English GCSE grade at 16 (β = .07); (6) literacy achievement at 12 and mathematics GCSE grade at 16 (β = .18). All the other cross-lagged cross-domain paths did not reach significance.

Table 4.5. Unstandardized and standardized parameters and 95% confidence intervals (95% CI) for the associations between self-efficacy and achievement explored in ***Model 1***.

Path	Unstandardized parameter	Standardized parameter	95% CI
lit9spa → lit12spa	0.435	0.424	[0.390, 0.456]
lit9spa → mat12spa	0.047	0.037	[0.001, 0.073]
lit9spa → lit12web	0.123	0.089	[0.052, 0.126]
lit9spa → mat12web	−0.407	−0.019	[−0.056, 0.018]
mat9spa → lit12spa	−0.025	−0.033	[−0.069, 0.002]
mat9spa → mat12spa	0.37	0.403	[0.368, 0.437]
mat9spa →lit12web	−0.029	−0.028	[−0.066, 0.010]
mat9spa → mat12web	2.562	0.165	[0.127, 0.202]
lit9teach →lit12spa	0.223	0.296	[0.241, 0.351]
lit9teach → mat12spa	−0.022	−0.024	[−0.081, 0.033]
lit9teach → lit12web	0.457	0.449	[0.393, 0.503]
lit9teach → mat12web	4.079	0.261	[0.204, 0.316]
mat9teach → lit12spa	0.003	0.004	[−0.053, 0.061]
mat9teach → mat12spa	0.268	0.293	[0.234, 0.350]
mat9teach → lit12web	0.172	0.17	[N A, 0.228]
mat9teach → mat12web	5.368	0.346	[0.289, 0.402]
lit12spa → eng16exam	0.315	0.179	[0.150, 0.207]
lit12spa → mat16exam	−0.004	−0.002	[−0.029, 0.024]
mat12spa → eng16exam	0.1	0.07	[0.040, 0.099]
mat12spa →mat16exam	0.344	0.209	[0.182, 0.237]
lit12web → eng16exam	0.413	0.317	[0.283, 0.351]
lit12web → mat16exam	0.267	0.179	[0.147, 0.211]
mat12web → eng16exam	0.024	0.286	[N A, N A]
mat12web → mat16exam	0.047	0.488	[0.457, 0.519]
mat9spa ⇔ lit9spa	0.233	0.33	[0.299, 0.361]
lit9teach ⇔ lit9spa	0.257	0.366	[0.332, 0.399]
mat9teach ⇔ lit9spa	0.191	0.27	[0.234, 0.306]
lit9teach ⇔ mat9spa	0.225	0.233	[0.197, 0.269]
mat9teach ⇔ mat9spa	0.364	0.374	[0.340, 0.407]
mat9teach ⇔ lit9teach	0.725	0.75	[0.733, 0.766]
mat12spa ⇔ lit12spa	0.127	0.192	[0.169, 0.215]
lit12web ⇔ lit12spa	0.069	0.094	[0.069, 0.119]
mat12web ⇔ lit12spa	0.408	0.036	[0.012, 0.061]
lit12web ⇔ mat12spa	0.026	0.028	[0.004, 0.053]
mat12web ⇔ mat12spa	2.027	0.147	[0.123, 0.172]
mat12web ⇔ lit12web	4.08	0.267	[0.243, 0.293]
mat16exam⇔eng16exam	0.52	0.27	[N A, 0.288]

Note: lit9spa = literacy self-efficacy wave1 (age 9); lit9teach = literacy achievement wave 1; mat9spa = mathematics self-efficacy wave1; mat9teach =

mathematics achievement wave1; lit12spa = literacy self-efficacy wave 2 (age 12); lit12web = literacy achievement wave 2; mat12spa = mathematics self-efficacy wave 2; mat12web = mathematics achievement wave 2; eng16exam = English GCSE score wave 3 (age16); mat16exam = mathematics GCSE score at 16; → = one-way path; ⇔ = two-way path.

Results of Model 1b, calculated after controlling for *g,* presented a slightly different picture. Three cross-lag, cross-domain paths were characterized by negative significant associations: (1) the path from mathematics self-efficacy at age 9 to literacy self-efficacy at 12 ($\beta = -.04$); (2) the path from mathematics self-efficacy at 9 to literacy achievement at 12 ($\beta = -.07$); and (3) the path from literacy achievement at 9 to mathematics self-efficacy at 12 ($\beta = -.10$). A small but significant positive link was observed from literacy self-efficacy at 9 to mathematics self-efficacy at 12 ($\beta = .06$), and from mathematics achievement at 12 to literacy achievement at 16 ($\beta = .07$). The remaining cross-lagged cross-domain links were not significant.

The cross-lagged cross-domain model including other measures of achievement and motivation: Model 2 and Model 3

Overall, Results of Model 2, including academic self-efficacy at wave 1 and 2, teacher-rated achievement at wave 1 and 2 and GCSE grades at wave 3 produced similar results (see Figure 4.2.a) were consistent with those found in Model 1. The same was observed after the association all variables shared with g was controlled for using linear regression (see Figure 4.2.b). The fact that results are comparable across Model 1 and Model 2 suggests that the association between self-efficacy and achievement is consistent irrespectively of whether achievement is assessed using teacher ratings or web-based tests.

Results of Model 3, exploring the longitudinal association between enjoyment and achievement in literacy and mathematics also produced similar results to those observed in Model 1 and Model 2 (see Figure 4.3.a). Additionally, associations were consistent across all the three models after accounting for *g* (see Figure 4.3.b). This indicates that the longitudinal association between achievement and motivation within and across the domains of literacy and mathematics is across several aspect of academic motivation.

Table 4.6. Unstandardized and standardized parameters and 95% confidence intervals for the associations explored in ***Model 1b*** between self-efficacy and achievement after accounting for *g*.

Path	Unstandardized parameter	Standardized parameter	95% CI
lit9spa → lit12spa	0.422	0.426	[0.384, 0.465]
lit9spa →mat12spa	0.073	0.06	[0.014, 0.105]
lit9spa →lit12web	0.145	0.128	[0.081, 0.176]
lit9spa →mat12web	0.2	0.012	[−0.038, 0.062]
mat9spa →lit12spa	−0.031	−0.043	[−0.085, −0.001]
mat9spa →mat12spa	0.362	0.403	[0.362, 0.443]
mat9spa →lit12web	−0.061	−0.074	[−0.120, −0.027]
mat9spa →mat12web	1.884	0.153	[0.104, 0.202]
lit9teach →lit12spa	0.176	0.22	[0.156, 0.284]
lit9teach →mat12spa	−0.102	−0.104	[−0.170, −0.038]
lit9teach →lit12web	0.276	0.303	[0.233, 0.370]
lit9teach →mat12web	0.2	0.015	[−0.060, 0.090]
mat9teach →lit12spa	−0.023	−0.029	[−0.094, 0.037]
mat9teach →mat12spa	0.227	0.23	[0.163, 0.295]
mat9teach →lit12web	0.033	0.036	[−0.035, 0.107]
mat9teach →mat12web	4.178	0.309	[0.233, 0.381]
lit12spa →eng16exam	0.38	0.25	[0.196, 0.302]
lit12spa →mat16exam	−0.011	−0.006	[−0.058, 0.045]
mat12spa →eng16exam	0.065	0.053	[−0.005, 0.111]
mat12spa →mat16exam	0.312	0.226	[0.171, 0.279]
lit12web →eng16exam	0.204	0.153	[0.094, 0.212]
lit12web →mat16exam	0.038	0.026	[−0.030, 0.081]
mat12web →eng16exam	0.006	0.072	[0.008, 0.136]
mat12web →mat16exam	0.033	0.33	[0.272, 0.386]
mat9spa ⇔ lit9spa	0.197	0.296	[0.264, 0.328]
lit9teach ⇔ lit9spa	0.194	0.319	[0.281, 0.355]
mat9teach ⇔ lit9spa	0.125	0.206	[0.166, 0.245]
lit9teach ⇔ mat9spa	0.114	0.138	[0.097, 0.178]
mat9teach ⇔ mat9spa	0.245	0.298	[0.260, 0.335]
mat9teach ⇔ lit9teach	0.51	0.679	[0.655, 0.701]
mat12spa ⇔ lit12spa	0.134	0.227	[0.198, 0.256]
lit12web ⇔ lit12spa	0.084	0.153	[0.122, 0.184]
mat12web ⇔ lit12spa	0.657	0.081	[0.049, 0.113]
lit12web ⇔ mat12spa	0.038	0.057	[0.026, 0.089]
mat12web ⇔ mat12spa	1.953	0.196	[0.164, 0.228]
mat12web ⇔ lit12web	2.842	0.307	[0.275, 0.339]
mat16exam ⇔ eng16exam	0.584	0.47	[0.436, 0.504]

Note: lit9spa = literacy self-efficacy wave1 (age 9); lit9teach = literacy achievement wave 1; mat9spa = mathematics self-efficacy wave1; mat9teach = mathematics achievement wave1; lit12spa = literacy self-efficacy wave 2 (age 12); lit12web = literacy achievement wave 2; mat12spa = mathematics self-efficacy wave 2; mat12web = mathematics achievement wave 2; eng16exam = English GCSE score wave 3 (age16); mat16exam = mathematics GCSE score at 16; → = one-way path; ⇔ = two-way path.

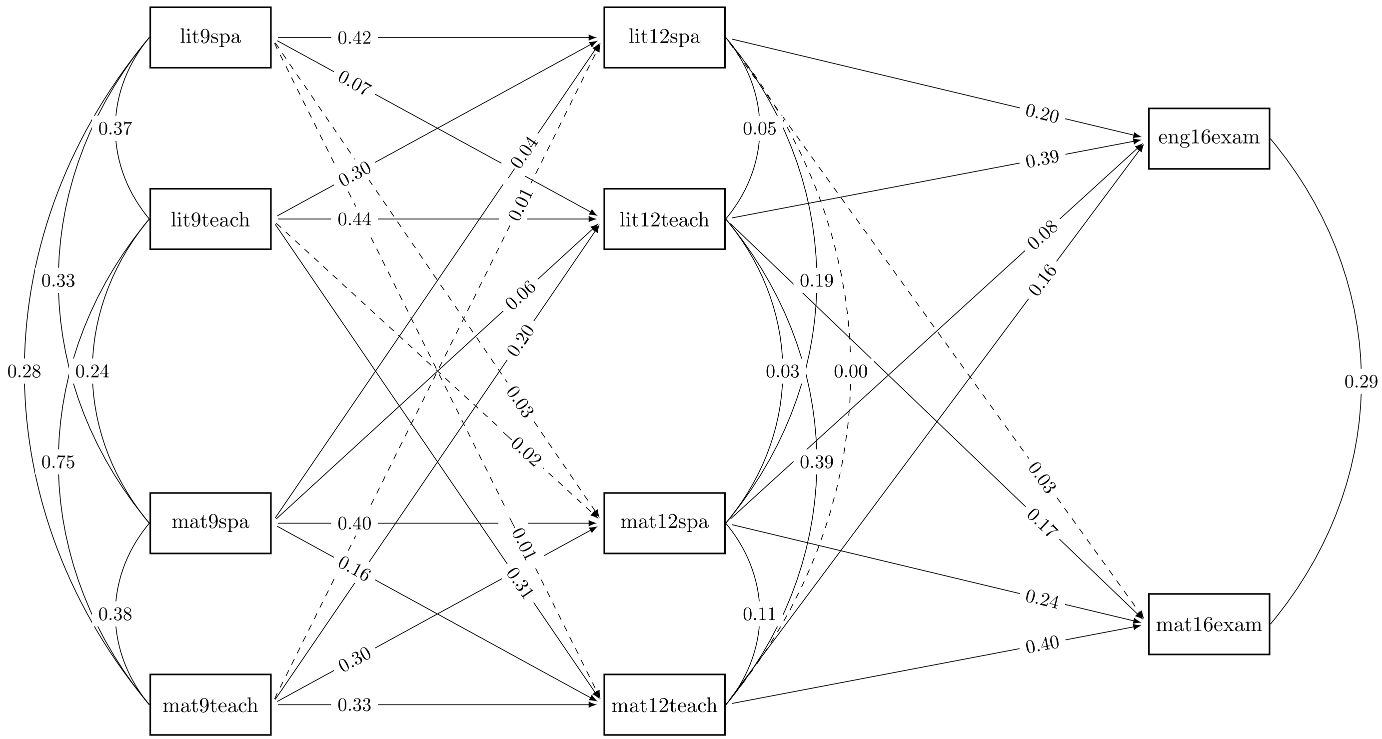

Figure 4.2.a. Path diagram for Model 2 including path estimates for all associations, dashed lines represent non-significant paths; lit9spa = literacy self-efficacy (self-perceived ability) at 9; lit9teach = teacher- rated literacy achievement at age 9; mat9spa = mathematics self-efficacy at 9; mat9teach = teacher-rated mathematics achievement at age 9; lit12spa = literacy self-efficacy at 12; lit12teach = teacher-rated literacy achievement at age 12; mat12spa = mathematics self-efficacy at 12; mat12teach = teacher-rated mathematics achievement at age 12; lit16exam = English GCSE score at 16; mat16exam = Mathematics GCSE score at 16.

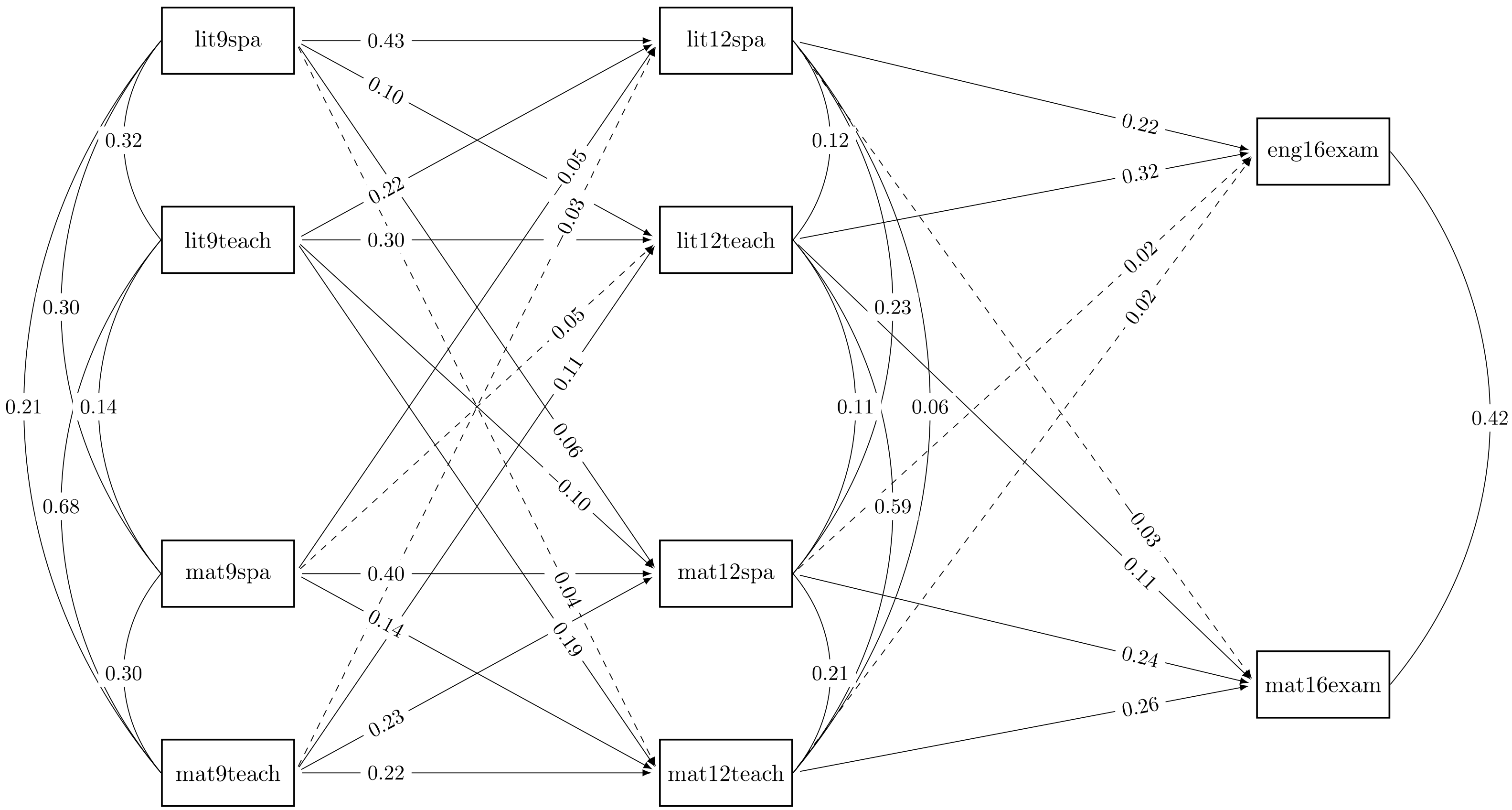

Figure 4.2.b. Path diagram for Model 2b, obtained after controlling for *g*, dashed lines represent non-significant paths; lit9spa = literacy self-efficacy (self-perceived ability) at 9; lit9teach = teacher- rated literacy achievement at age 9; mat9spa = mathematics self-efficacy at 9; mat9teach = teacher-rated mathematics achievement at age 9; lit12spa = literacy self-efficacy at 12; lit12teach = teacher-rated literacy achievement at age 12; mat12spa = mathematics self-efficacy at 12; mat12teach = teacher-rated mathematics achievement at age 12; lit16exam = English GCSE score at 16; mat16exam = Mathematics GCSE score at 16.

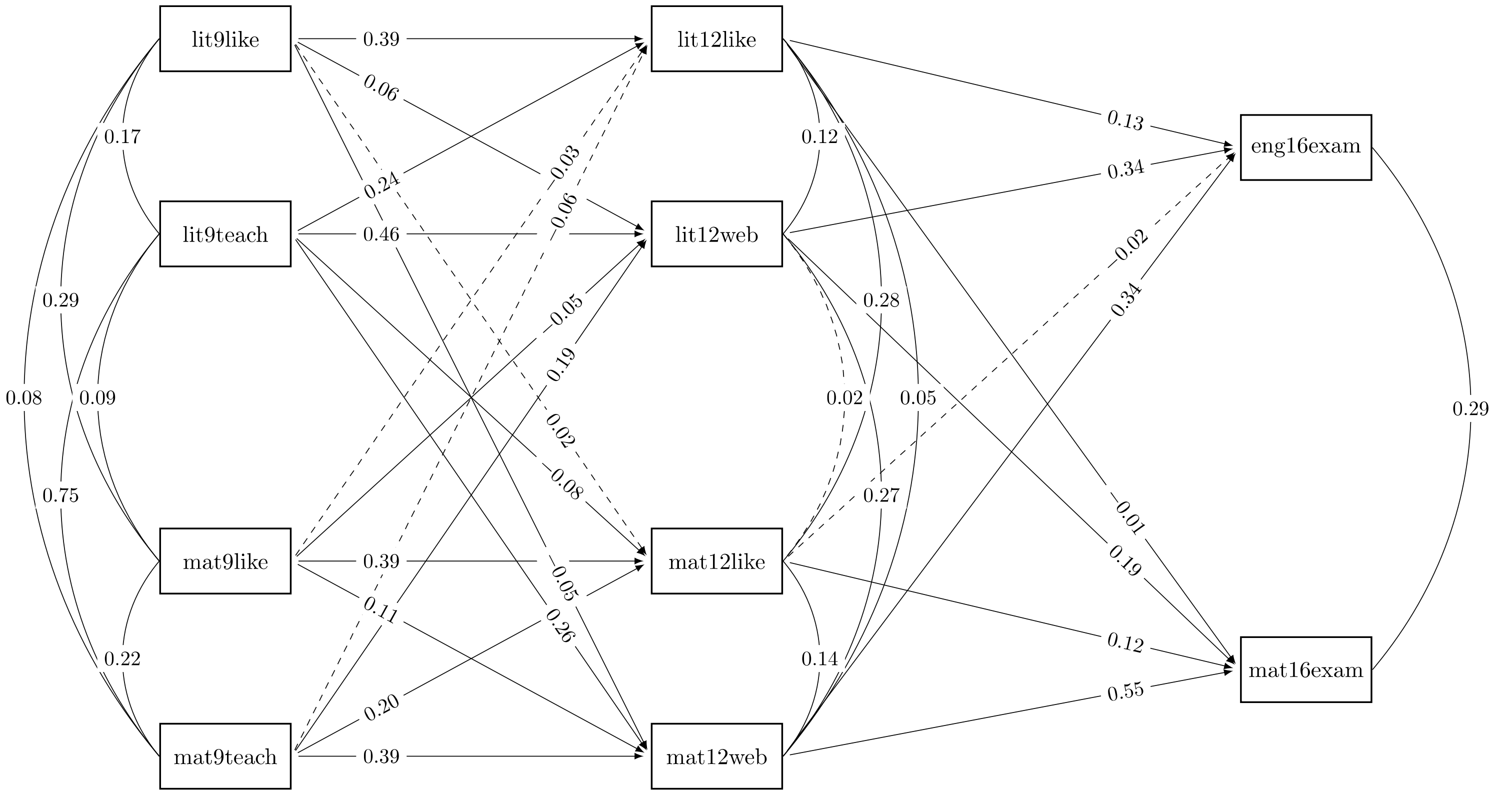

Figure 4.3.a. Path diagram for Model 3 including all path estimates, dashed lines represent non-significant paths; lit9like = literacy enjoyment at 9; lit9teach = teacher- rated literacy achievement at age 9; mat9like = mathematics enjoyment at 9; mat9teach = teacher-rated mathematics achievement at age 9; lit12like = literacy enjoyment at 12; lit12web = web-based literacy achievement at age 12; mat12like = mathematics enjoyment at 12; mat12web = web-based mathematics achievement at age 12; lit16exam = English GCSE score at 16; mat16exam = Mathematics GCSE score at 16.

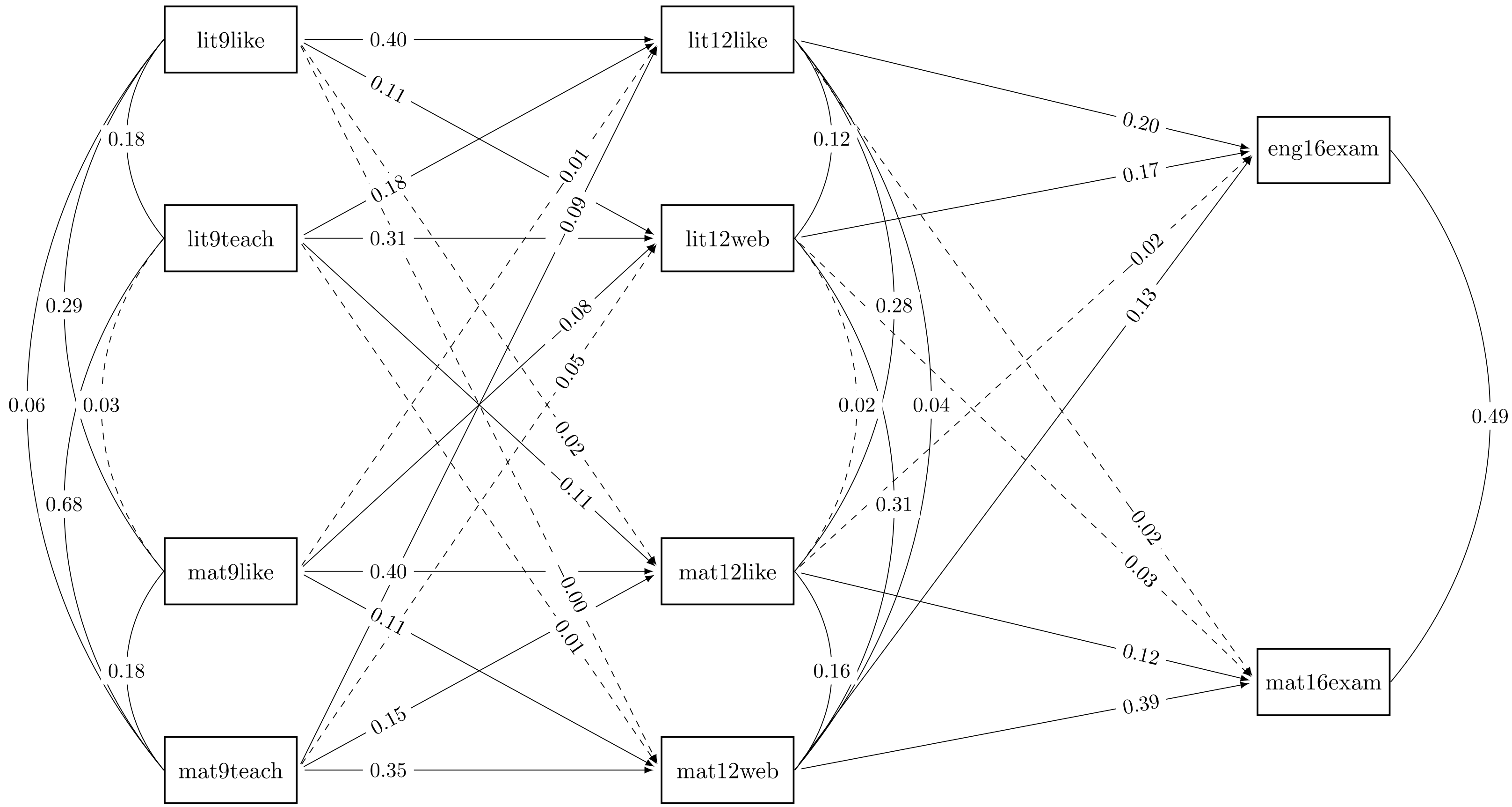

Figure 4.3.b. Path diagram for Model 3b, obtained after controlling for *g*, dashed lines represent non-significant paths; lit9like = literacy enjoyment at 9; lit9teach = teacher- rated literacy achievement at age 9; mat9like = mathematics enjoyment at 9; mat9teach = teacher-rated mathematics achievement at age 9; lit12like = literacy enjoyment at 12; lit12web = web-based literacy achievement at age 12; mat12like = mathematics enjoyment at 12; mat12web = web-based mathematics achievement at age 12; lit16exam = English GCSE score at 16; mat16exam = Mathematics GCSE score at 16

Table 4.7. Unstandardized and standardized path estimates for the association between literacy and mathematics self-efficacy and achievement explored in ***Model 2***

Path	Unstandardized parameter	Standardized parameter	95% CI
lit9spa → lit12spa	0.433	0.422	[0.388, 0.454]
lit9spa → mat12spa	0.043	0.034	[−0.002, 0.070]
lit9spa → lit12teach	0.090	0.067	[0.025, N A]
lit9spa → mat12teach	−0.009	−0.007	[−0.048, 0.034]
mat9spa → lit12spa	−0.028	−0.038	[N A, N A]
mat9spa → mat12spa	0.367	0.399	[0.364, 0.433]
mat9spa → lit12teach	0.060	0.061	[0.018, 0.103]
mat9spa → mat12teach	0.151	0.156	[0.114, 0.198]
lit9teach → lit12spa	0.225	0.300	[0.245, 0.355]
lit9teach → mat12spa	−0.017	−0.018	[−0.075, 0.038]
lit9teach → lit12teach	0.431	0.437	[0.374, 0.498]
lit9teach → mat12teach	0.305	0.315	[0.253, 0.376]
mat9teach → lit12spa	0.007	0.009	[−0.048, 0.066]
mat9teach → mat12spa	0.277	0.303	[0.245, 0.360]
mat9teach → lit12teach	0.197	0.201	[N A, N A]
mat9teach → mat12teach	0.320	0.333	[0.269, 0.395]
lit12spa → eng16exam	0.345	0.196	[0.166, 0.225]
lit12spa → mat16exam	0.051	0.026	[−0.003, 0.054]
mat12spa → eng16exam	0.120	0.084	[0.052, 0.115]
mat12spa → mat16exam	0.399	0.243	[0.213, 0.273]
lit12teach → eng16exam	0.522	0.389	[0.338, 0.440]
lit12teach → mat16exam	0.264	0.172	[0.122, 0.222]
mat12teach → eng16exam	0.225	0.165	[0.111, 0.218]
mat12teach → mat16exam	0.626	0.401	[0.350, 0.452]
mat9spa ⇔ lit9spa	0.233	0.331	[0.300, 0.361]
lit9teach ⇔ lit9spa	0.262	0.372	[0.338, 0.405]
mat9teach ⇔ lit9spa	0.197	0.277	[0.241, 0.313]
lit9teach ⇔ mat9spa	0.230	0.238	[0.202, 0.274]
mat9teach ⇔ mat9spa	0.368	0.378	[0.344, 0.411]
mat9teach ⇔ lit9teach	0.729	0.752	[0.735, 0.768]
mat12spa ⇔ lit12spa	0.124	0.186	[0.163, 0.209]
lit12teach ⇔ lit12spa	0.038	0.054	[0.027, 0.081]
mat12teach ⇔ lit12spa	0.002	0.003	[−0.024, 0.030]
lit12teach ⇔ mat12spa	0.028	0.032	[0.005, 0.060]
mat12teach ⇔ mat12spa	0.094	0.109	[0.082, 0.137]
mat12teach ⇔ lit12teach	0.356	0.387	[0.357, 0.417]
mat16exam ⇔ eng16exam	0.563	0.292	[0.273, 0.312]

Note: lit9spa = literacy self-efficacy wave1 (age 9); lit9teach = literacy achievement wave 1; mat9spa = mathematics self-efficacy wave1; mat9teach = mathematics achievement wave1; lit12spa = literacy self-efficacy wave 2 (age

12); lit9teach = literacy achievement wave 2; mat12spa = mathematics self-efficacy wave 2; lit9teach = mathematics achievement wave 2; eng16exam = English GCSE score wave 3 (age16); mat16exam = mathematics GCSE score at 16; →= one-way path; ⇔ = two-way path.

Table 4.8. Unstandardized and standardized path estimates for the association between literacy and mathematics enjoyment and achievement explored in ***Model 3***

Path	Unstandardized parameter	Standardized parameter	95% CI
lit9like → lit12like	0.377	0.393	[0.358, 0.426]
lit9like → mat12like	0.022	0.018	[−0.018, 0.055]
lit9like → lit12web	0.065	0.056	[0.020, 0.092]
lit9like → mat12web	−0.816	−0.046	[−0.082, −0.009]
mat9like → lit12like	−0.020	−0.028	[−0.064, 0.009]
mat9like → mat12like	0.348	0.387	[0.351, 0.421]
mat9like → lit12web	−0.045	−0.052	[−0.088, −0.016]
mat9like → mat12web	1.443	0.108	[0.072, 0.144]
lit9teach → lit12like	0.203	0.241	[0.182, 0.300]
lit9teach → mat12like	−0.084	−0.080	[−0.140, −0.019]
lit9teach → lit12web	0.466	0.457	[0.403, 0.511]
lit9teach → mat12web	4.082	0.261	[0.206, 0.316]
mat9teach → lit12like	−0.046	−0.056	[−0.117, 0.006]
mat9teach → mat12like	0.208	0.200	[0.138, 0.261]
mat9teach → lit12web	0.190	0.188	[0.131, N A]
mat9teach → mat12web	6.023	0.389	[0.334, 0.443]
lit12like → eng16exam	0.206	0.131	[0.103, 0.159]
lit12like → mat16exam	−0.022	−0.012	[N A, N A]
mat12like → eng16exam	−0.023	−0.018	[−0.046, 0.010]
mat12like → mat16exam	0.173	0.120	[0.094, 0.146]
lit12web → eng16exam	0.437	0.336	[0.302, 0.370]
lit12web → mat16exam	0.278	0.186	[0.154, N A]
mat12web → eng16exam	0.029	0.343	[0.308, N A]
mat12web → mat16exam	0.053	0.547	[0.516, 0.576]
mat9like ⇔ lit9like	0.289	0.294	[0.261, 0.325]
lit9teach ⇔ lit9like	0.142	0.169	[0.131, 0.208]
mat9teach ⇔ lit9like	0.065	0.076	[0.036, 0.115]
lit9teach ⇔ mat9like	0.101	0.090	[0.051, 0.129]
mat9teach ⇔ mat9like	0.252	0.222	[0.184, 0.259]
mat9teach ⇔ lit9teach	0.726	0.751	[0.734, 0.766]
mat12like ⇔ lit12like	0.239	0.282	[0.257, 0.306]
lit12web ⇔ lit12like	0.095	0.116	[0.089, 0.143]
mat12web ⇔ lit12like	0.631	0.050	[0.024, 0.076]
lit12web ⇔ mat12like	0.024	0.023	[−0.003, 0.050]
mat12web ⇔ mat12like	2.249	0.143	[0.117, 0.169]

mat12web ⇔ lit12web	4.074	0.267	[0.242, 0.293]
mat16exam ⇔ eng16exam	0.551	0.286	[N A, 0.304]

Note: lit9like = literacy enjoyment at 9; lit9teach = teacher- rated literacy achievement at age 9; mat9like = mathematics enjoyment at 9; mat9teach = teacher-rated mathematics achievement at age 9; lit12like = literacy enjoyment at 12; lit12web = web-based literacy achievement at age 12; mat12like = mathematics enjoyment at 12; mat12web = web-based mathematics achievement at age 12; lit16exam = English GCSE score at 16; mat16exam = Mathematics GCSE score at 16; →= one-way path; ⇔ = two-way path.

Discussion

The present study explored the longitudinal association between motivation and achievement in literacy and mathematics. This study extends the previous limited longitudinal research by investigating their association over 8 years and by considering multiple measures of achievement and of motivation. Furthermore, the study explored the role that general intelligence (*g*) plays in the achievement-motivation association within and across academic domains. Overall, the results were largely consistent across multiple measures of achievement and when considering self-efficacy and enjoyment. This indicates that over the course of 8 school years the relationship between self-efficacy and academic achievement is very similar to that between enjoyment and achievement. These longitudinal associations are also mostly in line with those observed by research exploring the association between self-concept, another subcomponent of the academic motivation construct, and achievement (e.g. Möller et al. 2011).

The current study set out to explore five main hypotheses. Firstly, it was hypothesized that the relationship between achievement and motivation within domains would have been positive and moderate. Consistent with the first hypothesis, correlations between academic achievement and motivation within academic domains (literacy and mathematics) were moderate at all time points. Importantly, the cross-sectional relationship between variables could not be entirely attributable to the relationships that motivation and achievement share with *g*. This is in line with previous research that found that academic self-concept was associated with achievement beyond *g* and socio-economic status (Marsh & O'Mara, 2010), with *g* accounting for only part of the associations between measures of academic achievement and motivation. These results show that those students who achieve highly in mathematics also tend to enjoy the subjects and to think that they are good at it, and the same is observed for literacy. Those students who do not enjoy mathematics and/or literacy are also more likely to show a lower self-perception of their ability in the disciplines, and to obtain lower grades.

Secondly, the study hypothesized that across academic domains; we would observe stronger correlations for measures of achievement than for measures of self-efficacy and enjoyment. Results also supported our second hypothesis as we found strong contemporaneous correlations between measures of achievement across academic domains. Cross-sectional correlations between measures of motivation across academic domains were modest to moderate; this was also in line with hypothesis 2. The observed positive modest association between measures of self-efficacy and enjoyment across domains is in opposition with the prediction of the rI/E model that argues for a small negative or negligible correlation between self-concept across domains (Moller et al., 2011). The results show that students who are good at mathematics also tend to be good at literacy; additionally, those students who enjoy mathematics and perceive themselves as competent in the subject, are also more likely to enjoy and perceive themselves as competent in literacy.

The third hypothesis predicted that the cross-lagged links between motivation and achievement within domains would be positive and reciprocal, but that the links from previous self-efficacy and enjoyment to later achievement would be weaker than those from achievement to later self-efficacy and enjoyment. The findings supported this third prediction. Mutual cross-lagged links were observed between motivation and achievement over time. The links from initial motivation to later achievement were weaker than the opposite links from initial achievement to motivation, supporting hypothesis 3. This suggests that achievement has an impact on the development of subsequent motivation, and motivation has an effect on the development of future achievement.

However, even though there is a mutual relationship students' academic achievement was found to play a greater role in the development of their future motivation if compared to the effect that their motivation had on influencing their later achievement. The results partly support the *Skill-Development Model* (Byrne, 1984; Calsyn & Kenny, 1977), according to which the relationship between achievement and motivation develops as a function of academic achievement. Our findings show that children who achieve highly in one school subject at the end of primary school will grow more confident in their abilities and will enjoy that subject more throughout secondary school if compared to those whose level of achievement is lower. This positive impact that academic achievement has on later self-efficacy and enjoyment was found to be greater than the positive impact that confidence in one's own ability and enjoying a subject have on future school achievement. Our findings are in line with evidence showing that the links from reading achievement to later reading self-concept are stronger than the opposite links from self-concept to later achievement (Retelsdorf et al., 2014).

However, we did find a reciprocal link between motivation and achievement within domains in both subjects. Although this link is not of similar effects, motivation and achievement were found to influence each other, partly supporting the *Reciprocal Model* (see Chapter 1 for a detailed description of the models proposed for the association between achievement and motivation). Other studies have supported the reciprocal model, finding that the cross-lagged links between achievement and motivation within academic domains had similar effects (e.g. Moller et al., 2011; Malanchini, Wang, Voronin, Schenker, Plomin, Petrill, & Kovas, in press).

A possible explanation of the observed inconsistencies in the findings is that the effects that motivation and achievement have on each other are observed within different time frames. It has been proposed that the impact that achievement has on motivation may be of longer-term and potentially increasing with time. On the other hand, the impact that motivation has on academic achievement may be stronger in the short-term, and the effect decreasing over time (e.g. Valentine, 2001). The present study explores the association between motivation and achievement over an extended period of time, with collection waves fare apart from each other. Therefore, the study design may have not been able to capture the more short-term effect of motivation on later achievement.

The fourth hypothesis predicted that across domains we would have observed a weak negative association between achievement and later self-efficacy or enjoyment and vice versa. The rI/E theory hypothesises that, after controlling for the domain-general variance of motivation and achievement by factoring their correlation into the model, that domain-specific links from motivation in one domain to achievement in another domain would be negative and moderate (Marsh et al., 2015). The current study found little support for hypothesis 4. Model 1 showed that, out of the twelve cross-lagged cross-domain links, none was significant and negative. Six weak to moderate positive longitudinal links emerged between self-efficacy and achievement and between achievement in one domain and subsequent achievement in another domain. The stronger positive link was observed between mathematics achievement at 12 and literacy achievement at 16 (.29). The remaining six links did not reach significance. The same was observed when exploring the association in our replication sample.

We found a slightly different pattern of associations after accounting for *g*. Results of our second model (Model 1b) showed that three of the twelve cross-lagged cross-domain links were negative and significant. In fact, a weak negative association was observed between achievement in literacy at age 9 and mathematics self-efficacy at 12 (-.10); between mathematics self-efficacy at age 9 and literacy achievement at 12 (-.07); and between mathematics self-efficacy at 9 and literacy self-efficacy at 12 (-.04). These links support the prediction of the rI/E model. However, two additional cross-lagged cross-domain links were positive and significant; namely, the link between literacy self-efficacy at 9 and mathematics self-efficacy at 12 (.06), and the link between mathematics achievement at 12 and literacy achievement at 16 (.07). The seven remaining cross-lagged cross-domain links were not significant. These findings are consistent with the only other longitudinal study to date, which found that, after controlling for *g*; the cross-lags between self-concept and achievement across academic domains were mostly not significant (Moller et al., 2011). However, the present study found that the cross-lagged cross-domain links were largely not significant even before controlling for *g*. Relationships were overall similar for Model 2 and Model 3 and Model 2b and Model 3b

Several factors could explain why we did not find support for the rI/E model. Firstly, the present study assessed the theoretical framework using slightly different, motivational constructs from self-concept: self-efficacy and enjoyment. These constructs are related, yet different, from self-concept –the construct central to the rI/E model. Previous research found weaker cross-lagged cross-domain links between achievement and self-efficacy than between achievement and self-concept (Marsh et al., 2015). On the other hand, other investigations have found very high correlations between self-concept and self-efficacy (e.g. Bong, Cho, Ahn, & Kim, 2012), questioning whether the two constructs should be considered separately. Furthermore, the current study found that the longitudinal associations between achievement and self-efficacy and achievement and enjoyment were highly similar, which suggests that similar associations may apply to several subcomponents of motivation. Longitudinal investigations including both self-concept and self-efficacy may enhance our understanding of their relationship as well as of their association with academic achievement within and across academic domains.

Our fifth hypothesis proposed general cognitive ability (*g*) would explain only a part of every association. As general intelligence is correlated with both achievement and self-efficacy and enjoyment (Greven et al., 2009; Chamorro-Premuzic et al., 2010), the present investigation explored all associations before and after accounting for *g*. Although *g* explained part of the associations between self-efficacy and enjoyment and achievement, most relationships remained significant after accounting for *g*. The greater impact of *g* was on the longitudinal associations between literacy and mathematics achievement. In fact, after accounting for the variance explained by *g*, the majority of the modest cross-lagged cross-domain links between measures of achievement became not significant. However, the impact of *g* on the cross-lagged associations within domain was smaller.

Overall, the present study found partial support for the predictions of the rI/E model. It may be that the model does not capture the complexity of how the association between motivation and achievement develops, and may omit to consider the role played by potential moderators. For example, differential frame of references may emerge from differences in the achievement profile of students. In most classrooms that include mixed ability levels, students show different profiles in their achievement in mathematics and literacy. Some students achieve highly in both subjects, whereas some others underachieve in both literacy and mathematics; additionally, other students show higher achievement in one subject if compared to the other, such as for example those who achieve high grades in literacy and lower grades in mathematics. It may be that those students, who are high achievers across the board and those who underachieve in every subject, compare their performance mostly using external frames of reference (i.e. the performance of their peers). This is because internal comparisons across domains would give them little information on their achievement, since it is consistent across domains. On the other hand, students who excel in one domain and struggle in the other domain, may be more likely to used an internal frame of reference to judge their performance. Therefore, they would tend to compare their achievement in one subject to their own achievement in the other domain, making judgment about their performance accordingly. Future research, including multi-group structural equation modelling (SEM), might be able to test this hypothesis by exploring the longitudinal prediction of the rI/E model across the three different achievement profiles described above.

Strengths and limitations

This study has several strengths, first of which is the very large sample. As the rI/E model proposed weak to modest negative cross-lagged cross-domain associations between self-concept and achievement, it was important to test this prediction with adequate power. The sample included in the current study had sufficient power to detect small longitudinal associations (Faul, Erdfelder, Lang, & Buchner, 2007). A second strength is in the nature of the sample, a twin sample, which allowed to examine the internal replicability of the results. The findings, obtained randomly selecting one twin out of each pair, replicated when the other twin in the pair was included in the analyses. A third strength of the present investigation is that it explored the same research question across multiple measures of achievement and motivation. The fact that the results were consistent across multiple measures strengthens the robustness of the findings. A fourth strength of the present investigation is its extended longitudinal time, spanning from the end of primary school, when the children were 9, to the end of secondary school, when the children were 16-yeas-old. No study to date has explored the mutual relation between achievement and motivation in different academic domains over such and extended time span encompassing the period of transition from primary to secondary school.

However, the present study also includes limitations. Firstly, it should be noted that the model fit indices for our three cross-lagged cross-domain models were significantly worse than the saturated model. Although this is most likely attributable to the large sample size, it may be due to the fact that our models did not allow for the examination of the direct links between motivation at 9 and achievement at 16. The presence of direct paths from age 9 to age 16 could possibly explain their comparatively poorer fit. Secondly, data at 16 were available for achievement but not for motivation measures, which does not allow to examine the cross-lagged predictions both ways between constructs measured at age 12 and age 16.

Conclusions

The present study investigated the longitudinal association between self-efficacy, enjoyment and achievement across two academic domains: literacy and mathematics. Results showed that both achievement and motivation were moderately stable over the course of eight school years. Children who achieve good grades in their final years of primary school also tend to be the high achievers at the end of secondary school, and the same applies to highly motivated students. General cognitive ability (*g*) contributed to, but did not entirely explain the stability of achievement and motivation over time. Achievement and motivation for the same school subject positively related to each other at every wave of data collection over primary and secondary school.

The relationship between measures of self-efficacy across academic domains was positive at all collection waves, and the same was found for measures of enjoyment and academic achievement. The stronger associations observed between measures of achievement across domains, if compared to those between self-efficacy and enjoyment, suggest that achievement is characterised by greater domain generality than motivation. It is likely that a large portion of the same underlying factors might influence variation in achievement in multiple academic domains, such as for example strong genetic correlations (Krapohl et al., 2014). On the other hand, the underlying factors influencing individual differences in motivation in multiple academic domains seem to overlap to a smaller extent. Chapter 5 of the present thesis explored the possibility that shared genetic influences underlie the longitudinal association between motivation and achievement in the domain of reading ability.

The present study also found that achievement had a greater impact on the development of subsequent motivation to learn than the impact that prior motivation has on the development of later achievement, suggesting that achievement drives their association. Contrasting with the prediction of the rI/E model, motivation and achievement across domains do not seem to be associated. Evidence from the present study did not support the negative implications that enhancing achievement in one domain would have on self-concept in a different domain and vice versa, proposed by the rI/E model. How much children enjoy learning (or are confident in their abilities in) literacy did not relate to their subsequent achievement in mathematics. Similarly, how much children achieved in literacy was not related to their future motivation to learn mathematics.

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Chapter 5

Reading self-perceived ability, enjoyment and achievement: A genetically informative study of their reciprocal links over time.

Abstract

Extant literature has established a consistent association between aspects of reading motivation, such as enjoyment and self-perceived ability, and reading achievement, in that more motivated readers are generally more skilled readers. However, the developmental aetiology of this relation is yet to be investigated. The present study explores the development of the motivation-achievement association and its genetic and environmental underpinnings. Applying cross-lagged design in a sample of 13,825 twins, the current investigation examined the relative contribution of genetic and environmental factors to the association between reading enjoyment and self-perceived ability and reading achievement. Children completed a reading comprehension task and self-reported their reading enjoyment and perceived ability twice in middle childhood: when they were 9 -10 and 12 years old. Results showed a modest reciprocal association over time between reading motivation (enjoyment and perceived ability) and reading achievement. Reading motivation at age 9-10 statistically predicted the development of later achievement, and similarly, reading achievement at age 9-10 predicted the development of later motivation. This reciprocal association was observed beyond the stability of the variables and their contemporaneous correlation and was largely explained by genetic factors.

Introduction

Reading motivation

Good reading ability is crucial in modern literate society. It has a fundamental role in how we acquire knowledge and has been associated with employment level and socio-economic status (e.g. Ritchie & Bates, 2013). Reading is also a cultural activity that many enjoy. There are vast individual differences in reading ability, partly attributable to cognitive skills such as verbal IQ and phoneme awareness (e.g. Warmington & Hulme, 2012; Oakhill & Cain, 2012). In addition, research suggests that reading motivation is related to the development of reading, above and beyond the effects of cognitive abilities (Morgan & Fuchs, 2007; Wigfield & Eccles, 2000).

Reading motivation refers to beliefs, attitudes, and values individuals hold specific to reading activities (Ryan & Deci, 2000; Wigfield, 1997). Two aspects of motivation that received much attention are reading enjoyment and reading self-perceived ability. Reading enjoyment indicates pleasure gained from a reading activity (Wigfield, 1997). Children may enjoy reading for many different reasons, including curiosity and eagerness for intellectual development and positive feedback on their reading skills. Enjoyment of reading is associated with frequent reading activities, intense concentration during reading and better reading performance (Baker & Wigfield, 1999; De Naeghel, Van Keer, Vansteenkiste, & Rosseel, 2012; Wigfield & Guthrie, 1997).

Reading self-perceived abilities - individuals' perceptions of their reading competence (Wigfield, 1997) - are also positively associated with objectively measured reading performance (Baker & Wigfield, 1999; Guay, Marsh, &Boivin, 2003; Morgan & Fuchs, 2007; Greven, Harlaar, Kovas, Chamorro-Premuzic & Plomin, 2009). In addition, reading self-perceived ability is positively related to how much children read in and out of school, how much they enjoy reading, how likely they are to choose more challenging reading materials, and their effort and perseverance when facing difficult reading tasks (Baker & Wigfield, 1999; Linnenbrink & Pintrich, 2003; Stipek, 1996).

Longitudinal Associations between Reading Achievement and Reading Motivation

Although several studies report modest to moderate correlations between reading achievement and several aspects of reading motivation, the findings are mixed with respect to the developmental nature of this association (e.g. Baker & Wigfield, 1999; Guthrie et al., 2006). One unresolved issue is how the motivation-achievement association develops. Several theories have been put forward addressing the causal ordering in the emergence of the motivation-achievement relationship. Early theories of the association between achievement and motivation favoured unidirectional approaches. Two contrasting early theoretical frameworks are the Self-Enhancement Model and the Skill Development Model.

According to the *Self-Enhancement Model*, individual differences in motivation influence subsequent development of academic performance (Calsyn & Kenny, 1977). Confident and interested readers are more invested in learning and mastering reading skills through frequent reading, and this frequent print exposure further results in better reading skills (Calsyn & Kenny, 1977). Support for this model comes from early educational experimental programs, demonstrating that interventions designed to increase motivation lead to significant improvements in children's reading ability (e.g. Guthrie et al., 1996; Wigfield, Guthrie, Tonks, & Perencevich, 2004; Guthrie et al., 2006). However, most of these studies did not consider the potential link from achievement to motivation.

This influence of achievement on subsequent motivation is central to the *Skill Development Model* (Calsyn & Kenny, 1977). For example, children at risk of reading failure are more likely to encounter difficulty and frustration in their early reading experiences, which may in turn lead to decreased motivation to read. The support for this model has been inconsistent. For example, one intervention study failed to observe improvements in children's reading motivation as a consequence of improved reading skills in a group of unskilled readers (Morgan, Fuchs, Compton, Cordray, & Fuchs, 2008). However, several longitudinal studies have supported the temporal precedence of achievement in the reading motivation-achievement relationship in samples of several ages – from early elementary school to middle school ages (e.g. Aunola, Leskinen, Onatsu-Arvilommi, & Nurmi, 2002; Chapman & Tunmer, 1997; Skaalvik &

Valas, 1999). These studies utilized cross-lagged longitudinal analyses in which the longitudinal effect of one construct on another is estimated beyond the stability of each construct and the concurrent correlation between constructs. Specifically, these studies demonstrated that individual differences in children's reading performance predicted subsequent variation in children's reading motivation, whereas reading motivation failed to predict subsequent reading performance (Aunola et al., 2002; Chapman & Tunmer, 1997; Skaalvik & Valas, 1999). However, these studies involved relatively small samples and may have been underpowered to detect reciprocal links between reading motivation and achievement.

The reciprocal relationship is central to a third theoretical framework, according to which achievement and motivation have a mutual influence on one another (Morgan & Fuchs, 2007). The *Reciprocal Model* has been supported by longitudinal studies that have explored the motivation-achievement relation in several academic domains including literacy and mathematics (e.g. Guay et al., 2003; Luo, Haworth, & Plomin, 2010; Marsh & Martin, 2011; Muijs, 1997).

Several methodological differences may explain the inconsistencies found among previous studies with respect to the temporal and causal ordering between reading achievement and reading motivation. Differences in sample size and sample characteristics, study design, and statistical methods could all contribute to the discrepancies in the literature. For example, some studies examined children in the normal range of reading ability (e.g., Guthrie et al., 1996), whereas others focused on poor readers (e.g. Morgan et al., 2008). Some studies used experimental designs but only examined immediate or short-term outcomes (e.g., Guthrie et al., 1996), while others relied on correlational designs to investigate longer-term outcomes (e.g., Marsh & Martin, 2011).

Genetic and Environmental Aetiology

Examining the genetic and environmental aetiology of the longitudinal links between reading motivation and reading achievement can provide new insights into processes through which the two constructs interact. Research exploring factors contributing to variation in academic motivation and its association with achievement has largely focused on the role of environments (Deci & Ryan, 2008; Wigfield & Eccles, 2000; Stipek, 1996). In particular, family environment, relationships with parents, parents' and teachers' educational expectations and attitudes, teachers' instructional style and quality, and teacher-student and peer relationships have all been found to be associated with academic motivation (Deci & Ryan, 2008; Stipek, 1996; Wigfield & Eccles, 2000). A number of recent studies, using genetically informative approaches, have demonstrated that genetic factors are also involved in explaining individual differences in academic motivation (Kovas et al., 2015).

For example, a recent international twin study of over 13,000 children demonstrated that genetic factors account for approximately 40% of individual differences in self-perceived ability and enjoyment of learning in numerous academic domains, including language, mathematics, and science (Kovas et al., 2015). This was consistent across a wide age range and across 6 countries that were included in the study. Environmental influences stemmed entirely from unique individual experiences and did not contribute to similarity in academic motivation in children raised in the same family. This study suggests that resemblance among family members in academic motivation is entirely attributable to genetic influences, whereas dissimilarities among family members are largely explained by individual specific environmental factors. Even objectively shared environments, such as family educational resources and classroom environments, seem to be non-shared in terms of the actual experience.

Several studies examined the genetic and environmental aetiology of the concurrent and longitudinal relations between academic motivation and academic achievement. For example, in a sample of 13-year-old twins from Germany, the contemporaneous correlations between motivation and academic performance in language and mathematics were mostly explained by genetic factors (Gottschling, Spengler, Spinath, & Spinath, 2012). In the large UK Twins Early Development Study (TEDS), academic self-perceived ability and overall academic performance of 9-year old children correlated primarily for genetic reasons (Greven et al., 2009). The study also found that the link from self-perceived ability at age 9 to achievement at age 12 was mostly explained by genetic factors.

Using the same TEDS sample, Luo et al. (2010) examined the longitudinal cross-lagged relations between a domain general composite of self-perceived ability and academic performance between ages of 9 and 12. In line with the reciprocal model, modest mutual links were found between domain general academic motivation and achievement. These cross-lagged reciprocal relations were mediated largely through genetic pathways (Luo et al., 2010). Only one study has examined the aetiology of the reciprocal association between motivation and achievement in a domain specific context. This investigation, also using TEDS data, explored the cross-lagged associations between motivation and achievement specific to mathematics (Luo, Kovas, Haworth, & Plomin, 2011). The prediction from teacher-rated mathematics achievement at age 9 to subsequent mathematics motivation at age 12 was attributable to genetic factors, whereas the link from early motivation to subsequent achievement was mediated through both genetic and child-specific environmental pathways (Luo et al., 2011).

The aims of the present study

Overall, findings from genetically informative twin studies point to the importance of genetic influences and child-specific environmental experiences in the aetiology of academic motivation in diverse academic domains. Shared environmental factors are found to have negligible effects on individual differences in academic motivation. Additionally, although the longitudinal association between domain general motivation and achievement is largely mediated by genetic factors, the domain-specific association between mathematics achievement and motivation is affected by both genetic and non-shred environmental factors. These differences in the aetiology of longitudinal links in domain-general versus mathematics specific achievement and motivation suggest potential differences in the underlying mechanisms and provide rationale for the study of other specific domains, such as reading. The present study used a genetically sensitive cross-lagged approach to explore the longitudinal association between reading motivation and reading achievement.

Based on the existing literature summarized above, the following hypotheses are proposed:

1. Reciprocal longitudinal links of similar strength exist between reading motivation (enjoyment and self-perceived ability) and reading achievement;
2. Similar to the domain of mathematics, both genetic and nonshared environmental factors contribute to the observed longitudinal cross-lagged associations between reading motivation and reading achievement.

Methods

Participants

Participants (N = 13,825) are members of the Twins Early Development Study (TEDS), a population-based longitudinal study of twins that focuses on the longitudinal relations of cognitive and behavioral traits from infancy to young adulthood. Over 15,000 families from England and Wales with twins born between 1994 and 1996 have participated over the years (Haworth, Davis &Plomin, 2013). The families in TEDS are representative of the British population in their socio-economic distribution, ethnicity and parental occupation (Oliver &Plomin, 2007).

The present study included two waves of data collection. The first wave took place when the twins were between the age of 9 and 10, and the second wave when the twins were 12 years old. For each wave of data collection, children completed a series of questionnaires and cognitive assessments online. In total, data from 6927 twin pairs (2502 MZ pairs and 4425 DZ pairs; 53% female) were used in the current investigation, excluding those who had reported medical or neurological conditions. Sample sizes varied across time and measures, and details regarding the sample size for each measure can be found in Table 5.1. Data collections at age 9/10 and age 12 received approval by the Institute of Psychiatry ethics committee.

Measures

Reading Motivation: Reading Enjoyment and Self-perceived ability

At age 9/10 and age 12, the twins completed a series of questionnaires about their attitudes towards several academic subjects. Two items assessed their motivation for reading (NAEP, 2003). The first item measured reading self-perceived ability: ‘How good do you think you are at reading?’ rated on a scale from 1 to 5, with 1 = “very good” and 5 = “not at all good”. The second item measured reading enjoyment: ‘How much do you like reading?’ rated on a scale from 1 to 5, with 1 = “very much” and 5 = “not at all”. The scores for reading self-perceived ability and reading enjoyment were moderately correlated at both waves (r = .54 and .57 at age 9/10 and age 12, respectively). As the two aspects of reading motivation are conceptually distinct, analyses on the reading enjoyment and reading self-perceived ability measures were conducted separately. Analyses were also conducted on a reading motivation composite that was computed at each wave by reverse scoring and then averaging the two items. The results from the three analyses were highly consistent. Therefore the Results section mostly focuses on discussing the results of the analyses on the reading motivation composite. The results of the separate analyses for reading self-perceived ability and enjoyment are reported in Table 5.7 and Table 5.8of the Results section.

Reading Achievement

At age 9/10 and age 12, reading achievement was measured via the Reading Comprehension subtest of the Peabody Individual Achievement Test (PIAT; Markwardt 1997). Children were asked to read a series of sentences and to select the one picture (out of four choices) that best depicts the meaning of the sentence. The PIAT included a total of 89 items arranged in the order of increasing difficulty. For example, one of the initial items was “Some kittens are in the bed”. The test became increasingly more complex and one of the final items was “The verdant countryside is prodigiously arable; however, a squalid domicile sullies the otherwise exquisite panorama”. Children were given up to 20 seconds to read each sentence and another 20 seconds to make their choices. A total reading achievement score was computed by summing the points across all 89 items.

Analytic Strategies

After running descriptive and correlation analyses, structural equation modelling (SEM) was applied to examine the longitudinal relations between reading achievement and reading motivation, as well as the underlying genetic and environmental aetiologies of these longitudinal associations. These analyses were conducted using the OpenMx package for R (Neale et al., 2015; R Core Team, 2015).

The phenotypic cross-lagged model

In order to test the first hypothesis, a phenotypic cross-lagged model was fitted (Figure 5.1.a). The cross-lagged model (also described in Chapter 4 of the present thesis) allows for the estimation of the strength of the link from reading motivation at age 9/10 to reading achievement at age 12, and of the opposite link from reading achievement at age 9/10 to reading motivation at age 12. The cross-lagged associations are estimated independently of the stability of the measures and their initial contemporaneous correlations. In order to formally compare the magnitude of the cross-lagged links, they were constrained to be equal. This allowed us to examine whether such constraints would worsen model fit, indicating differences in the magnitude of the paths.

The twin design (described in detail in Chapter 2 of the present thesis) was used to test the second hypothesis. The twin method allows for the examination of the relative contribution of genetic and environmental factors to the longitudinal relations between reading achievement and reading motivation. The method is based on the comparison of the concordance between monozygotic (MZ) twins, who share 100% of their genetic make up, and dizygotic (DZ) twins, who share on average 50% of their segregating genes. Genetic and environmental influences can be calculated by comparing correlations for MZ and DZ twins for the same trait (intraclass correlations). A stronger intraclass correlation between MZ twins than between DZ twins indicates that genetic factors are involved in explaining individual differences in that trait. This allows for the decomposition of the total variance of a trait into: heritability, shared environmental, and non-shared environmental influences.

Heritability (A) refers to the proportion of the phenotypic (i.e., observed) individual differences attributable to genetic influences. The remaining variance in the trait is further divided into shared and non-shared environmental influences. Shared environment (C) refers to any non-genetic influences that contribute to twin similarities. Non-shared environment (E) refers to any non-genetic influences that contribute to dissimilarities between two twins raised in the same family, and includes measurement error.

The twin method can be extended to examine the aetiology of the covariance between multiple traits. Multivariate models are based on the cross-twin cross-trait correlations. Cross-twin cross-trait correlations describe the association between two traits, with twin 1’s score on the first trait correlated with twin 2’s score on the second trait. Cross-twin cross-trait correlations are computed separately for MZ and DZ twins. A higher cross-twin cross-trait correlation for MZ than for DZ twins indicates that genetic factors have a degree of influence on the phenotypic variance shared by two traits. For example, in the present study, the cross-twin cross-trait correlation between reading motivation at age 9/10 and Reading achievement at age 9/10 was .22 for MZ twins and .05 for DZ twins. This suggests that genetic factors are implicated in the aetiology of the covariance between reading motivation at age 9/10 and reading achievement at age 9/10.

The ACE cross-lagged model

Specifically, to test the second hypothesis the study applied the ACE cross-lagged model (Figure 5.1.b to Figure 5.1.d). This model allowed to examine the aetiologies of the cross-lagged associations between reading motivation and reading achievement. The limitation of previously used cross-lagged models, using a multivariate Cholesky decomposition approach (see Figure 5.3 and Figure 5.4), is that the two cross-lagged paths can only be estimated in two separate models, prohibiting direct comparisons of their effects (phenotypically or etiologically). The ACE cross-lagged model used in this study overcomes this limitation by estimating all the paths within the same model.

The ACE cross-lagged model is based on the Reticular Action Model (RAM) definition (McArdle & McDonald, 1984): $C = F\ (I - A)^{-1}\ S\ (I - A)^{-1'}\ F'$ where I is the identity matrix, S the matrix defining two-way relationships or symmetric relationships (i.e., variances and co-variances), A is the matrix defining one-way relationships or asymmetric relationships (i.e., stability and cross-lagged paths in the case of cross-lagged model), and F is the filter matrix defining observed variables (not used here). The A and S matrices are n x n matrices, where n is the number of observed variables. In the ACE cross-lagged model, the twin design allows us to decompose the variance and covariance into the genetic (Figure 5.1.b), shared environmental (Figure 5.1.c), and non-shared environmental (Figure 5.1.d) components, using the formulae reported below. The formulae were introduced into the model as matrix algebra to allow for the estimation of 95% confidence intervals.

The ACE cross-lagged model decomposes the variance and covariance into the genetic, shared environmental, and nonshared environmental components using the following formulae: $C_A = T_A\ (I - A_A)^{-1}\ S_A\ (I - A_A)^{-1'} T_A'$;$C_C = T_C\ (I - A_C)^{-1}\ S_C\ (I - A_C)^{-1'}\ T_C'$; $C_E = T_E\ (I - A_E)^{-1}\ S_E\ (I - A_E)^{-1'}\ T_E'$, where $C_A + C_C + C_E = C_P$ (total observed covariance matrix). T_A, T_C, and T_E are diagonal n x n matrices, and they respectively index the impact of genetic, shared environmental, and nonshared environmental factors on the total observed variance of the variable of interest. C_A, C_C, and C_E are all constrained to 1 so that A and S matrices provide standardized relations between genetic and environmental factors. Variance components are used to define cross-twin cross-trait covariance matrices for MZ and DZ twin pairs:

$$C_{MZ} = \begin{bmatrix} C_A + C_C + C_E & C_A + C_C \\ C_A + C_C & C_A + C_C + C_E \end{bmatrix}$$

$$C_{DZ} = \begin{bmatrix} C_A + C_C + C_E & 0.5 \times C_A + C_C \\ 0.5 \times C_A + C_C & C_A + C_C + C_E \end{bmatrix}$$

The proportion of variance for variable *i* accounted for by the genetic, shared environmental, and nonshared environmental components is respectively estimated via dividing each variance component (C_A, C_C, and C_E) by the phenotypic variance of variable *i* taken from the covariance matrix (C_P) using the following formulas: $C_{A\,i,i}/\,C_{P\,i,i}$, $C_{C\,i,i}/\,C_{P\,i,i}$, and $C_{E\,i,i}/\,C_{P\,i,i}$. The genetic, shared environment, and nonshared environment path estimates are obtained from the A and S matrices, and represent the relations between genetic and environmental factors underlying the phenotypic relations. The proportion of the observed relation between two given variables *i* and *j* that is attributable to the genetic, shared environmental, and nonshared environmental influences is estimated based on the following formula, introduced in the model as matrix algebra to allow for the estimation of 95% confidence intervals.

$$A^{\%}_{A_{i,j}} = \frac{T_{A_i} A_{A_{i,j}} T_{A_j}}{T_{A_i} A_{A_{i,j}} T_{A_j} + T_{C_i} A_{C_{i,j}} T_{C_j} + T_{E_i} A_{E_{i,j}} T_{E_j}}$$

$$A^{\%}_{C_{i,j}} = \frac{T_{C_i} A_{C_{i,j}} T_{C_j}}{T_{A_i} A_{A_{i,j}} T_{A_j} + T_{C_i} A_{C_{i,j}} T_{C_j} + T_{E_i} A_{E_{i,j}} T_{E_j}}$$

$$A^{\%}_{E_{i,j}} = \frac{T_{E_i} A_{E_{i,j}} T_{E_j}}{T_{A_i} A_{A_{i,j}} T_{A_j} + T_{C_i} A_{C_{i,j}} T_{C_j} + T_{E_i} A_{E_{i,j}} T_{E_j}}$$

$$S^{\%}_{A_{i,j}} = \frac{T_{A_i} S_{A_{i,j}} T_{A_j}}{T_{A_i} S_{A_{i,j}} T_{A_j} + T_{C_i} S_{C_{i,j}} T_{C_j} + T_{E_i} S_{E_{i,j}} T_{E_j}}$$

$$S^{\%}_{C_{i,j}} = \frac{T_{C_i} S_{C_{i,j}} T_{C_j}}{T_{A_i} S_{A_{i,j}} T_{A_j} + T_{C_i} S_{C_{i,j}} T_{C_j} + T_{E_i} S_{E_{i,j}} T_{E_j}}$$

$$S^{\%}_{E_{i,j}} = \frac{T_{E_i} S_{E_{i,j}} T_{E_j}}{T_{A_i} S_{A_{i,j}} T_{A_j} + T_{C_i} S_{C_{i,j}} T_{C_j} + T_{E_i} S_{E_{i,j}} T_{E_j}}$$

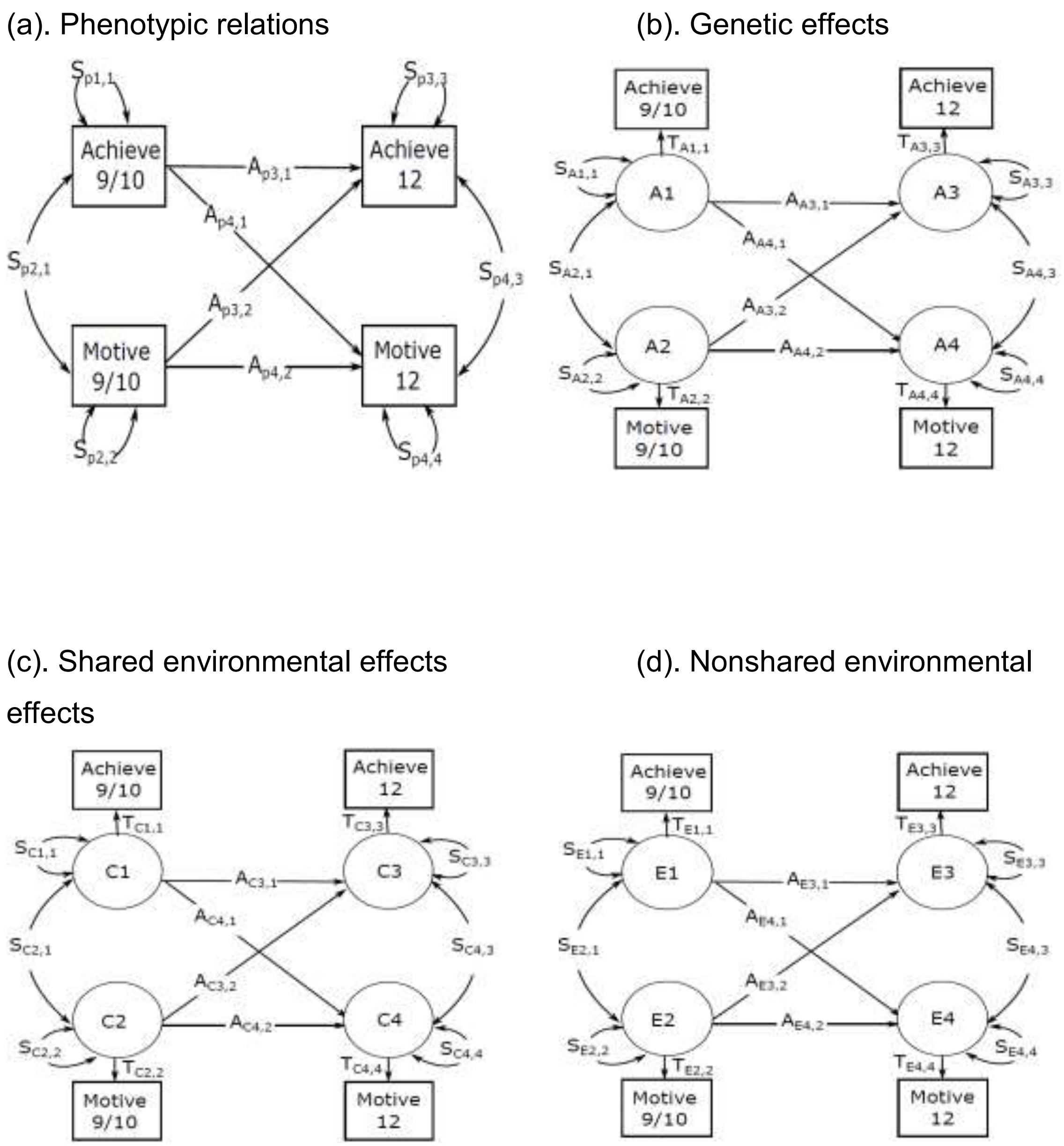


Figure 5.1. Phenotypic cross-lagged model (panel a) and ACE cross-lagged model (panel b, c, and d). S and A matrices respectively capture symmetric and asymmetric relations. T matrix captures the impact of A, C, and E components on the total phenotypic variance of each variable. In the ACE cross-lagged model, S and A matrices are further decomposed into genetic (A; panel b), shard environmental (C; panel c), and nonshared environmental (E; panel d) components. Achieve = reading achievement; motive = reading motivation; 9/10 = age 9/10; 12 = age 12.

The cross-lagged approach using multivariate Cholesky decompositions

In order to validate the results obtained with the ACE cross-lagged model, the same research question was explored using the multivariate Cholesky decomposition approach (described in Chapter 3 of the present thesis), previously used to investigate the aetiology of cross-lagged associations in several studies (e.g. Luo et al., 2010; Luo et al., 2011). When variables are entered in the appropriate order, the Cholesky model allows for the estimation of genetic and environmental influences on the variance of a single trait. In addition, it allows for the examination of the genetic and environmental factors underlying the covariance between multiple traits, including their longitudinal stabilities, contemporaneous correlations, and cross-lagged predictions. The model works similarly to a phenotypic hierarchical regression, so that the influence of one variable on another is calculated after controlling for the effect of the variables that were previously entered in the model.

As previously mentioned, the Cholesky approach only allows for the estimation of one cross-lagged path within one model. Therefore, the cross-lagged link from reading achievement at age 9/10 to reading motivation at age 12 (Cholesky cross-lag model, Figure 5.3) was examined first, entering the variables into the model in the following order: (1) reading motivation age 9/10, (2) reading achievement age 9/10, (3) reading achievement age 12, and (4) reading motivation age 12.

In this model, tracing paths from the factors A1, C1, and E1it is possible to derive four sets of genetic, shared environmental, and nonshared environmental estimates for: (a)the variance in reading motivation at age 9/10 (a_{11} x a_{11}, c_{11} x c_{11}, e_{11} x e_{11}), (b) the contemporaneous covariance between reading achievement and reading motivation at 9/10 (a_{11} x a_{21}, c_{11} x c_{21}, e_{11} x e_{21}), (c) the cross-lagged covariance between reading achievement at 9/10 and reading motivation at 12 (a_{11} x a_{31}, c_{11} x c_{31}, e_{11} x e_{31}) –however, this cross-lagged estimate does not account for stability of reading motivation; (d) and the stability of reading achievement over time (a_{11} x a_{41}, c_{11} x c_{41}, e_{11} x e_{41}). Tracing paths from factors A2, C2, and E2 it is possible to derive the genetic, shared environmental, and non-shared environmental estimates for:(e) the residual variance of reading achievement at age 9/10 (a_{22} x a_{22}, c_{22} x c_{22}, e_{22} x e_{22}); (f) the stability of reading achievement over time (a_{22} x a_{32}, c_{22} x c_{32}, e_{22} x e_{32}), (g) and the cross-lagged covariance between reading achievement at age 9/10 and reading motivation at age 12 (main research interest; a_{22} x a_{42}, c_{22} x c_{42}, e_{22} x e_{42}) independent of reading motivation at age 9/10. Tracing paths from factors A3, C3, and E3 it is possible to obtain the genetic, shared environmental, and non-shared environmental estimates for: (h) the residual variance of reading achievement at age 12 (a_{33} x a_{33}, c_{33} x c_{33}, e_{33} x e_{33}); (i) and the contemporaneous covariance between reading motivation and reading achievement at age 12 (a_{33} x a_{43}, c_{33} x c_{43}, e_{33} x e_{43}) independent of reading motivation and reading achievement at age 9/10. Finally, A4, C4, and E4 respectively capture the residual genetic, shared environmental, and non-shared environmental variance unique to reading motivation at age 12 after controlling for reading motivation at age 9/10 and reading achievement at both ages (a_{44} x a_{44}, c_{44} x c_{44}, e_{44} x e_{44}).

Next, a second Cholesky decomposition was conducted to examine the opposite cross-lagged link, from reading motivation at age 9/10 to reading achievement at age 12 (see Cholesky cross-lagged model B and Figure 5.4). For this second model, the same variables were entered in a different order: (1) reading achievement age 9/10; (2) reading motivation age 9/10; (3) reading motivation age 12; and (4) reading achievement age 12.Similar path tracing rules were used as described above.

Results

Descriptive Statistics and Correlations

One twin out of each pair was randomly selected for further analyses to control for non-independence of observation. Table 5.1 reports descriptive statistics. All variables were distributed widely. Distributions for reading achievement and reading motivation were similar across waves. Descriptive statistics were repeated using the other twin within the pair providing an inbuilt replication. The results were highly similar for the two samples (twin 1 and twin

2). Additionally, Table 5.2 reports descriptive statistics separately for MZ, same sex DZ, and opposite sex DZ twins. All zygosity groups were included in the analyses.

Table 5.1. Descriptive statistics for reading motivation and achievement at both collection waves.

	Motivation 9/10	Motivation 12	Achievement 9/10	Achievement 12
N*	3363	5876	3095	5521
Mean	4.16	3.99	46.19	57.30
Std. Deviation	0.85	0.87	13.53	11.13
Skewness (std. error)	-0.97 (0.04)	-0.74 (0.03)	-0.35 (0.04)	-0.65 (0.03)
Kurtosis (std. error)	0.59 (0.08)	0.22 (0.06)	-0.13 (0.09)	0.46 (0.07)
Minimum	1.00	1.00	1.00	1.00
Maximum	5.00	5.00	80.00	81.00

Note: N = sample size; * = one twin out of each pair was selected to control for non-independence of observation.

Phenotypic correlations between all variables are reported in Table 5.3. Correlations between reading motivation and reading achievement were modest at age 9/10 and age 12 (r = .26 and r = .31, respectively). The correlation between reading motivation at age 9/10 and age 12 was moderate (r = .50).The correlation between achievement at age 9/10 and age 12 was also moderate (r = .53). Prior to the genetic analyses, the effects of age and sex were controlled for, using linear regression.

All variables were Van der Waerden transformed. Van der Waerden transformation is a rank-based inverse normal transformation, which transforms the sample distribution of continuous variables to make them appear more normally distributed (see Beasley & Erickson, 2009 for additional information). Analyses were run before and after Van der Waerden transformation. As the ranked-based transformation was found not to have an impact on the results, we ran our analyses using the transformed data.

Table 5.3. **Correlations between study variables.**

Variables	1	2	3	4
1. Motivation 9/10	1	.51**	.26 **	.23 **
N	3363	2680	2516	2374
2. Motivation 12		1	.36 **	.31 **
N		5874	2433	4750
3. Achievement 9/10			1	.53 **
N			3095	2272
4. Achievement 12				1
N				5521

Note: N = pairwise sample size; One twin was randomly selected out of each pair to control for non-independence of observation; * $p< .05$; ** $p< .01$.

Twin Correlations

Table 5.4 presents the intraclass correlations between measures of reading achievement and reading motivation separately for MZ and DZ twins. For reading motivation at both waves, twin correlations were substantially larger for MZ than for DZ twins, indicating significant genetic but negligible shared environmental influences. The same was observed for reading achievement at age 12. For reading achievement at age 9/10, the MZ correlation did not double that of DZ twins, indicating both genetic and shared environmental influences. MZ correlations for all variables were below 1, indicating non-shared environmental influences on all variables.

Table 5.4 also reports heritability, shared and nonshared environment estimates from univariate twin model fitting. Reading motivation at age 9/10 and age 12 was moderately heritable, with genetic factors explaining 38% and 51% of the variance, respectively. The remaining variance in reading motivation at both waves was attributable to nonshared environmental influences. Reading achievement at ages 9/10 and 12 was also moderately heritable, with genetic factors explaining 39% and 34% of the phenotypic variance, respectively. Shared environmental influences were modest for reading achievement at age 9/10 (28%), but did not contribute to individual differences in reading achievement at age 12. Nonshared environmental influences, which also include measurement error, were modest for reading achievement at age 9/10 (33%) and large for reading achievement at age 12 (66%).

Table 5.5 reports cross-twin cross-trait correlations for all pairwise associations. Cross-twin cross-trait correlations were generally moderate for MZ twins and weak for DZ twins, indicating genetic influence on the covariance between each pair of variables. Some of the twin correlations indicated an ADE model –decomposing the variance into additive genetic (A), non-additive genetic (D) and nonshared environmental effects (E)–as DZ correlations were less than half the MZ correlations. However, fitting an ADE did not improve model fit indices. Consequently, results of ACE models are reported, as these are in line with analyses presented by previous research.

Table 5.4. Intraclass correlations and univariate estimates for genetic (A), shared (C) and nonshared (E) environmental influences on reading motivation and reading achievement.

Variable	*r*MZ	*r*DZ	A (CIs)	C (CIs)	E (CIs)
Achievement 9/10	.67	.47	.39 (.30 - .48)	.28 (.20 - .35)	.33 (.30 - .36)
Motivation 9/10	.42	.10	.38 (.33 - .42)	-	.62 (.58 - .67)
Achievement 12	.35	.15	.34 (.30 - .37)	-	.66 (.63 - .70)
Motivation 12	.56	.14	.51 (.48 - .53)	-	.49 (.47 - .52)

Note: Twin correlations and univariate estimates were obtained after regressing for age and sex; CIs = 95% confidence intervals.

Table 5.5. Cross-twin cross-trait correlations for all pairwise associations.

Pairs of variables	rMZ	rDZ
Motivation 9/10& Achievement 9/10	.22	$.05^{ns}$
Motivation 9/10& Motivation 12	.33	$.06^{ns}$
Motivation 9/10& Achievement 12	.33	$.05^{ns}$
Achievement 9/10& Achievement 12	.38	.14
Achievement 9/10& Motivation 12	.39	.15
Motivation 12& Achievement 12	.55	.13

Note: Cross-twin cross-trait correlations for all pairs of variables were obtained after regressing for age and sex; $^{ns}p > .05$.

Table 5.2. Descriptive statistics separately for MZ, same sex (SS) DZ and opposite sex (OS) DZ twins

	N*	Mean	St Deviation	Skewness (St error)	Kurtosis (St error)	Minimum	Maximum
Motivation 9/10 **MZ**	1230	4.16	.84	-1.03 (.07)	.84 (.14)	1.00	5.00
Motivation 9/10 **DZ SS**	1084	4.16	.84	-.95 (.07)	.38 (.15)	1.00	5.00
Motivation 9/10 **DZ OS**	1033	4.16	.86	-.94 (.07)	.54 (.15)	1.00	5.00
Reading 10 **MZ**	1112	45.47	13.65	-.30 (.07)	-.06 (.14)	1.00	79.00
Reading 10 **DZ SS**	985	46.57	13.56	-.36 (.07)	-.25(.15)	1.00	77.00
Reading 10 **DZ OS**	983	46.74	13.31	-.39 (.07)	-.06 (.15)	3.00	80.00
Motivation 12 **MZ**	2107	3.97	.88	-.69 (.05)	-.05 (.10)	1.00	5.00
Motivation 12 **DZ SS**	1904	4.00	.84	-.62 (.05)	.00 (.11)	1.00	5.00
Motivation 12 **DZ OS**	1839	4.02	.87	-.65 (.05)	-.26 (.11)	1.00	5.00
Reading 12 **MZ**	1990	56.62	11.13	-.52 (.05)	-.05(.11)	3.00	79.00
Reading 12 **DZ SS**	1764	57.78	11.10	-.73 (.06)	.88 (.11)	3.00	81.00
Reading 12 **DZ OS**	1739	57.67	11.01	-.71 (.05)	.72 (.11)	1.00	79.00

Note: * = 1 twin out of each pair was randomly selected

Phenotypic cross-lagged model

The phenotypic cross-lagged model allows to explore three main issues: correlation between variables measured at the same collection wave, stability of the variables, and cross-lagged association between different variables. Results from the phenotypic cross-lagged model are reported in Figure 5.2.a and Table 5.6. The phenotypic model showed a positive modest correlation between reading motivation at age 9/10 and reading achievement at age 9/10 (r = .24). Reading motivation was moderately stable over time (.37), and the same was observed for reading achievement over time (.38).

Reciprocal longitudinal links between reading motivation and reading achievement were observed. The cross-lagged link from reading motivation at age 9/10 to reading achievement at age 12 was modest (.24). The opposite cross-lagged link from reading achievement at age 9/10 to reading motivation at age 12 was very similar (.26). Constraining the two cross-lagged paths to be equal did not result in worse model fit (X^2 = 1.76, Δdf = 1, p = 0.18), suggesting that the two cross-lagged paths are of similar magnitude. Finally, a moderate residual positive correlation between reading motivation and reading achievement at age 12 (r = .44) was observed. Overall the model suggests that reading motivation at age 9/10 contributes to the variance in reading achievement at age 12 beyond the stability of achievement. Similarly and with similar strength, reading achievement at 9/10 contributed to the variance in reading motivation at age 12 beyond its stability.

ACE Cross-lagged Model

The second hypothesis regarding the aetiology of the observed longitudinal associations between reading motivation and reading achievement was tested using the ACE cross-lagged model. The same analyses were run separately for enjoyment and self-perceived ability and results are presented in Table A2 and A3. Results from the ACE cross-lagged model are shown in Figure 5.2.b, 5.2.c, 5.2.d, and Table5.6. The stability in reading motivation over time was explained by both genetic (around44%) and non-shared environmental factors (approximately55%). The stability in reading achievement was attributable to genetic (57%), shared environmental influences (36%), and only a small portion of variance was explained by nonshared environmental factors (7%). The contemporaneous correlation between reading achievement and reading motivation was explained by both genetic (78%) and nonshared environmental (22%) influences. Importantly, genetic factors explained a substantial proportion of the cross-lagged link from early reading motivation to later reading achievement (58%). The remaining variance in this cross-lagged link was attributable to nonshared environment influences.

The cross-lagged link from reading achievement at age 9/10 to reading motivation at age 12 was almost entirely explained by genetic factors (94%), with shared and nonshared environment explaining a negligible part of the covariance (2% and 4%, respectively). Finally, genetic factors, shared environmental factors, and nonshared environmental factors respectively accounted for 37%, 2%, and 61% of the residual contemporaneous correlation between reading motivation and reading achievement at age 12.

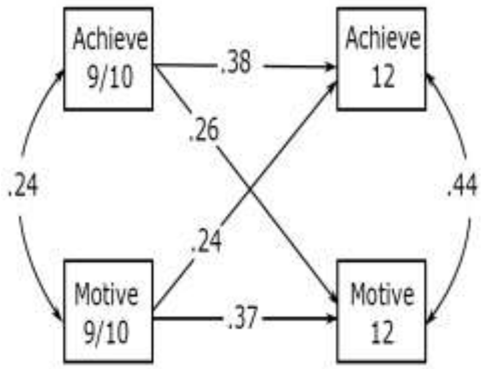
The same analyses were run exploring the association between reading self-perceived ability and reading enjoyment separately (see Table 5.7 and Table 5.8). Results obtained with the reading motivation composite score were highly consistent with those observed when the two measures of motivation were considered separately.

The Cholesky Decomposition approach

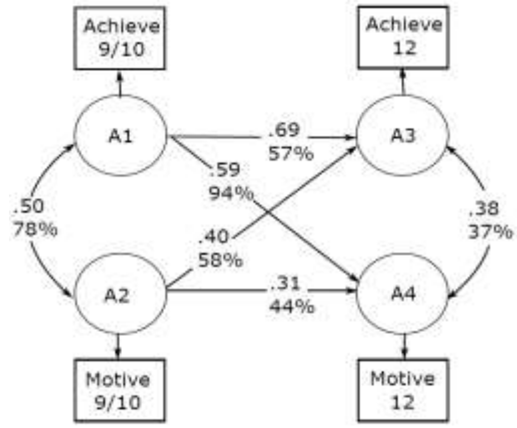
The data were re-analysed using the traditional Cholesky decomposition approach. Standardized path estimates of Cholesky cross-lag model A and B are shown in Figure 5.3.b and Figure 5.4.b. Contemporaneous correlations, stability, and cross-lagged prediction derived from the standardized path estimates are shown in Table 5.7. Overall, the results obtained fitting the Cholesky decomposition models were consistent with those obtained with the ACE cross-lagged model. Pertinent to our main research questions, reading achievement and reading motivation reciprocally predicted each other longitudinally after accounting for their stabilities and contemporaneous correlations.

Similarly to what we observed using the ACE cross-lagged model, the link from reading motivation at age 9/10 to reading achievement at age 12 was explained by both genetic (35%) and nonshared environmental (65%) factors; and the link from reading achievement at age 9/10 to reading motivation at age 12 was almost entirely explained by genetic influences (88%) with the remaining variance explained by non-shared environmental factors (12%).

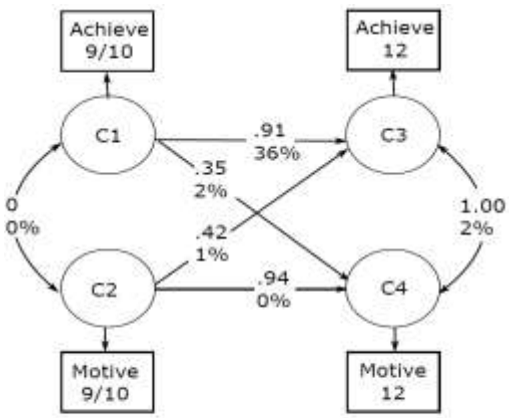
(a). Phenotypic relations



(b). Genetic effects



(c). Shared environmental effects



(d). Nonshared environmental effects

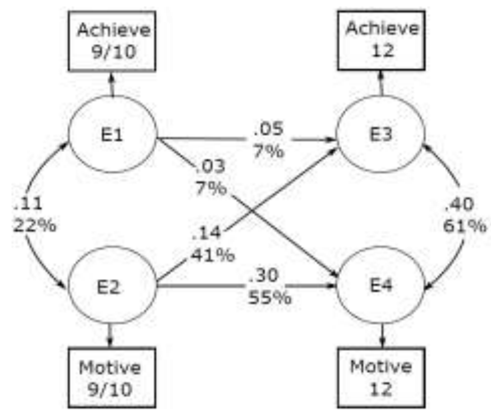


Figure 5.2. Phenotypic cross-lagged model (panel a) and ACE cross-lagged model (panel b, c, and d) with standardized path estimates. Numbers in % represent the percentage of phenotypic relations attributable to genetic, shared environmental, and nonshared environmental influences. Note that some shared environment path estimates are large whereas the corresponding % numbers are small. For example, stability for motivation in the shared environment model is .94, whereas the % number is 0. This is because shared environmental influences were very small for motivation; however, the limited shared environmental influences contributing to variance in motivation largely overlap across 2 waves, resulting in a high stability of the C path. However, comparing to the contribution of genes and nonshared environment, shared influences were rather small, taking up around 0% of the total phenotypic stability in motivation; Achieve = reading achievement; Motive = reading motivation.

Table 5.6. Phenotypic cross-lagged model and ACE cross-lagged model for the association between **reading achievement** and **reading motivation**: Model fit indices, standardized path estimates, and percentage of variance attributable to genetic (A), shared environmental (C), and nonshared environmental (E) influences.

Path	Phenotypic	A	C	E	A(%)	C(%)	E(%)
Contemporaneous correlation	0.24	0.50	0.00	0.11	78%	0%	22%
Motivation 9/10⇔Achievement 9/10	(0.22, 0.26)	(0.49, 0.59)	(-0.02,1.02)	(0.06, 0.17)	(75,89)%	(0%, 16%)	(10,34)%
Contemporaneous residual correlation	0.44	0.38	1.00	0.40	37%	2%	61%
Motivation 12⇔Achievement 12	(0.43, 0.46)	(0.25, 0.39)	(0.84, 1.01)	(0.39, 0.44)	(26,37)%	(0, 6)%	(60,70)%
Stability	0.37	0.31	0.94	0.30	44%	0%	55%
Motivation 9/10⇨Motivation 12	(0.35, 0.39)	(0.18, 0.31)	(0.00, 1.00)	(0.21, 0.33)	(29,57)%	(0, 0)%	(44,72)%
Stability	0.38	0.69	0.91	0.05	57%	36%	7%
Achievement 9/10⇨Achievement 12	(0.36, 0.40)	(0.44, 0.86)	(0.91, 1.00)	(0.01, 0.11)	(38,57)%	(20,52)%	(2, 15)%
Cross-lagged relation	0.24	0.40	0.42	0.14	58%	1%	41%
Motivation 9/10⇨Achievement 12	(0.21, 0.26)	(0.15, 0.66)	(0.00, 0.47)	(0.09, 0.17)	(56,75)%	(0, 9)%	(41,49)%
Cross-lagged relation	0.26	0.59	0.35	0.03	94%	2%	7%
Achievement 9/10⇨Motivation 12	(0.24, 0.28)	(0.57, 0.68)	(0.02, 0.70)	(0.00, 0.07)	(78,98)%	(0, 2)%	(2, 15)%
Phenotypic cross-lagged model fit	-2LL(df) = 64171.93 (23107)		AIC = 17957.93		CFI = 1.00	RMSEA = 0.00	
ACE cross-lagged model fit	-2LL(df) = 62993.05 (23087)		AIC =16819.05		CFI =0.98	RMSEA = 0.01	

Note. All estimates were obtained after regressing for age and sex; number in parentheses are 95% confidence interval; -2LL = negative 2 times log likelihood; df = degrees of freedom; AIC = Akaike information criterion; CFI = Bentler comparative fit index; RMSEA = root mean square error of approximation.

Table 5.7. Phenotypic and ACE cross-lagged model for the longitudinal association between **reading achievement and reading self-perceived ability (SPA)**: Model fit indices, standardized path estimates, and percentage of variance attributable to genetic (A), shared environmental (C), and nonshared environmental (E) influences.

Path	Phenotypic	A	C	E	A(%)	C(%)	E(%)
Contemporaneous correlation SPA 9/10⇔Achievement 9/10	0.24 (0.23, 0.24)	0.53 (0.52, 0.53)	0.02 (0.02, 0.36)	0.10 (0.04, 0.18)	79% (70, 94)%	1% (0%, 17%)	20% (6, 32)%
Contemporaneous residual correlation SPA 12⇔Achievement 12	0.37 (0.36, 0.38)	0.37 (0.37, 0.63)	-0.01 (-0.01, 0.02)	0.31 (0.30, 0.34)	42% (36, 48)%	0% (0, 0)%	58% (51, 76)%
Stability SPA 9/10⇨SPA 12	0.24 (0.24, 0.26)	0.08 (0.07, 0.08)	0.02 (0.02, 1.00)	0.24 (0.18, 0.24)	19% (0, 33)%	0% (0, 0)%	81% (80, 84)%
Stability Achievement 9/10⇨Achievement 12	0.39 (0.37, 0.41)	0.71 (0.52, 0.73)	0.93 (0.76, 0.95)	0.06 (0.06, 0.07)	59% (58, 79)%	33% (21, 44)%	8% (2, 9)%
Cross-lagged relation SPA 9/10⇨Achievement 12	0.17 (0.15, 0.19)	0.29 (0.23, 0.75)	0.00 (0.00, 0.07)	0.10 (0.10, 0.10)	58% (57, 58)%	0% (0, 1)%	42% (17, 82)%
Cross-lagged relation Achievement 9/10⇨SPA 12	0.28 (0.27, 0.30)	0.67 (0.50, 0.79)	0.14 (0.02, 1.00)	0.05 (0.04, 0.10)	93% (93, 100)%	0% (0, 7)%	7% (2, 7)%
Phenotypic cross-lagged model fit	-2LL(df) = 90361.5 (33705)		AIC = 22951.55		CFI = 1.00	RMSEA = 0.00	
ACE cross-lagged model fit	-2LL(df) = 88287.8 (33685)		AIC =20917.87		CFI =0.98	RMSEA = 0.01	

Note. All estimates were obtained after regressing for age and sex; number in parentheses are 95% confidence interval; -2LL = negative 2 times log likelihood; df = degrees of freedom; AIC = Akaike information criterion; CFI = Bentler comparative fit index; RMSEA = root mean square error of approximation.

Table 5.8. Phenotypic and ACE cross-lagged model for the longitudinal association between **reading achievement and reading enjoyment**: Model fit indices, standardized path estimates, and percentage of variance attributable to genetic (A), shared environmental (C), and nonshared environmental (E) influences.

Path	Phenotypic	A	C	E	A(%)	C(%)	E(%)
Contemporaneous correlation	0.17	0.31	0.00	0.11	71%	0%	29%
Enjoyment 9/10⇔Achievement 9/10	(0.16, 0.17)	(0.28, 0.32)	(0.00, 0.03)	(0.07, 0.17)	(59, 79)%	(0%, 0%)	(29, 30)%
Contemporaneous residual correlation	0.40	0.31	0.00	0.35	36%	0%	64%
Enjoyment 12⇔Achievement 12	(0.38, 0.42)	(0.16, 0.46)	(0.00, 1.00)	(0.32, 0.36)	(35, 37)%	(0, 6)%	(55, 65)%
Stability	0.37	0.48	0.00	0.22	64%	0%	36%
Enjoyment 9/10⇨Enjoyment 12	(0.34, 0.39)	(0.40, 0.48)	(0.00, 1.00)	(0.17, 0.27)	(62, 72)%	(0, 0)%	(27, 44)%
Stability	0.40	0.82	0.91	0.05	65%	29%	6%
Achievement 9/10⇨Achievement 12	(0.40, 0.43)	(0.62, 0.91)	(0.74, 1.00)	(0.01, 0.11)	(54, 79)%	(17, 32)%	(0, 6)%
Cross-lagged relation	0.22	0.33	0.00	0.14	56%	0%	44%
Enjoyment 9/10⇨Achievement 12	(0.22, 0.24)	(0.19, 0.42)	(0.00, 1.00)	(0.09, 0.14)	(38, 63)%	(0, 0)%	(27, 65)%
Cross-lagged relation	0.23	0.49	0.00	0.02	96%	0%	4%
Achievement 9/10⇨Enjoyment 12	(0.21, 0.23)	(0.35, 0.61)	(0.00, 1.00)	(0.02, 0.08)	(73, 100)%	(0, 13)%	(4, 14)%
Phenotypic cross-lagged model fit	-2LL(df) = 89153.1 (33675)		AIC = 21807.11		CFI = 1.00	RMSEA = 0.00	
ACE cross-lagged model fit	-2LL(df) = 87083.9 (33653)		AIC =19777.96		CFI =0.98	RMSEA = 0.01	

Note. All estimates were obtained after regressing for age and sex; number in parentheses are 95% confidence interval; -2LL = negative 2 times log likelihood; df = degrees of freedom; AIC = Akaike information criterion; CFI = Bentler comparative fit index; RMSEA = root mean square error of approximatio (a). Cholesky cross-lag model A.

(b). Cholesky cross-lag model A with std path estimates.

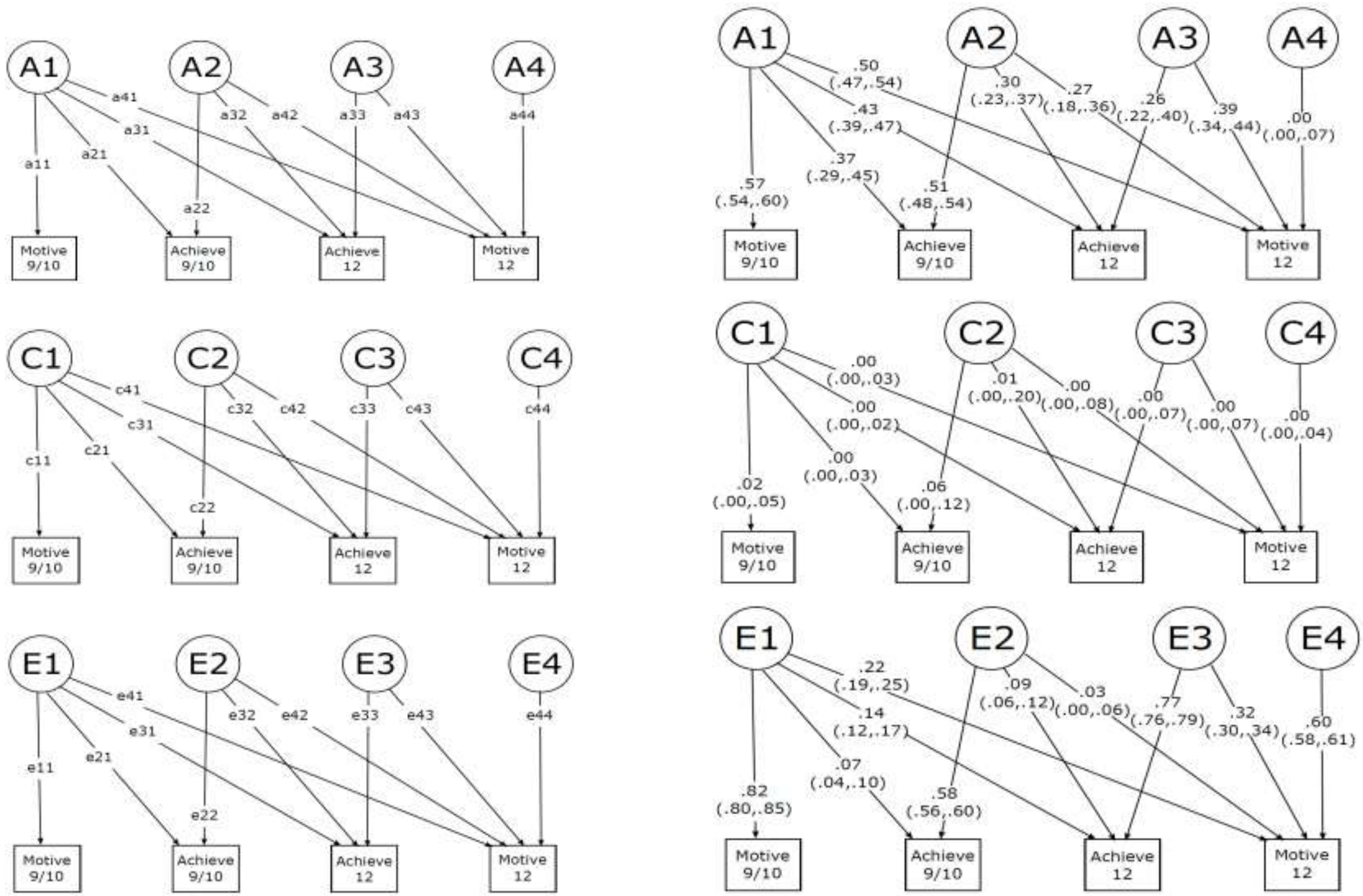


Figure 5.3. Cholesky Cross-lagged Model A. This model was used to examine the cross-lagged association between reading achievement at age 9/10 and reading motivation at age 12. See Figure 1 for abbreviation

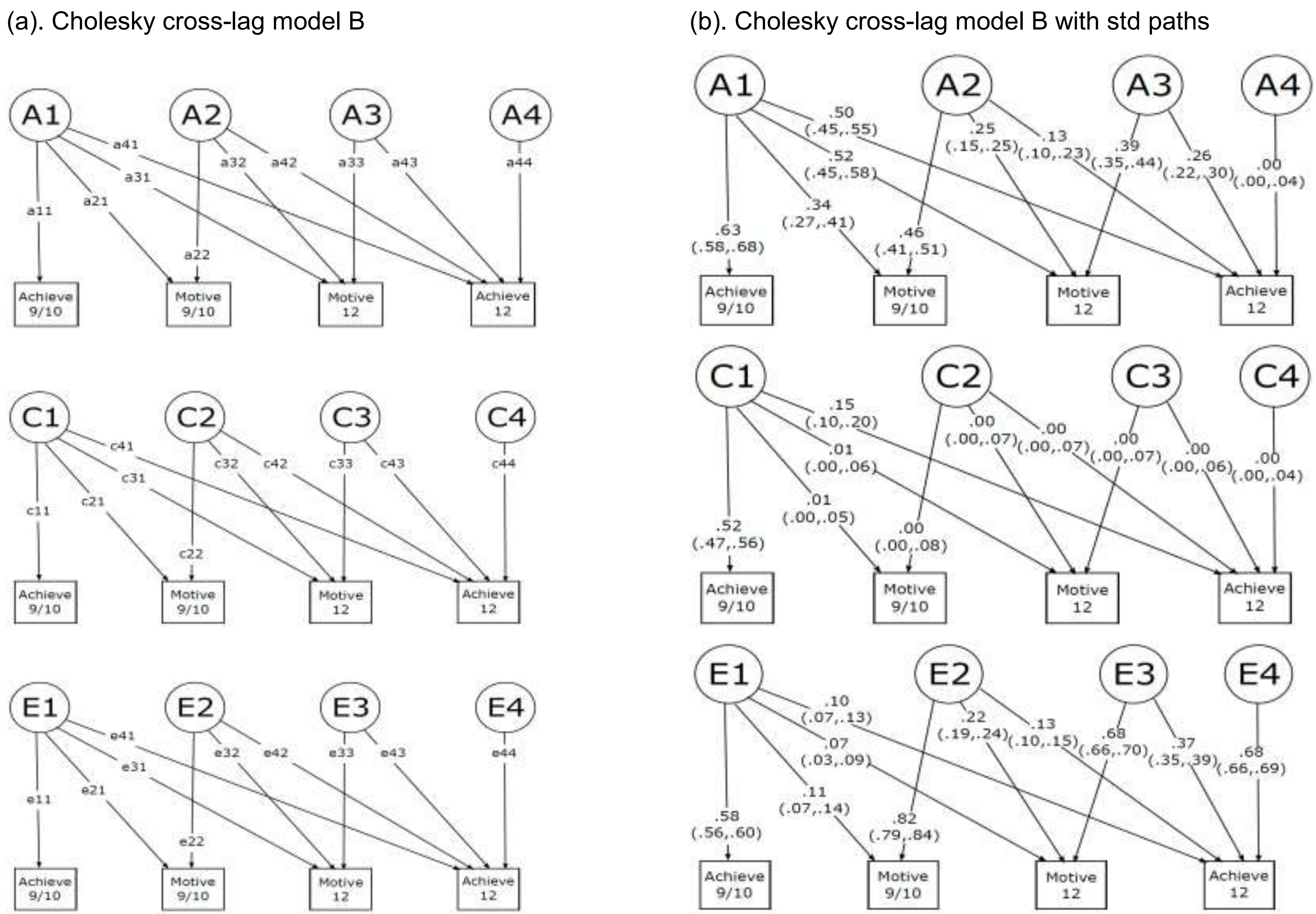


Figure 5.4. Cholesky Cross-lagged Model B. This model was used to examine the cross-lagged association between reading motivation at age 9/10 and reading achievement at age 12. See Figure 1 for abbreviation.

Table 5.9. Cholesky cross-lagged model: Variance components and percentage of phenotypic variance explained by genetic (A), shared environment (C), and nonshared environment (E).

	Phenotypic= A + C + E	A	C	E	A (%)	C (%)	E (%)
Contemporaneous correlation [a,b] Motivation 9/10 ⇔ Achievement 9/10	.26	.21 $a_{11} \times a_{21}$	.00 $c_{11} \times c_{21}$	.05 $e_{11} \times e_{21}$	81%	0%	19%
Contemporaneous residual correlation [a,b] Motivation 12 ⇔ Achievement 12	.35	.10 $a_{33} \times a_{43}$	.00 $c_{33} \times c_{43}$	.25 $e_{33} \times e_{43}$	29%	0%	71%
Stability [a] Motivation 9/10 ⇨ Motivation 12	.47	.29 $a_{11} \times a_{41}$	.00 $c_{11} \times c_{41}$	.18 $e_{11} \times e_{41}$	62%	0%	38%
Stability [b] Achievement 9/10 ⇨ Achievement 12	.46	.32 $a_{11} \times a_{41}$	.08 $c_{11} \times c_{41}$	.06 $e_{11} \times e_{41}$	70%	17%	13%
Cross-lagged relation [b] Motivation 9/10 ⇨ Achievement 12	.17	.06 $a_{22} \times a_{42}$	.00 $c_{22} \times c_{42}$	.11 $e_{22} \times e_{42}$	35%	0%	65%
Cross-lagged relation [a] Achievement 9/10 ⇨ Motivation 12	.16	.14 $a_{22} \times a_{42}$	.00 $a_{22} \times a_{42}$	.02 $a_{22} \times a_{42}$	88%	0%	12%

Note. All estimates were obtained after accounting for age and sex. Results were combined in this table in order to allow for an easier comparison with the results obtained with the ACE cross-lagged model. [a] path estimates are obtained from Cholesky cross-lagged model A in which the order of the variables are entered in the order: motivation 9/10, achievement 9/10, achievement 12, and motivation 12.[b] path estimates are obtained from Cholesky cross-lagged model B in which the order of the variables are entered in the order: achievement 9/10, motivation 9/10, motivation 12, and achievement 12.

Discussion

Using a genetically informative design, the present study tested two main hypotheses: (1) that the longitudinal relation between reading motivation and reading achievement is reciprocal, with cross-lagged links characterized by similar effect sizes; and (2) that both genetic and nonshared environmental factors contribute to the aetiology of the longitudinal association between reading motivation and reading achievement.

To address the first hypothesis, a phenotypic cross-lagged model was fitted. In order to test the second hypothesis a novel quantitative genetic model, the ACE cross-lagged model, was conducted. Unlike other models that had been previously used in the literature (e.g. the Cholesky decomposition method), the ACE cross-lagged model allows to examine the aetiologies of all cross-lagged links within the same model, allowing for the comparison of the effect sizes of the longitudinal links and taking into account the stability of both achievement and motivation over time. To validate the results obtained with the novel ACE cross-lagged model, a multivariate Cholesky decomposition was fitted, which had been previously used to estimate the aetiology of cross-lagged links. Results were found to be consistent between the two approaches. Because the effects of all associations were estimated within one model (the ACE cross-lagged model) it was possible to directly compare the effects of the two cross-lagged links (from reading motivation at age 9/10 to reading achievement at age 12 and the opposite link from reading achievement at age 9/10 to reading motivation at age 12).

At the phenotypic level, results revealed a reciprocal relation between reading motivation and achievement: early reading achievement longitudinally predicted subsequent reading motivation over and above the effects of early reading motivation; conversely, early reading motivation also statistically predicted subsequent reading achievement controlling for the effects of early reading achievement. This indicates that, compared to their peers, children with more confidence and interests in reading are more likely to become more competent readers over time, and more skilled readers are also more likely to become more confident in their ability to read and interested in reading. The effects of the two cross-lagged links were both modest and similar in magnitude, reflecting a reciprocal association between affect and cognition in the domain of reading.

These empirical findings add to the existing literature supporting the view that a reciprocal relation exists between reading achievement and reading motivation. However, previous research mostly explored the longitudinal relationship between motivation and achievement in a domain general context (Guay et al., 2003; Marsh & Martin, 2011; Muijs, 1997), or in other specific academic domains (e.g. mathematics, Luo et al., 2011). The present study provides evidence supporting a reciprocal association between motivation and achievement also in the domain of reading. This reciprocal association was also observed when reading enjoyment and reading self-perceived ability were considered separately.

Several features of the current study may have contributed to the discrepancies between the current results and those that failed to demonstrate a reciprocal association between motivation and achievement. First, our results revealed that the cross-lagged links were modest in magnitude. Previous investigations might have had insufficient statistical power to detect such weak reciprocal relations. Second, it is possible that the observed reciprocal link between reading achievement and reading motivation is unique to this particular developmental stage. The developmental period from 9 to 12 years old is a period shortly after when children make the transition from “learning to read” to “reading to learn” (Chall, 1983; Harlaar, Dale, & Plomin, 2007). For younger children, development in reading skills is mainly reflected in the aspects of letter and word level processing. Improvement in these reading skills may not lead to subsequent increase in reading interests which are based primarily on comprehending reading materials for aesthetic, social, or learning reasons (Morgan et al., 2008). As children get older, the main focus of reading instruction and curricula shifts to reading comprehension. Drastic improvement in children’s comprehension skills during this stage may lead to better understanding and appreciation of reading activities, which in turn drives children to further refine their skills. As a result, mutual influences between reading motivation and reading achievement may be particularly evident at this unique developmental stage. As children get older and more fluent in reading comprehension, their growth in reading achievement levels off (Francis, Shaywitz, Stuebing, Shaywitz, & Fletcher, 1996; Wang et al., 2015), and smaller changes in reading achievement over time may be increasingly harder to predict from other non-cognitive constructs, including motivation. Because the current data are only available over a 2-year span, it was not possible to explore how the motivation-achievement relation extends to other developmental periods. Future studies over an extended time are needed to investigate the dynamic nature of the development of the motivation-achievement link in the domain of reading.

In addition to phenotypic associations, the genetic and environmental aetiologies of reading motivation and achievement and of their cross-lagged links were also investigated. The aetiology of individual differences in reading achievement at age 9/10 was attributable in similar parts to genetic (39%), shared (28%) and nonshared (33%) environmental influences. Variation in reading achievement at age12 was explained moderately by genetic (34%) and mostly by nonshared environmental influences (66%). Individual differences in reading motivation at both collection waves were largely accounted for by nonshared (child specific rather than family-wide) environmental factors (~65%). The contribution of genetic factors was moderate. This is in line with a recent large international twin study which found that around 60% of individual differences in motivation in several other academic subjects could be attributed to nonshared environmental factors, and approximately 40% of the variance to genetic influences (Kovas et al., 2015).

Although nonshared environmental factors explained a substantial portion of variance in reading motivation and reading achievement at both ages, the cross-lagged links between them were largely genetic in origin. It is possible that children at genetic risk of poorer reading abilities experience more obstacles in learning to read and subsequently become more avoidant of reading activities (Harlaar, Deater-Deckard, Thompson, DeThorne, &Petrill, 2011). As a result, the less they read, the less pleasure and confidence they gain from reading. Similarly, development in reading achievement not only stemmed from genetic and environmental influences specific to reading, but was partially attributable to motivational processes by means of genetic influences.

It is important to consider that genes and environments do not operate independently. Therefore, the A, C, and E components in the variance-covariance decomposition models need to be interpreted in light of the dynamic interplay between genes and environments, which is subsumed under these variance components. Two types of gene-environment interplay may be at work: gene-environment correlation (described in detail in Chapter 1 of the present thesis) and gene by environment interaction. For example, children who have a genetic predisposition for high reading motivation may actively seek out reading activities, which in turn provide them with opportunities to practice and improve their reading skills. This process is known as active gene-environment correlation (Plomin et al., 1977). Alternatively, children with a genetic predisposition for good reading skills may elicit more praise and recognition from their parents and teachers, which further fosters their interests and confidence in reading activities – a process known as evocative gene-environment correlation (Plomin et al., 1977; Tucker-Drob & Harden, 2012a). Although the present results point to the possibilities of such gene-environment correlations, the current analyses do not allow us to disentangle these dynamic processes from the variance components estimation. In order to identify these gene-environment correlations, future studies should focus on examining whether relevant environmental experiences mediate the longitudinal relations between motivation and achievement through genetic pathways (Tucker-Drob, in press).

Genetically influenced individual differences drive the dynamic gene-environment correlation processes, but the existence of adequate opportunities in the environment is a necessary condition for such processes (Tucker-Drob, in press). Children who are genetically disposed to high reading motivation can only practice their reading skills when reading materials and opportunities are available to them; genetically influenced better reading skills may not result in more motivation to read without proper feedback from parents and teachers. Limitations in environment may constrain the “realization of genetic potentials”, whereas optimal environmental inputs may facilitate the translation from genetic advantage to desirable outcomes (Taylor, Roehrig, Soden-Hensler, Connor, & Schatschneider, 2010; Tucker-Drob & Harden, 2012). The process through which environment moderates genetic effects on outcomes is known as gene by environment interaction.

Another layer of complexity of gene-environment interplay is that environment is usually not randomly assigned to each individual (Scarr, 1996); rather, those with more genetic risks associated with poor reading abilities and low reading motivation are also potentially under more environmental risks as well (e.g., lack of supporting environment and positive feedback) –a process known as passive gene-environment correlation. These negative gene-environment processes may explain why improving reading skills and reading motivation in at-risk children can be difficult (Morgan et al., 2008).

Limitations

One limitation of the present study is that it focused on a specific aspect of reading achievement, reading comprehension, not considering other skills, such as reading fluency. In the same sample, reading comprehension was found to be less heritable than all other reading measures, including reading fluency (Kovas, Haworth, Dale &Plomin, 2007). The focus on reading comprehension may explain the discrepancy between the heritability estimates for reading achievement obtained in the present study and those reported in the literature, which are usually higher (Kovas, et al., 2007). Similarly, the present study specifically focused on the enjoyment and self-perceived ability aspect of motivation. Reading motivation is a multi-dimensional construct (Baker & Wigfield, 1999), and different aspects of reading motivation may be related to reading achievement via distinct mechanisms. Therefore, the present findings may not generalize to the relations between other reading cognition and other dimensions of reading motivation. For example, a recent study on a sample of 10-year old US twins used a composite reading motivation score that comprises several different motivation dimensions (i.e., reading self-efficacy, reading curiosity, reading for challenges, reading for recognition, and reading for grades), and found that the concurrent association between reading comprehension and the multi-dimensional reading motivation was mostly accounted for by nonshared environmental influences (Schenker & Petrill, 2015). The next chapter of the present thesis, Chapter 6, explores how several dimensions of motivation relate to achievement in the domain of second language (L2) learning, also considering the role of L2 anxiety.

Additionally, the reading motivation measure included in the present study was comprised of only 2 items, which did not allow to fully assess its psychometric properties. A short measure is likely to have lower reliability as compared to other reading motivation measures (e.g., Motivation for Reading Questionnaire; Wigfield, Guthrie, & McGough, 1996). Lower reliability may lead to underestimation of relations between constructs and overestimation of nonshared environmental influences. Therefore, replication of the present results using other measures of reading motivation is needed.

As mentioned earlier, the current data are only available at 2 time points over a 2-year span, which does not allow us to generalize the present findings to other developmental periods. Another drawback for a 2-wave cross-lagged design is that we are unable to examine the goodness of fit of our model to the data in the phenotypic cross-lagged model. Genetically sensitive studies with more repeated assessments on achievement and motivation over an extended time are needed in order to decipher the aetiology of the dynamic achievement-motivation transactions.

A further limitation of the present study is that it does not allow for the identification of the potential mechanisms underlying the observed genetic associations. In fact, genetic associations could indicate that the same genes influence variation in both reading motivation and reading achievement, a concept known as pleiotropy. Alternatively, the observed genetic association might reflect genetic causality, whereby genetic factors influence one trait, for example reading motivation, and in turn reading motivation influences another trait, for example reading achievement (Ligthart & Boomsma, 2012). Our analysis does not allow disentangling between these two.

Conclusion

To sum up, the present study was the first in the literature to explore the longitudinal relations between achievement and motivation in the domain of reading using a genetically sensitive design. Findings from the phenotypic analyses indicated that reading motivation statistically predicted later reading achievement and reading achievement also statistically predicted subsequent reading motivation; these cross-lagged effects of similar in size, and both are independent the effects of initial reading achievement and motivation. The present findings also indicated that the longitudinal links between reading motivation and achievement primarily stem from genetic differences among individuals. The same was observed when two different aspects of the reading motivation construct, enjoyment and self-perceived ability, were considered separately. This indicates that similar mechanisms account for the longitudinal association between the two aspects of motivation and reading achievement. The specific genetic factors involved are yet to be discovered. However, the finding that genetic differences among people are the primary drive in this relation represents a step forward towards understanding the mechanisms underlying the association between the cognitive and non-cognitive processes implicated in reading development.

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Chapter 6

Emergent relations among motivation, anxiety and second language learning

Abstract

This study explored the development of the relationship between motivation, emotion and achievement in the context of second language (L2) learning. Participants were 11-12 year-old students (*N* = 348) attending the first year of secondary school in the United Kingdom, formally learning a modern foreign language for the first time. Participants were assessed on measures of motivation, anxiety and achievement three times during one academic year. A measure of general cognitive ability (*g*) was also available for each child. Achievement, motivation and anxiety were found to be highly stable over time (with path coefficients ranging from .69 to .85). L2 achievement and L2 motivation correlated modestly (average *r* = .21) at every assessment wave. Initial levels of L2 motivation and L2 achievement were moderately related to *g*, but *g* was not associated with L2 anxiety. The results of cross-lagged analyses suggest that links between L2 achievement and L2 motivation are already present very early in the learning process. At the initial stage, achievement contributes to motivation, whereas motivation does not seem to significantly influence later achievement. These longitudinal associations were found to be highly similar across several subcomponents of motivation. Interestingly, a positive association between L2 anxiety and L2 motivation was observed, and the strength of the association was found to increase over the academic year. L2 anxiety and L2 achievement were not directly associated cross-sectionally or longitudinally, suggesting that the association between anxiety and achievement might emerge later in the learning experience. Overall, the results highlight the importance of studying the development of the relations between motivation, anxiety and achievement from the beginning of the learning process.

Introduction

The subcomponents of academic motivation and achievement

Motivational factors have been implicated in promoting academic success (Elliot, & Dweck, 2005). However, despite claims of the importance of academic motivation in fostering learning, the mechanisms of its effects remain poorly understood (Singh, Granville & Dika, 2002; Mega, Ronconi, & DeBeni, 2014). As described in Chapter 1 of the present thesis, several subcomponents of the broad construct of academic motivation have been identified, including: self-efficacy – a person's belief in being capable to bring about a desired outcome (Bandura, 1997); self-concept – a self-perception of performance in a specific field in comparison to that of other peers (Marsh, 1992); enjoyment –the positive feelings associated with learning, and confidence in correctness of one’s answers after a test (Stankov & Kleitman, 2008). These motivational concepts are usually share moderate to strong correlations (Morony, Kleitman, Lee, & Stankov, 2013), as also observed in Chapter 4 and Chapter 5 of the present thesis.

Several studies have investigated the associations between these motivational constructs and academic achievement (Ryan & Deci, 2000), in domain general (e.g. Chamorro-Premuzic, Harlaar, Greven, & Plomin, 2010) and domain specific contexts (e.g. Wigfield & Eccles, 2000; Luo et al., 2011; Garon-Carrier et al., 2016), with some indication that domain-specifically assessed motivation is more predictive of academic achievement than domain-general motivation (Steinmayr & Spinath, 2009; Marsh, Lüdtke, Nagengast, Trautwein, Abduljabbar, Abdelfattah, & Jansen, 2015).

Self-Determination Theory (SDT; Ryan & Deci, 2000; see Chapter 1 of the present thesis for more details on SDT) distinguishes between two main motivational concepts: intrinsic and extrinsic motivation. Intrinsic motivation is based on interest for new experiences, challenges and learning. Extrinsic motivation refers to a behaviour that is guided by the desire for an outcome, usually a reward or approval (Ryan & Deci, 2002). Research found that the links between academic attainment and intrinsic motivation are stronger and more long lasting than with extrinsic motivation (Ryan & Deci, 2000; Deci & Ryan, 2008).

One longitudinal study found that academic self-concept, one aspect of intrinsic motivation, shared a reciprocal relation with academic achievement. Initial self-concept predicted later achievement and previous achievement predicted later self-concept, with similar modest to moderate effects. Furthermore, the study found that academic self-concept was substantially stable over the course of primary school (Guay, Marsh, & Boivin, 2003). Similarly, another study found that self-efficacy, another aspect of intrinsic motivation, predicted future achievement and achievement predicted future self-efficacy with comparable effect sizes in the period of transition from primary to secondary school (Chamorro-Premuzic, et al, 2010).

Reciprocal relations between aspects of intrinsic motivation and achievement have also been observed in domain-specific contexts such as mathematics and reading. One study found reciprocal longitudinal links between mathematics self-evaluation and achievement, with links characterised by similar effects (Luo, Kovas, Haworth, & Plomin, 2011). Another recent investigation explored the longitudinal association between reading self-perceived ability and enjoyment and reading achievement, finding mutual links of similar effects between them (Malanchini, Wang, Voronin, Schenker, Plomin, Petrill, & Kovas, in press; see Chapter 5 of the present thesis) Altogether, evidence from these domain-general and domain-specific investigations suggest that the relation between several aspects of intrinsic motivation and achievement is mutual and characterised by similar effects, and has already emerged at the beginning of primary school (Guay et al., 2003)

However, recent evidence did not find support for this mutual association between intrinsic motivation and achievement in the domain of mathematics (Garon-Carrier, Boivin, Guay, Kovas, Dionne, Lemelin et al., 2016). In a large sample of primary school children from Canada, mathematics achievement collected over three waves from age 7 to age 10, predicted later mathematics motivation at all waves. On the other hand, mathematics intrinsic motivation was not found to predict later mathematics achievement at any point over the four-year longitudinal study (Garon-Carrier et al., 2016). Similarly, longitudinal evidence in the domain of reading found that reading achievement predicted the development of later motivation, but reading motivation was not a significant predictor of following achievement (Aunola, Leskinen, Onatsu-Arvilommi, & Nurmi, 2002). Therefore, the evidence is mixed regarding the emergence and development of the association between numerous aspects of intrinsic motivation and achievement across several academic domains.

The association between motivation and achievement in the domain of second language (L2) learning

Cross-sectional studies have found positive associations between measures of L2 motivation and L2 achievement in adolescent and adult samples (Ushioda, 2010; Dixon, Zhao, Shin, Wu, Su, Burgess-Brigham, et al., 2012; Kormos & Kiddle, 2013). Relationships between achievement and intrinsic motivation were stronger (ranging from .29 to .46) than between achievement and extrinsic motivation (ranging from .01 to .22) L2 (Khodadady & Khajavy, 2013). Another study found moderate to strong correlations between L2 motivation and L2 achievement in two samples of Spanish students learning English as a second language, in grades 2 and 4 (Gardner, 2007).

Another recent study explored the association between different sub-components of L2 intrinsic motivation (instrumental and integrative motivation) and L2 achievement in a sample of 10-17-year-olds from Australia (Anton-Mendez, Ellis, Coventry, Byrne, van Daal, 2015). The study found that instrumental motivation and integrative motivation were highly correlated, and constituted one broad L2 intrinsic motivation component. Intrinsic motivation was found to predict 6% of the variance in teacher-rated L2 achievement, and 18% of the variance in self-reports of L2 achievement. Furthermore, intrinsic motivation was found to be the best predictor of L2 achievement out of several non-cognitive and environmental characteristics such as affect, bilingualism, and the age when students started learning a second language (Anton-Mendez et al., 2015).

Limited literature has explored the development L2 motivation and of its association with L2 academic achievement using longitudinal designs. One longitudinal study (Busse, & Walter, 2013) explored the stability of L2 motivation over the course of one academic year in a sample of university students, finding a slight decline in L2 intrinsic motivation. The decline in intrinsic motivation over the academic year was observed in conjunction with a decline in L2 self-efficacy beliefs (Busse, & Walter, 2013). However, longitudinal relations between L2 motivation and L2 achievement remain largely unexplored. Consequently, it is unclear how the association between L2 motivation and achievement emerges and develops.

Second Language (L2) anxiety and achievement

Another non-cognitive factor that has been explored in relation to L2 achievement is anxiety. Second Language (L2) anxiety describes “the worry and negative emotional reaction aroused when learning or using a second language” (MacIntyre, 1999, p. 27). Numerous factors have been implicated in variation in L2 anxiety, including self-perceived proficiency and frequency of use of L2, with more proficient and frequent users feeling less anxious; and age, with older participants feeling less anxious (Dewaele, & Al-Saraj, 2013). Several investigations have found moderate negative correlations (ranging from −.20 to −.43) between L2 achievement and L2 anxiety, the anxiety experienced in situations involving teaching and learning of a foreign language (Horwitz, 2001; Liu, 2013; Liu & Zhang, 2013; Khodadady & Khajavy, 2013).

However, other studies have found L2 anxiety to be a facilitating factor in L2 acquisition (e.g. Frantzen & Magnant, 2005 in Liu & Zhang, 2013). A recent investigation explored the association between L2 anxiety and achievement in a sample of monozygotic (identical) twins. Using the monozygotic twin differences design, which explores how differences between identical twins in one trait predict their differences in another trait (see Viding, Fontaine, Oliver, & Plomin, 2009 for additional information on this methodology), the study found that L2 anxiety positively predicted L2 achievement (β = .35; Anton-Mendez et al., 2015).

Therefore evidence is mixed with respect to the association between anxiety and performance in the domain of second language; with some studies finding L2 anxiety to be negatively related to L2 achievement while other studies found a moderate positive correlation. Furthermore, as observed for L2 motivation, the directionality of the association between L2 anxiety and achievement remains unclear – calling for longitudinal investigations exploring the emergence and development of the association.

The triadic interaction between L2 motivation, anxiety and achievement

Studies have also investigated the triadic interaction between achievement, motivation and anxiety. One study used structural equation modelling (SEM) to explore the association between several sub-components of L2 motivation, L2 anxiety and L2 achievement and found that, while L2 motivation positively predicted L2 achievement (β = .53 - .18), L2 anxiety negatively predicted both L2 motivation (β = .19) and L2 achievement (β = -.23; Gardner, 2007). The results replicated across two samples, one of 9 year-old and another of 7-year-old, Spanish students learning English as a foreign language (Gardner, 2007).

Another study looked at the triadic interaction between L2 achievement, L2 motivation and L2 anxiety finding a positive association between L2 anxiety and extrinsic L2 motivation, but a negative association between L2 anxiety and intrinsic L2 motivation (Khodadady & Khajavy, 2013). L2 intrinsic motivation was found to be the strongest direct positive predictor of L2 achievement (cross-sectional); and mediated the negative moderate relationship between L2 achievement and L2 anxiety (Khodadady & Khajavy, 2013). These results suggest that higher levels of achievement may contribute to higher levels of intrinsic motivation, which in turn may reduce anxiety, with no direct links between anxiety and achievement.

This is in line with evidence suggesting that academic motivation mediates the association between academic achievement and anxiety (Mega, Ronconi, & DeBeni, 2013). In their study, Mega et al. found a link between anxiety and motivation, as well as between motivation and achievement, but no direct link between anxiety and achievement (Mega, Ronconi, & DeBeni, 2013). Nevertheless, cross-sectional investigations are unable to shed light on the directionality of the associations between motivation, anxiety and achievement in the domain of second language, a research question that remains to date unexplored.

The role of general intelligence (g) in the motivation-achievement anxiety association

The link between academic achievement and intrinsic motivation can be partially explained by their relationship with *g*. However, the link has been found even after controlling for the effects of *g* (Spinath, Spinath, Harlaar & Plomin, 2006; Steinmayr & Spinath, 2009; Chamorro-Premuzic, Harlaar, Greven, & Plomin, 2010). One study, using cross-lagged methodology, found that achievement and self-perceived ability – an aspect of intrinsic motivation – mutually influenced each other (average $\beta = .12$) over the course of three years (ages 9 to 12), after accounting for *g* (Chamorro-Premuzic et al., 2010). These observed links were largely explained by genetic factors (Greven, Harlaar, Kovas, Chamorro-Premuzic, & Plomin, 2009).

The same was observed for the association between motivation (self-perceived ability and enjoyment) and achievement in the fields of literacy and mathematics (Malanchini, Voronin, Plomin, & Kovas, in preparation; see Chapter 4 of the present thesis). In a sample followed from age 9 to age 16, the links between literacy and mathematics motivation and achievement were partly, but not entirely explained by *g.* In fact, mutual associations between the constructs were observed after accounting for *g.*

Another study (Luo at al., 2011) found a modest longitudinal link (average $r = .20$) from mathematics achievement at age 9 to mathematics self-evaluation at age 12 and from self-evaluation at 9 to achievement at 12, after controlling for *g*, with the links also mostly explained by genetic factors (Luo, Kovas, et al., 2011). However, no study to date has explored the role that *g* plays in the longitudinal association between L2 motivation, anxiety and achievement.

The present study

The present study applies longitudinal modelling to the exploration of the triadic association between L2 motivation, anxiety and achievement. Data were collected three times over the fist year of secondary school, at the end of each school term (autumn, spring and summer term). Since students in the UK formally start learning a second language in secondary school, the data allowed for the exploration of how the association between L2 achievement, motivation and anxiety emerges. The present study has four main aims:

1. To investigate the longitudinal association between L2 achievement and several sub-components of L2 motivation.
2. To explore the development of the association between L2 achievement and L2 anxiety.
3. To apply longitudinal SEM to examine the triadic association between L2 achievement, L2 motivation and L2 anxiety over the course of the first year of secondary school.
4. To explore the role that *g* plays in the emergence and development of the longitudinal associations between L2 achievement, L2 motivation, and L2 anxiety.

Method

Participants

353 students attending the first year of secondary school participated in this study. The age of participants ranged from 11 to 12 years of age (*M* = 11.19 years, *SD* = .807 year; 47% female). The exact number of participants with complete data differed at every collection wave: 320 in the first, 308 in the second, and 324 in the third. All participants were formally learning a modern foreign language (French, German or Spanish) for the first time. Learning a foreign language is a compulsory part of the UK National Curriculum for secondary schools. Participants were recruited by means of a letter sent to their schools. Parents were given detailed information about the study and offered the opportunity to ‘opt out’ from the data collection. The research project received ethical approval from Goldsmiths University’s Ethics Committee.

Measures

Second Language (L2) History

Four questions about students’ past experiences with learning a second language were developed in order to account for foreign language history. Participants provided Yes/No answers to items such as ‘*Aside from English, do* *you speak any other language at home?*' and '*At the moment, are you learning any other language(s) outside school hours?*' Although a considerable number of children had bilingual parents (*N* = 122), none of the participants had previous formal experience with the foreign language they were learning in secondary school.

L2 Motivation and L2 Anxiety

A self-report measure, the *Motivation for Learning a Second Language Questionnaire* (Csizér & Kormos, 2009) was used at each of the 3 waves. The questionnaire assesses 13 non-cognitive characteristics associated with second language learning: ideal L2 self; intrinsic motivation; instrumental motivation; self-efficacy; peer-pressure; parental encouragement; anxiety; technology-based learning approach; resources-based learning approach; satiation control; self-regulation; motivational intensity; and international orientation. The measure included 66 items, which participants had to rate on a five-point scale, from '*Absolutely true*' to '*Not true at all*'.

The questionnaire was originally developed for use with older adolescent samples (Kormos, Kiddle, & Csizer, 2011). To examine he structure of the questionnaire in the current younger sample, internal validity of each one of the 13 sub-categories was estimated using Cronbach's alpha at every collection wave. Three out of the thirteen sub-categories (technology-based learning approach; resources-based learning approach; satiation control; and motivational intensity) showed low Cronbach's α (< .7) and were excluded from further analyses. The remaining 9 sub-categories showed high internal validity at all 3 waves (α > .7) and were included in the analyses: *Ideal L2 Self; Intrinsic Motivation; Instrumental Motivation; Self-efficacy; Peer-Pressure; Parental Encouragement; Anxiety; Self-Regulation; and International Orientation*.

The association between L2 achievement and these 9 subcategories of L2 motivation and L2 anxiety was explored separately for each sub-component, which are conceived as different, yet related, aspects of the L2 motivation umbrella. In addition, the principal component analysis (PCA) was conducted in order to explore the factor structure of the measure. From PCA, two clear factors emerged. The first factor, named ***L2 motivation*** (average α across the 3 waves = .93) included 6 sub-components of the Motivation for Learning a Second Language Questionnaire: (1) international orientation; (2) ideal L2self; (3) self-efficacy; (4) instrumental motivation; (5) intrinsic motivation; and (6) self-regulation. This first factor explained on average 64% of the variance in L2 learning motivation and included questions such as: '*I study L2 because I'd really like to be good at it'*, and '*When I imagine my future job, I see myself using L2*'.

The second factor, named ***L2 anxiety*** (average *α* across the 3 collection waves = .85) explained on average 14.8% of the variance and included 7 items asking questions such as: '*I worry about the consequences of failing tests, assignments and exams in L2*' and '*I feel more tense and nervous in my L2 class than in my other classes*'. Two subcategories of the original questionnaire (Parental encouragement and Peer Pressure) were not included into the L2 motivation composite as their factor loadings on the L2 motivation composite were low.

Longitudinal analyses were re-run on these two factors (L2 motivation and L2 anxiety) separately. L2 motivation, L2 anxiety and L2 achievement variables were entered all together in one model in order to explore their triadic interaction.

L2 Achievement scores

L2 achievement was measured using the National Curriculum levels of Achievement scores for key stage 3. Levels for Key stage 3 modern foreign language range from 1 to 8, with each level including three sublevels (c, b and a) where 'c' is the lowest, 'b' the intermediate, and 'a' the highest of the three. Levels were re-coded into continuous scores starting from 1c, scored as 1; 1b, scored as 2; 1a scored as 3; 2c, scored as 4 – up to 8c, 8b and 8a, scored as 22, 23 and 24, respectively. Teachers provided achievement scores three times: (1) the end of the autumn term; (2) end of the spring term; and (3) end of the summer term. Every assessment included four key ability areas: Listening, Speaking, Reading and Writing. Scores were combined into a mean L2 achievement score for every student at each wave.

General cognitive ability (g)

The Cognitive Ability Test Fourth Edition (CAT4; www.gl-assessment.co.uk) was used as a measure of general cognitive ability. The CAT4 was administered to all students during the last year of primary school and results were passed onto their secondary schools. The CAT4 comprises 168 items testing verbal (N = 48), nonverbal (N = 48), quantitative (N = 36) and spatial (N = 36) abilities. Items are awarded a single mark for each correct answer. The raw scores are then adjusted for age and standardized by placing them on a scale that compares them with a nationally representative sample of same age pupils across the UK. A mean CAT score, including scores from all the four subsections was used for the purpose of the present study as a measure of general intelligence (*g*).

Procedure

Participants were tested in their own classrooms as part of their L2 lesson, with both the teacher and the researchers present. Data were collected four times during one academic year. The first contact with the students took place at the beginning of the academic year, and was considered the baseline. During this first session, each participant was given a booklet containing the measures in the following order: (1) age and gender; (2) L2 history; and (3) Motivation for Learning a Second Language Questionnaire. Data on the Motivation for Learning a L2 Questionnaire that were collected during this first contact have not been included I the current analyses. The first contact is considered a baseline, 'wave zero' in the present study. Before the first testing session, each participant was allocated an identification number that remained the same throughout the study. The following data collections were carried out at the end of the autumn term (term 1), spring tem (term 2) and summer term (term 3), and are described as 'wave1', 'wave 2' and 'wave 3' in the present study. During these data collection sessions, only the Motivation for Learning a L2 Questionnaire was administered. The teachers provided the general intelligence (*g*) scores obtained at the end of the previous year, and L2 achievement scores at the end of the autumn, spring and summer term.

Analyses

Cross-lagged panel analysis (see Chapter 4 of the present thesis for a detail description) was used to investigate the longitudinal association between L2 achievement, motivation and anxiety. The cross-lagged design allows to examine the stability (or change) of variables over time (autoregressive effects) and to assess their reciprocal influences over time, accounting for their stability and their initial correlation. In other words, a cross-lagged effect refers to the influence of one, temporally preceding, variable on another variable, beyond autoregressive and cross-sectional effects (Geiser, 2013). Cross-lagged analyses were run using the MPlus7.0 software.

In exploring the association between motivation and achievement, an example of an autoregressive effect is examining how L2 motivation at time 1 predicts L2 motivation at time 2, by regressing L2 motivation at the end of term 2 on L2 motivation at the end of term 1. An example of cross-sectional effect is the relationship between L2 motivation and L2 achievement at the end of term 1 or any other correlational relationship, indicated in Figure 6.1 by double-headed arrows. And finally, an example of cross-lagged effect is the link from L2 motivation at the end of term 1 to L2 achievement at the end of term 2.

Results

Descriptive Statistics

Descriptive statistics are presented in Table 6.1. All variables were normally distributed, as indicated by the values of skewness and kurtosis. Although Table 6.1 only reports the descriptive statistics for the composite score of L2 motivation, all other subcomponents of the Learning a Second Language Questionnaire were also normally distributed.

Table 6.1. Descriptive statistics. Mean, standard deviation, minimum and maximum scores, skewness, kurtosis and number of participants for all continuous variables: L2 motivation; L2 achievement; L2 anxiety; and *g*

Variable	M	SD	Min	Max	Skew	Kurt	N
L2 mot T1	2.94	.85	1.02	4.76	−.17	−.60	320
L2 mot T2	2.83	.88	1.00	5.00	.09	−.56	310
L2 mot T3	2.89	.91	1.00	4.90	−.13	−.64	324
L2 achievement T1	4.48	1.41	1.00	7.00	.05	−.85	348
L2 achievement T2	6.68	1.68	2.50	10.00	−.02	−.56	347
L2 achievement T3	8.61	2.03	3.50	12.00	.17	−.63	348
L2 anxiety T1	2.60	.97	1.00	5.00	.44	−.63	320
L2 anxiety T2	2.49	.94	1.00	5.00	.59	−.31	309
L2 anxiety T3	2.55	.99	1.00	5.00	.36	−.71	324
g	101.2	11.77	68.00	138.0	.03	.13	336

Note: M = mean; SD = standard deviation; Min = minimum score; Max = maximum score; Skew = skewness; Kurt = kurtosis, N = number of observations.

Correlations between variables

Table 6.2 shows the correlational relationships between L2 motivation, L2 anxiety, L2 achievement, and *g* (measured through the cognitive ability test scores). Correlations for individual constructs across all waves of measurement were strong (average $r = .72$), indicating their stability over one academic year. Positive modest correlations (average $r = .21$) were observed between L2 motivation and L2 achievement across the three assessment waves. The correlation between L2 intrinsic motivation and L2 anxiety was not significant at wave 1, but became significant and modest in size at wave 3 ($r = .20$, $p < .001$).

No relationship was observed between L2 achievement and L2 anxiety, with the exception of a small negative relationship ($r = -.12$, $p < .05$) at the start of the academic year. A modest correlation was observed at all waves between L2 achievement and *g* (average $r = .25$) and L2 motivation and *g* (average $r = .17$). The relationship between *g* and L2 anxiety was not significant.

Cross-lagged links between the different components of L2 motivation and achievement

The present study applied cross-lagged panel analysis to study the emergence and development of the association between L2 achievement and several subcomponents of L2 motivation over the course of one academic year. Several cross-lagged models were conducted examining the longitudinal links between L2 achievement and: (1) Ideal L2 self (2); L2 intrinsic motivation; (3) L2 instrumental motivation; (4) L2 self-efficacy; (5) L2 peer pressure; (6) Parental encouragement; (7) L2 self-regulation; and (8) L2 international orientation. These analyses allowed to explore whether some aspects of L2 motivation are more closely related to achievement then others over time

Figure 6.1 (a, b, c, and d) and 6.2 (e, f, g, and h) show the longitudinal associations between L2 achievement and the different subcomponents of L2 academic motivation included in the present study. Results were mostly consistent across all subcomponents of L2 motivation. All L2 motivation constructs were found to be stable over one academic year with path coefficients for autoregressive effects ranging from $\beta = .67$ to $\beta = .76$. L2 achievement was similarly stable from term 1 to term 2 ($\beta = .69$), and its stability increased over the academic year ($\beta = .86$), indicating that achievement is already highly stable from the first year of learning a foreign language.

The initial correlations between L2 achievement and measures of L2 motivation were moderate (with *r* ranging from .12 to .20). Cross-lagged links from previous achievement to later L2 motivation were highly consistent across all measures, with the exception of two sub-components: self-regulation and international orientation. L2 achievement at the end of term 1 predicted L2 motivation at the end of term 2, and achievement at the end of term 2 predicted later motivation measured at the end of the school year (term 3).

The links from previous achievement to later L2 motivation were found to be significant but characterised by small effects (with path coefficients ranging from $\beta = .06$ to $\beta = .14$). The two exceptions were L2 self-regulation and L2 international orientation for which the prediction from previous L2 achievement to later self-regulation and international orientation was not significant (see Figure 6.2.g and 6.2.h). The cross-lagged links from previous L2 motivation to later achievement was found to be very small or not significant across all L2 motivation variables. Previous motivation predicted later achievement only for two sub-components of L2 motivation: intrinsic motivation (see Figure 6.1.b) and parental encouragement (see Figure 6.2.b), with very small effects ($\beta = .04$, and .07). For most measures of L2 motivation the cross-lagged links to later achievement were not significant. L2 motivation measured as: Ideal L2 self (see Figure 6.1.a), instrumental motivation (see Figure 6.1.c), L2 self-efficacy (see Figure 6.1.d), L2 peer pressure (see Figure 6.2.a), L2 self-regulation (see Figure 6.2.c); and L2 international orientation (see Figure 6.2.d) did not predict subsequent L2 achievement, beyond their initial correlation.

Table 6.2. Correlations between L2 motivation, L2 anxiety, L2 achievement at the three collection waves and *g*

	L2 Mot 1	L2 Mot 2	L2 Mot 3	L2 Anx 1	L2 Anx 2	L2 Anx 3	L2 Ach 1	L2 Ach 2	L2 Ach 3	*g*
L2 Mot 1	1	.76**	.77**	.11	.05	.11	.20**	.19**	.19**	.22**
L2 Mot 2		1	.81**	.01	.11	.09	.26**	.23**	.20**	.16**
L2 Mot 3			1	.06	.08	.20**	.23**	.19**	.18**	.11*
L2 Anx 1				1	.72**	.68**	−.08	−.00	−.02	−.06
L2 Anx 2					1	.72**	−.10	−.07	−.06	.02
L2 Anx 3						1	−.12*	−.09	−.10	−.08
L2 Ach1							1	.69**	.70**	.35**
L2 Ach 2								1	.86**	.20**
L2 Ach 3									1	.19**
g										1

Note: ** = p< .01; * = p < .05; L2 Mot 1 = L2 Motivation at the end of term 1; L2 Mot 2 = L2 Motivation at the end of term 2; L2 Mot 3 = L2 Motivation at the end of term 3; L2Anx1 = L2 Anxiety at the end of term 1; L2Anx2 = L2 Anxiety at the end of term 2; L2Anx3 = L2 Anxiety at the end of term 3; L2Ach1 = L2 Achievement at the end of term 1; L2Ach2 = L2 Achievement at the end of term 2; L2Ach3 = L2 Achievement at the end of term 3; *g* = general cognitive ability.

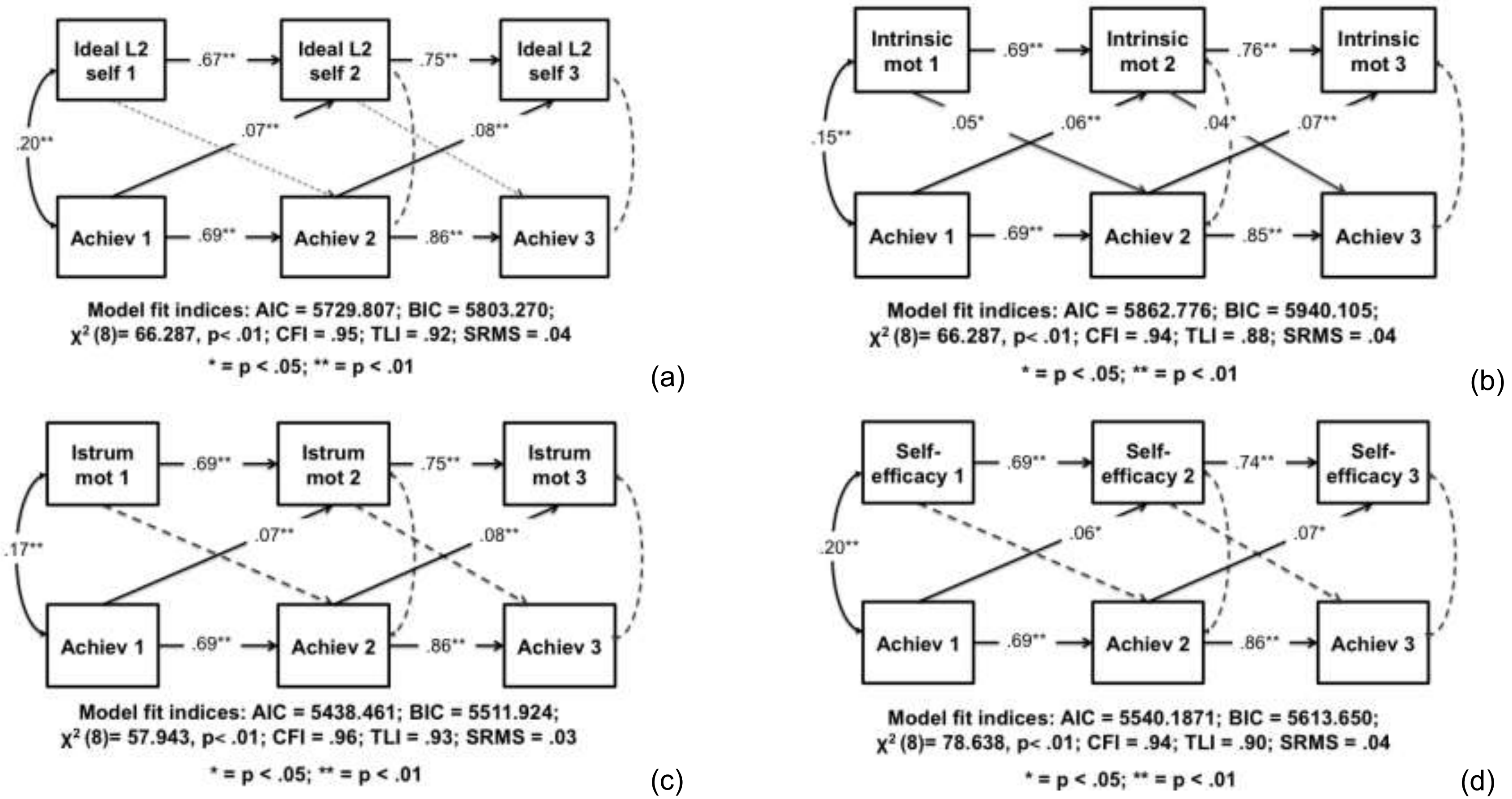


Figure 6.1. (a) Longitudinal association between ideal L2 self and L2 achievement; (b) Longitudinal relation between L2 intrinsic motivation and achievement; (c) Association between instrumental motivation and achievement; (d) Association between self-efficacy and L2 achievement; AIC = Akaike information criterion, BIC = Bayesian information criterion; χ2 = chi squared; CFI = Bentler comparative fit index; TLI = Tucker-Lewis index; SRMS = standardized root mean square residual.

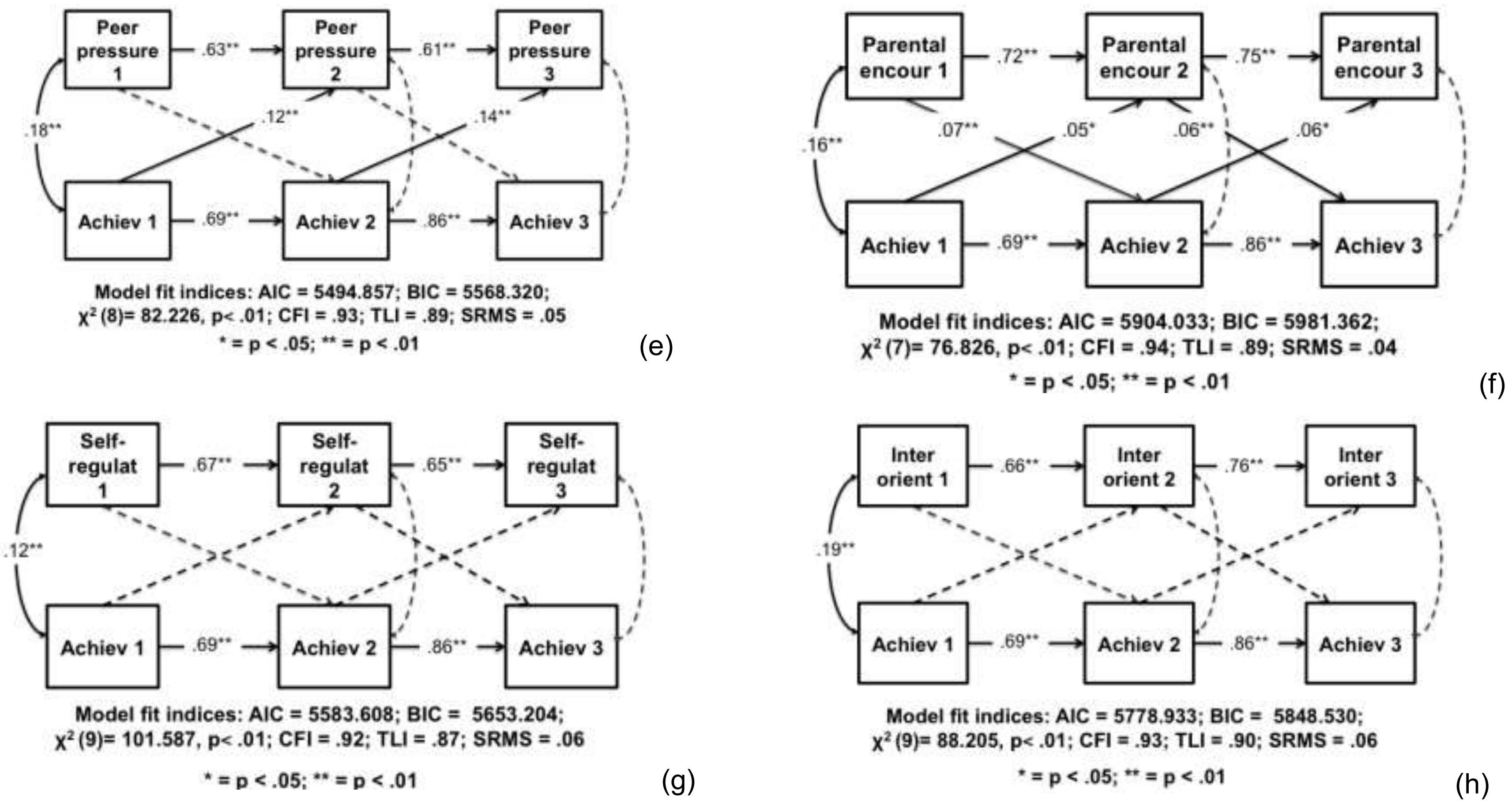
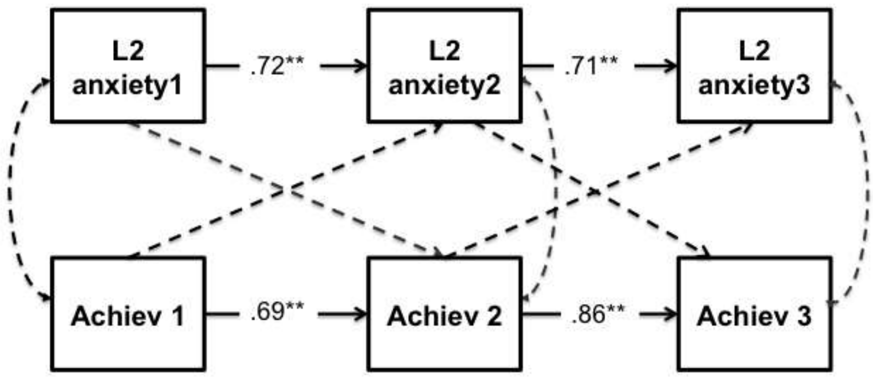


Figure 6.2. (e) longitudinal association between L2 peer pressure and L2 achievement; (f) longitudinal relation between L2 parental encouragement and achievement; (g) association between L2 self-regulation and achievement; (h) association between L2 international orientation and L2 achievement; AIC = Akaike information criterion, BIC = Bayesian information criterion; χ^2 = chi squared; CFI = Bentler comparative fit index; TLI = Tucker-Lewis index; SRMS = standardized root mean square residual.

When analyses were conducted using a composite of L2 motivation, the same pattern of associations was observed. The analysis showed that both L2 motivation and L2 achievement were stable, from the start of the L2 learning experience. The L2 motivation composite at the end of term 1 was moderately correlated with L2 achievement at the same collection wave (*r* = .20). The association between the measures was not found to increase over time, as the cross-sectional relationships at the end of term 2 and term 3 were not significant beyond their association at the end of term 1. The only significant cross-lagged link was observed between achievement at the end of term 1 and motivation at the end of term 2 (see Figure 6.4). Therefore, achievement was found to contribute to the development of later motivation, but motivation was not found to contribute to the development of later achievement.

The longitudinal association between L2 anxiety and L2 achievement

A further cross-lagged analysis was conducted to explore the longitudinal association between L2 anxiety, measured three times over one academic year, and L2 achievement, measured over the same collection waves. The model (see figure 6.3) showed that L2 anxiety was stable over the course of the first year of secondary school (average β = .71). L2 anxiety was found not to be associated with L2 achievement at any point in the academic year, as cross-sectional relationships and cross-lagged links between L2 anxiety and achievement did not reach significance (see Figure 6.3).



Model fit indices: AIC = 5597.323; BIC = 5666.920;
χ^2 (9)= 75.075, p< .01; CFI = .94; TLI = .91; SRMS = .04

*** = p < .05; ** = p < .01**

Figure 6.3. Cross-lagged model for the longitudinal association between L2 achievement and L2 anxiety over the course of one academic year; AIC = Akaike information criterion, BIC = Bayesian information criterion; χ^2 = chi squared; CFI = Bentler comparative fit index; TLI = Tucker-Lewis index; SRMS = standardized root mean square residual.

The triadic interaction between L2 achievement, L2 motivation and L2 anxiety over one academic year

A further cross-lagged model explored the longitudinal relations between achievement, motivation, and anxiety, all measured three times over the first year of secondary school. Figure 6.4 reports the standardized path estimates for the longitudinal associations between the variables. Only those links that reached significance are reported in Figure 6.4. The model showed acceptable fit, as indicated by CFI and TLI indices of above .90 and the SRMS index below .05. This model, including cross-lagged associations, was a better fit (AIC = 7415.719, *N* = 353) than the alternative baseline model in which cross-lagged relationships were not included (AIC = 7422.78, *N* = 353). Better fit is indicated by a lower AIC value.

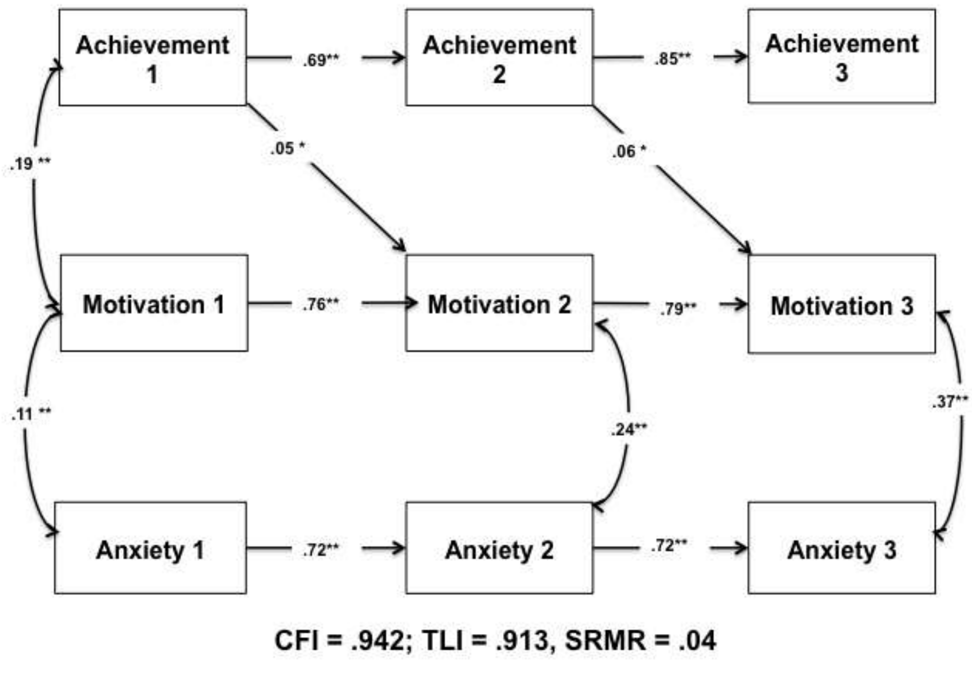


Figure 6.4. Cross-lagged analysis exploring the triadic longitudinal association between L2 achievement, L2 motivation and L2 anxiety; CFI = Bentler comparative fit index; TLI = Tucker-Lewis index; SRMS = standardized root mean square residual; for clarity only the links that reached significance are shown in the figure.

The model showed that the 3 constructs (L2 achievement, L2 motivation and L2 anxiety) were highly stable over time, with standardized path coefficients for autoregressive effects ranging from $\beta = .69$ to $\beta = .85$. After accounting for autoregressive effects, the cross-sectional relationship between L2 achievement and L2 motivation at the end of term 1 was modest but significant, $r = .19$, $p < .01$. The cross-sectional relationship between L2 motivation and L2 anxiety was only small at the end of term 1 ($r = .11$, $p < .05$), but increased to modest ($r = .24$, $p < .01$) at the end of term 2 and to moderate ($r = .37$, $p < .01$) by the end of term 3. Interestingly, the association between anxiety and motivation was positive at all collection waves. The cross-sectional relationships between L2 achievement and L2 anxiety were not significant beyond autoregressive effect.

The only cross-lagged links that reached significance were those from previous achievement at the end of term1 and term 2 to L2 motivation at the end of term 2 and term 3 ($\beta = .05$, $p < .05$; and $\beta = .06$, $p < .05$, respectively). Cross-lagged paths from initial achievement to subsequent anxiety and from initial anxiety from subsequent achievement and motivation did not reach significance. The R^2, measuring the variance explained for each dependent variable by the sum of time-preceding autoregressive and cross-lagged effects, was .48 and .74 for L2 achievement time 2 and 3, respectively; .59 and .69 for L2 motivation at time 2 and 3, respectively; and .52 and .52 for L2 anxiety at time 2 and time 3, respectively.

Table 6.3. Standardised path estimates for the associations between L2 achievement, L2 motivation and L2 anxiety over the three collection waves.

Path	Std Estimate	Std error	*p*
ach1 → ach2	0.69	0.03	0.00
ach2→ ach3	0.86	0.01	0.00
mot1→ mot2	0.76	0.02	0.00
mot2→ mot3	0.79	0.02	0.00
anx1→ anx2	0.73	0.03	0.00
anx2→ anx3	0.72	0.03	0.00
ach1→ mot2	0.05	0.02	0.02
ach2→ mot3	0.06	0.02	0.02
mot1→ ach2	0.03	0.03	0.49
mot2→ ach3	0.02	0.02	0.27
mot1→ anx2	-0.01	0.03	0.91
mot2→ anx3	-0.01	0.03	0.91
anx1→ach2	-0.02	0.01	0.16
anx2→ach3	-0.02	0.01	0.16
ach1→anx2	0.03	0.05	0.49
ach2→anx3	0.03	0.05	0.49
ach1⇔ mot1	0.19	0.05	0.00
ach1⇔ anx1	−0.09	0.05	0.09
anx1⇔ mot1	0.11	0.05	0.04
ach2⇔mot2	0.04	0.06	0.54
ach2⇔anx2	-0.06	0.06	0.32
anx2 ⇔ mot2	0.24	0.06	0.00
ach3⇔ mot3	−0.01	0.056	0.85
ach3⇔ anx3	−0.05	0.056	0.32
anx3⇔ mot3	0.37	0.050	0.00

Note: ach1 = L2 achievement at the end of term 1; ach2 = L2 achievement at the end of term 2; ach3 = L2 achievement at the end of term 3; mot1 = L2 motivation at the end of term 1; mot2 = L2 motivation at the end of term 2; mot3 = L2 motivation at the end of term 3; anx1 = L2 anxiety at the end of term 1; anx2 = L2 anxiety at the end of term 2; anx3 = L2 anxiety at the end of term 3.

The role of g in the association between L2 achievement, L2 motivation and L2 anxiety

A second cross-lagged model (see Figure 6.5) examined the development of the relationship between L2 achievement, L2 motivation and L2 anxiety accounting for the variance explained by *g*.

Figure 6.5 shows standardized path coefficients (see also Table 2) for the alternative model including *g* as a covariate. Model fit indices information is reported at the bottom of Figure 6.5. This model showed adequate fit. Similar to the previous model that did not account for *g*, the model including cross-lagged associations was found to be a better fit (AIC = 6977.77) than the alternative baseline model not including cross-lagged paths (AIC = 6987.81).

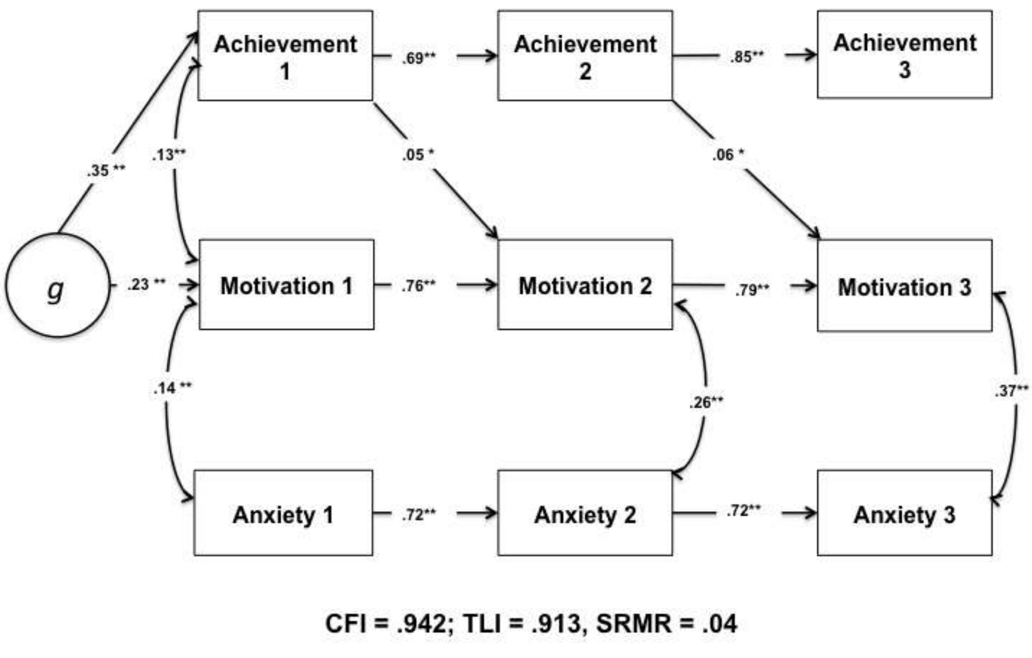


Figure 6.5. Cross-lagged model exploring the longitudinal association between L2 achievement, L2 motivation and L2 after accounting for the variance explained by *g*; only the links that reached significance are presented in the figure.

Standardised paths for this second model including g as a covariate are highly similar to those reported in the previous model exploring the triadic interaction between L2 achievement, L2 motivation and L2 anxiety. This indicates that hat the observed associations are observed largely independent from the influence of *g*. The links from *g* to L2 motivation and L2 achievement at wave 1 were significant and modest to moderate in size (β = .23, $p < .01$ and β = .35, $p < .01$, respectively). The relationship between *g* and L2 motivation and achievement was found to be stable as paths from g to L2 motivation and L2 achievement at the following collection waves did not reach significance above and beyond the links observed at wave 1. The paths from *g* to L2 anxiety were not significant.

The R^2, measuring the variance explained for each dependent variable by the sum of time-preceding autoregressive and cross-lagged effects, was: R^2 = .124, p <. 01 (achievement at wave 1); R^2 = .474, p <. 01 (achievement at wave 2); and R^2 = .731, p <. 01 for L2 (achievement at wave 3); R^2 = .052, p <. 05 (motivation at wave 1), R^2 = .49, p <. 01 (motivation at wave 2), and R^2 = .73, p <. 01 (motivation at wave 3); and R^2 = .004, p > .05 (anxiety at wave 1); R^2 = .541, p< .01(anxiety at wave 2), and R^2 = .530, p< .01 (anxiety at wave 3).

Discussion

The present study examined the developmental relation between second language achievement, motivation and anxiety over one academic year, when students were 11-12 years old. Data on L2 achievement, motivation and anxiety were collected over three waves during one academic year: at the end of the first, second and third (and final) term. Because students were learning a foreign language for the first time, it was possible to explore how these relationships emerged, free from the confounding effects of previous experiences of achievement, motivation and anxiety for learning a second language.

The study had four main aims. Firstly, it examined the longitudinal relation between L2 achievement, calculated as a composite score of listening, speaking, reading and writing abilities in either German, French or Spanish, and several sub-components of the L2 motivation umbrella. The aim of this first set of analyses was to test whether some aspects of L2 motivation were more closely associated with L2 achievement over time. Overall, results showed that achievement and motivation were stable across the three waves, with stability increasing towards the end of the academic year. This contradicts previous evidence obtained in the domain of second language motivation, which finds a decline in motivation over time (Busse & Walter, 2013). However, the present sample of 11-12-year-old students may be characterised by substantially different profiles from the sample of university students who contributed data in the study by Busse & Walter.

All the eight components of L2 motivation assessed in this first set of analyses were correlated with achievement at the end of the first term, and all associations were modest and positive. The relation between L2 motivation, measured as eight different sub-components, and L2 achievement was stable over the course of the academic year. The study also found that previous achievement at the end of term 1 and 2 had a small effect on the development of later motivation. This was observed for all the subcomponents of L2 motivation, with the exception of L2 self-regulation and L2 international orientation. On the contrary, the eight sub-components of L2 motivation were largely not linked to the development of later achievement. Motivation predicted the development of subsequent L2 achievement only when two sub-components were assessed: L2 intrinsic motivation and L2 parental encouragement, but the effects were small.

Results are mixed in that two analyses found support for the *Reciprocal Model* of the association between motivation and achievement (Morgan & Fuchs, 2007), whilst the majority of the present analyses supported the *Skills Development Model* (Caslyn & Kenny, 1977). The former theory argues that motivation and achievement mutually influence each other in the learning process, this has been supported by longitudinal evidence finding reciprocal links between motivation and achievement (e.g. Luo et al., 2010; Luo et al., 2011) and by two investigations included in the current thesis, presented in Chapter 4 and Chapter 5. The latter theory argues that motivation emerges as a function of previous achievement, and has also been supported by longitudinal evidence, mostly obtained in young student samples and not specific to the domain of L2 learning (e.g. Garon-Carrier, 2016).

Although the same pattern of associations was not observed across all measures of L2 motivation, it is important to notice that the links between achievement and motivational constructs, after accounting for their stability and initial correlations, are very weak. This indicates that achievement plays only a very small role in the development of later motivation, at this stage of L2 learning. The sample included in the present study had only just started learning a second language; consequently, students had only received a very small amount of feedback on their achievement. It is possible that the relation between motivation and achievement strengthens as a function of achievement feedback, becoming reciprocal after a certain amount of exposure to learning the discipline. In fact, most investigations that found support for the *Reciprocal Model* had explored the achievement-motivation relation in samples of student who had already been learning, and received feedback on their achievement, for some time (e.g. Chamorro-Premuzic et al., Luo et al., 2011). Findings of the present investigation are in line with the hypothesis that the links between achievement and motivation become stronger and reciprocal later n the learning process.

The second aim of the present study was that of exploring how the association between L2 achievement and L2 anxiety emerged and developed over the course of one academic year. This is the first study to date that has investigated the longitudinal links between anxiety and achievement in the domain of second language learning. The results showed no association between anxiety and achievement over the first year of learning a second language. This is in line with findings in the domain of mathematics in young samples of primary school students (Dowker, Bennett, & Smith, 2012). It may be that the association between L2 anxiety and L2 achievement emerges later in development. Alternatively, the absence of a direct relationship might indicate the existence of potential moderators. One factor that was found to moderate the association between anxiety and performance in the field of mathematics was motivation (Wang, Lukowski, Hart, Lyons, Thompson, Kovas et al., 2015). This hypothesis that will be explored in the future using data from the present sample. Longitudinal investigations over a more extended time span will be able to establish at what point in the learning process the observed direct relationship between L2 anxiety and L2 achievement (e.g. Liu & Zhang, 2013; Khodadady & Khajavy, 2013) emerges.

The third aim of the present study was that of investigating the triadic interaction between L2 achievement, motivation and anxiety. The L2 motivation variable was a composite of six sub-components of the L2 motivation questionnaire, which emerged from principal component analysis. These components were: international orientation, ideal L2 self, self-efficacy, instrumental motivation, intrinsic motivation, and self-regulation. The results of this trivariate longitudinal model were overall similar to those observed in the previous cross-lagged models. The only significant longitudinal links, beyond the stability of the measures and their initial correlations, were the links from previous achievement to later motivation, characterised by weak effects. The positive relation between L2 motivation and L2 anxiety grew over the course of the academic year, going from weak at the end of term 1 to moderate by the end of term 3. This increase in the positive association between L2 motivation and L2 anxiety is of interest, as it seems to emerge and develop independently from the mutual influence that the two constructs have on each other (i.e. not though cross-lagged paths), and from the influence of L2 achievement. It is possible that other factors, not accounted for by the model (such as for example parental involvement in child's education or classroom environment) play a role in the strengthening of the L2 motivation–L2 anxiety relationship over one academic year. The positive correlations observed between the two constructs are in line with previous evidence that found L2 anxiety to be a facilitating factor in learning a second language (e.g. Frantzen & Magnant, 2005). In fact, it is possible to speculate that an optimal level of anxiety may be beneficial for L2 learning by increasing the level of attention and awareness in the L2 classroom. Anxiety becomes negative for performance when it exceeds an optimal level. This is supported by studies that have investigated the association between general anxiety and cognitive performance (Smith, 2014).

The fourth aim of the present study was to explore the role played by *g* in the trivariate association between L2 achievement, anxiety and motivation. The moderate effect sizes observed for the association between *g* and L2 achievement at all collection waves are lower than those usually found between *g* and achievement in other academic domains (e.g. literacy and mathematics, see Chapter 4 of the present thesis). However, these effects are in line with previous research in the field of L2 learning; for example, a correlation of .26

was observed between IQ and L2 achievement in a sample of high school students (Pishghadam, & Khajavy, 2012). Overall, *g* was found not to impact on the association between the three constructs.

Although, *g* was associated moderately with L2 achievement and modestly with L2 motivation, it did not account for the stability of the measures or their longitudinal associations. In fact, the observed links between L2 achievement and subsequent L2 motivation remained the same after *g* was included as a covariate to the model. This pattern of results is in line with previous research, which found significant longitudinal associations between motivation and achievement in other academic domains, after controlling for *g* (e.g. Steinmayr & Spinath, 2009; Chamorro-Premuzic, Harlaar, Greven, & Plomin, 2010; Lou et al., 2011). L2 anxiety was not related to *g* at any point during the first year of second language learning.

The results of the present study are somewhat surprising, as several investigations have observed *g* to partly contribute to the stability of academic achievement and motivation (e.g. Greven et al., 2009; Chamorro-Premuzic et al., 2010; Chapter 4 of the present thesis). Recent evidence suggests that several factors, such as self-esteem, personality and wellbeing, are related to academic achievement beyond the impact of *g* (Krapohl, Rimfeld, Shakeshaft, Trzaskowski, McMillan, Pingault, et al., 2014). These same factors might be implicated in the stability of motivation, as well as the stability of its relation with achievement.

It is also possible that the emergence and high stability of L2 achievement, L2 motivation and L2 anxiety are influenced by achievement, motivation and anxiety for other disciplines. For example, as children learn English and Mathematics throughout primary school, it is possible that the achievement, motivation and anxiety they developed for these academic disciplines could influence the subsequent L2 achievement, L2 motivation and L2 anxiety at the start of secondary school. This hypothesis is in line with findings from a recent genetically informative study that found that L2 achievement shared a genetic link with achievement in English leant as fist language (Rimfeld, Dale, & Plomin, 2015). The study found that genetic (56%), shared (24%) and non-shared (20%) environmental factors contributed to the aetiology of L2 achievement.

Some of the genetic effects contributing to variation in L2 achievement were also implicated in differences in English as a first language and *g*.

The origins of individual differences in L2 motivation and of its relation with L2 achievement remain to date unexplored. As phenotypic associations between motivation, achievement, anxiety and *g* present a somewhat different profile from that shown by the same constructs in other academic domains, investigating their aetiology is of interest. In fact, L2 motivation, and its association with anxiety and achievement might present different aetiological profiles from those observed in other domains. Research on the aetiology of motivation in other academic domains (i.e. mathematics) suggests that individual differences in motivation stem largely from genetic and individual specific (rather than family-wide) environmental factors (e.g. Luo, Kovas et al., 2011; Kovas et al., 2015). Genetic and nonshared environmental factors were also found to contribute to the origins of the association between motivation and achievement (Luo, Kovas et al., 2011; Greven et al., 2009), and that between motivation and anxiety (see Chapter 3 of the present thesis) in the domain of mathematics. It is possible that these aetiological factors may also contribute to the origin of individual variation in L2 motivation and of its covariance with L2 achievement and L2 anxiety. Alternatively, it is possible that environmental factors that are shared between siblings growing up in the same families (e.g. home environment; same experiences abroad, such as holidays and school trips, same family living in different countries etc.) may play a greater role in the L2 context.

Strengths and Limitations

The present study has several strengths. Firstly, the investigation explored the triadic interaction between L2 achievement, motivation and anxiety from the start of the L2 learning process, which to date remained unexplored. Secondly, the present study was able to control for whether students had previously learnt a second language, and therefore eliminated the possible confounds of previous L2 experience. Thirdly, this study was the first to explore the role that *g* played in the association between L2 achievement, motivation and anxiety.

The current study also presents a number of limitations. The model fit indices for the cross-lagged model were acceptable, but not excellent, as indicated by significant chi squared values. This may be due to the presence of second-order autoregressive effects. These are autoregressive links directly connecting variables at the end of term 1 with those at the end of term 3. Another limitation is a relatively modest sample size (N = 353), which may not have been sufficient to detect the longitudinal effects with adequate power. The modest sample size also meant that we could not explore the specificity of the results to the language that students were learning. It may be that motivation for learning a foreign language varies depending on the language that is studied.

Conclusions

To conclude, the current study was the fist to explore the longitudinal association between achievement, motivation, and anxiety in the domain of second language learning. Results showed that, in a sample of students who had just started learning a second language, the sub-components of the L2 motivation were highly stable over one academic year. The same was observed for L2 achievement and L2 anxiety. All aspects of L2 motivation shared a modest association with L2 achievement, and these associations remained stable over the course of the academic year. On the other hand, L2 anxiety was not related to L2 achievement at any point during the academic year. The association between L2 motivation and L2 anxiety was found to be positive and to increase over the course of the first year of secondary school. After considering the stability of the measures and their initial correlations, achievement was related to later L2 motivation, but the effects were weak, On the other hand, motivation mostly did not have an impact on L2 achievement. The results are in line with recent evidence obtained in the domain of mathematics in a sample of primary school children (Garon-Carrier, et al., 2016), and are consistent with the *Skill-Development Model* of academic motivation.

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Chapter 7

General discussion, implications and future directions

The present thesis aimed to address several unexplored questions regarding the association between non-cognitive characteristics and academic achievement. The five investigations included in the current work focused on two main constructs: academic anxiety and motivation - constructs that have been found to relate to educational achievement beyond their mutual association with general intelligence (*g*; Ashcraft & Moore, 2009; Krapohl et al., 2014). The findings emerging from the present work generated new knowledge, which is likely to have implications for both future research and practice. A summary of the main findings, implications of the current work, and future directions are discussed in this concluding chapter.

The first chapter of the present thesis provided an overview of the main findings in the area of academic anxiety, with a specific focus on the domain of mathematics (the most widely researched domain-specific academic anxiety) and in the area of academic motivation. The chapter focused on introducing the association between these non-cognitive characteristics and academic achievement, reviewing the most influential theories in the fields. The chapter identified several research questions that regarding how the association between non-cognitive characteristics and achievement emerges and develops, as well concerning the factor structure and the aetiology of non-cognitive constructs and of their association with educational achievement and cognitive skills. Each empirical chapter included in the current work contributes evidence that addresses these outstanding research questions. The main findings and implications of the remaining chapters, as well as future research plans are discussed below.

Anxiety is a multifactorial construct: potential implications for interventions and future research directions

Chapter 2 addressed one fundamental question that to date remained unanswered in the academic anxiety literature; namely: are academic anxiety constructs domain-specific or do they constitute a unitary factor? Additionally, are these academic anxiety constructs distinguishable in their aetiology? The investigation explored these research questions across the domains of mathematics and spatial anxiety, also including a measure of general (trait) anxiety. The results supported a multifactorial view of anxiety, both at the phenotypic and aetiological level, which points to the importance of studying anxiety for specific domains. Although specific anxiety constructs showed a moderate association with general anxiety, considering general anxiety alone is likely to provide only a partial picture of the apprehension experienced by individuals struggling with anxiety in the specific fields of mathematics and spatial cognition. This has important potential implications for interventions aimed at reducing academic anxiety. The findings presented in Chapter 2 advocate the need to intervene at the domain-specific level, suggesting that interventions targeting the general level of anxiety experienced by students might only address a small part of the problem.

To date, a large portion of interventions designed to alleviate the negative consequences of academic anxiety have been developed in the field of mathematics. These interventions have mostly applied techniques that were found to be successful in diminishing general anxiety. For example, techniques such as systematic desensitization (SD; Wolpe, 1973) and acceptance and commitment therapy (ACT; Hayes, Strosahl, & Wilson,1999), originally developed to improve the negative consequences of general anxiety, were found to be successful in reducing self-report measures of mathematics anxiety, after a treatment period of six weeks (Zettle, 2003). ACT was also found to be associated with diminished avoidance of mathematics-related activities. However, neither SD nor ACT corresponded to improvements in mathematics performance (Zettle, 2003). Another technique, relaxation training, was found to significantly decrease levels of mathematics anxiety in a sample of undergraduate students (Sharp, Coltharp, Hurford & Cole, 2000). Relaxation training was found to have a small effect in improving performance in a mathematics problem-solving task, but the observed effect was not long lasting (Sharp et al., 2000).

A recent literature review has suggested that, since mathematics anxiety correlates positively with other anxiety constructs, other interventions that are known to be successful for general anxiety, (e.g. mindfulness) should be explored in the context of mathematics anxiety (Chang & Beilock, 2016). The results presented in Chapter 2 of the current thesis are not in line with this suggestion. On the contrary, evidence has shown that mathematics anxiety is largely independent from general anxiety and from other domain-specific anxieties. This phenotypic and aetiological domain-specificity of mathematics anxiety should be considered when developing interventions aimed at alleviating its symptoms and performance correlates.

A small number of interventions specifically targeted at reducing mathematic anxiety and its negative consequences, have been developed with mixed outcomes. A recent study (Supekar, Iuculano, Chen, & Menon, 2015) found that an eight-weeks one-on-one mathematics tutoring programme (Fuchs et al., 2013), was effective in decreasing mathematics anxiety, in a group selected for high mathematics anxiety using a median split. Furthermore, the study observed changes in the brain activation associated with mathematics anxiety in the sample of 7–9 years old students. Tutoring was found to have an effect in diminishing the aberrant functional responses and connectivity in the amygdala and basolateral areas (both part of the emotion-related brain network). However, tutoring did not bring about an improvement in performance in the mathematically anxious group (Supekar et al., 2015). A further intervention, specifically developed for mathematics anxiety, applied transcranial direct-current stimulation (tDCS) to the dorsolateral prefrontal cortex, and area often implicated in emotion regulation (Sarkar et al., 2014). The study found that tDCS was effective in improving reaction time in simple arithmetic tasks and in reducing cortisol levels. However, the intervention impaired reaction time in the low mathematically anxious group, providing inconsistent results.

A further issue that should be considered when developing interventions aimed at reducing mathematics anxiety, and its negative consequences, is the direction of effects between anxiety and performance. Interventions aimed at reducing mathematics anxiety are likely to have a positive impact on performance only if mathematics anxiety is implicated in the development of subsequent achievement. On the contrary, if the association between mathematics anxiety and achievement develops as a consequence of previous achievement, interventions aimed at increasing mathematics achievement should have a positive impact on mathematics anxiety. Additional longitudinal studies, which are part of our future plans, will be able to clarify the direction of effects between mathematics anxiety and performance. A recent review has argued for the possibility that the association between mathematics anxiety and achievement is reciprocal (Carey, Hill, Devine, & Szücs, 2015), a possibility that future longitudinal investigations will help clarifying.

As well as domain-specificity and directionality of effects, interventions that are developed for alleviating the symptoms and performance correlates of mathematics anxiety (and anxiety in other academic domains) should consider the possibility that other factors may be implicated in the anxiety-performance association. One factor that was found to moderate the relation between anxiety and performance is intrinsic motivation (Wang, Lukowski, Hart, Lyons, Thompson, Kovas, et al., 2015). Interventions should take these potential moderators into consideration. One intervention considered how a specific meta-cognitive learning strategy, the know-want-learn (KWL), could ease feelings of anxiety towards mathematics in a student population. The KWL strategy encourages students to appreciate their knowledge about the task they are presented with. The KWL learning strategy was observed to mildly improve mathematics achievement and meta-cognitive skills in the experimental group; however, it was not effective in diminishing mathematics anxiety levels (Tok, 2013).

Therefore, in order to successfully reduce mathematics anxiety and its negative implications, interventions should take into account the three main issues discussed above, namely: (1) the domain-specificity of mathematics anxiety; (2) the directionality of effects between mathematics anxiety and performance outcomes; and (3) possible other factors moderating or mediating the association between mathematics anxiety and performance. Future longitudinal, multivariate studies, which are part of our plans, will provide further evidence, which is likely to contribute to the development of successful interventions for mathematics anxiety (and anxiety in other academic domains).

The same issues should be considered in the development of interventions aimed at alleviating anxiety in other domains, such as for example spatial anxiety. To date, interventions specifically aimed at reducing spatial anxiety and its negative consequences have not been developed. The results of Chapter 2 show that spatial anxiety incudes two main components, which are different phenotypically and aetiologically. This separation between aspects of spatial anxiety should also be taken into consideration when developing future interventions. In fact, the findings presented in the current thesis suggest that interventions should be targeted at specific aspects of spatial anxiety. Interventions aimed at reducing navigation anxiety and its negative consequences are likely to have little success in improving rotation/visualization anxiety and vice versa. It remains unknown whether the domain-specificity of spatial anxiety constructs is reflected in their association with performance. Namely, whether navigation anxiety is specifically associated with performance in navigation tasks, and whether rotation/visualization anxiety shares a specific association with performance in smaller scale spatial tests. Furthermore, it remains unclear whether navigation, rotation and visualization are in fact different abilities. Recent evidence showed that rotation and visualization are largely overlapping abilities, phenotypically and genetically (Shakeshaft et al., 2016), however the study did not include a measure of navigation ability. Exploring the specificity of the association between navigation and rotation/visualization anxiety and different measures of spatial ability (including, amongst others, navigation, rotation and visualization) is part of our future research plans.

The domain specific association between mathematics anxiety, performance and motivation is largely genetic in origin

Chapter 3 of the present thesis explored the specificity of the association between anxiety, motivation and achievement in several aspects of mathematics. The results showed that mathematics anxiety was similarly related to different aspects of motivation (self-efficacy and interest), and to several measures of mathematics performance (GCSE exam scores, understanding numbers and problem solving ability), sharing moderate correlations with all constructs. Number sense ability was an exception as it was only weakly correlated. Bivariate models showed that the observed negative correlations were attributable to genetic and individual-specific environmental influences. The multivariate Cholesky model showed a substantial genetic overlap between mathematics anxiety and all other measures of motivation and achievement. Family-wide environmental influences were found to be very weak, but common to all variables, whereas individual-specific environmental influences were found to be largely specific for every construct. The results also showed that, although general anxiety shared part of its aetiology with mathematics anxiety, the genetic links between general anxiety and mathematics motivation and performance were very weak or not significant.

Therefore, the results presented in the current thesis have shown that, not only mathematics anxiety is a domain specific construct (as shown in Chapter 2), but also that it is specifically associated with mathematics performance and motivation. This specificity of the association between anxiety, motivation and achievement has implications for research in this field. It is possible that anxiety is specifically associated with motivation and performance in other academic domains.

This domain-specific association between anxiety, motivation and achievement was found to be largely due to shared genetic influences, which were not shared between general anxiety, mathematics performance and motivation. It is possible that genes implicated in the non-cognitive correlates of achievement are more domain-specific than those implicated in cognitive abilities and academic achievement. The generalist genes account of learning abilities and disabilities (Plomin & Kovas, 2005) proposes that the majority of the genes that are implicated in variation in academic achievement and abilities are shared between traits. This account has been supported by evidence from several genetically informative investigations (e.g. Haworth, Meaburn, Harlaar, & Plomin, 2007; Trzaskowski, Davis, DeGries, Yang, Visscher & Plomin, 2013).

The study presented in Chapter 3 of the present thesis found support for the pleiotropic effects of genes working not only between measures of achievement, but also across the non-cognitive correlates of achievement within the domain of mathematics. However, the study also found that the same genes implicated in the overlap between mathematics anxiety, motivation and achievement, were not shared with general anxiety.

This suggests that, contrary to the generalist association between genes involved in cognition and achievement, the genes implicated in non-cognitive traits (and their relation with achievement) show a greater deal of specificity. The results of Chapter 2 and Chapter 3 of the present thesis support this hypothesis. Additional support for this hypothesis is provided by other investigations that found specific genetic links between motivation and achievement in the domain of mathematics (Luo et al., 2011) and reading (Malanchini et al., in press). Future studies exploring the aetiological co-variation between measures of academic motivation and anxiety (and of their associations with performance) across different domains will be able to either substantiate or contradict this hypothesis. These investigations are part of our future plans.

As part of our future plans we also aim to apply genome-wide polygenic scores (GPS; Krapohl & Plomin, 2016), calculated from findings of recent genome-wide association studies (GWAS), to predict individual differences in the non-cognitive correlates of academic achievement. GWAS aimed at identifying individually significant single-nucleotide polymorphisms (SNPs) have explained only a very small fraction of the genetic variance in complex traits. However, recent evidence shows that the combination of the markers not achieving genome-wide significance can explain a meaningful portion of phenotypic variation in complex traits (Selzam, Krapohl, von Stumm, O'Reilly, Rimfeld, Kovas et al., 2016). In order to construct these GPS, genetic markers are identified in a discovery sample and the GPS are then calculated in an independent replication sample by adding up for each individual the alleles associated with the trait of interest, weighted by their effect size (Krapohl & Plomin, 2016).

The investigation presented in Chapter 2 of the present thesis has shown a genetic link between domain-specific anxiety and general anxiety. However, variation in mathematics and spatial anxiety was also found to include genetic influences that are independent from general anxiety, and specific to each construct. Moreover, the results presented in Chapter 3 consistent with findings of previous research (Wang et al., 2014), showed that mathematics anxiety shared a specific genetic link with mathematics performance, independent of general anxiety. This suggests that, genes that are implicated in general anxiety and genes that are implicated in performance contribute to variation in mathematics anxiety. One of our future aims is to use findings from existing GWAS of anxiety (Otowa, Hek, Lee, Byrne, Mirza, Nivard et al., 2016), ability (Davies, Armstrong, Bis, Bressler, Chouraki, Giddaluru at al., 2015) and achievement (Rietveld, Medland, Derringer, Yang, Esko, Martin, et al., 2013) to predict variation in mathematics anxiety and other academic anxiety constructs. This will constitute the first molecular investigation of genetic influences on academic anxiety.

As GWAS include larger and larger samples, increasing their power to identify genetic variants associated with measured phenotypes, future investigations might identify additional genetic variants associated with individual differences in anxiety and educational achievement in different fields. Exploring the prediction from GPS calculated from GWAS in specific academic fields might bring us even closer to the identification of the molecular basis of mathematics anxiety and other domain-specific academic anxiety constructs.

The evidence is mixed with regards to the direction of effects in the association between academic motivation and achievement

Three main accounts regarding the emergence and directionality of the association between academic motivation and achievement have been presented in Chapter 1. These are: (1) the *Self-Enhancement Model* (Calsyn & Kenny, 1977) proposing that individual differences in motivation influence the development of subsequent achievement; (2) the *Skills Development Model* (Calsyn & Kenny, 1977) arguing that motivation emerges and develops as a function of previous academic achievement; (3) and the *Reciprocal Model*

(Morgan & Fuchs, 2007) proposing that the relation between motivation and achievement is reciprocal.

Chapter 4, Chapter 5 and Chapter 6 explored the development of the association between motivation and achievement in different academic domains at different stages in the learning process, with mixed findings. Chapter 4 investigated the longitudinal association between self-efficacy, enjoyment and achievement across two academic domains: literacy and mathematics. Results showed that, although the longitudinal links between motivation and achievement were reciprocal from age 9 to age 12, achievement had a greater effect on the development of subsequent motivation than vice versa. This was observed for both the domain of literacy and mathematics, and suggests that achievement drives their association. The results also showed that *g* explained only part of these longitudinal links, indicating that self-efficacy and enjoyment relate to achievement not only because both constructs are associated with *g*.

Therefore the results of the investigation presented in Chapter 4 of the current thesis partly support the Reciprocal Model, in that the longitudinal links between measures of motivation and achievement were significant both from motivation to later achievement and vice versa. Nevertheless, the effect sizes of the links from motivation to later achievement were significantly weaker than the opposite links from achievement to subsequent motivation. Therefore, the results of the study presented in Chapter 4 are also partly consistent with the prediction of the Skills Development model of motivation and achievement.

On the other hand, the results presented in Chapter 5 found full support for the Reciprocal Model of motivation and achievement in the domain of reading. The study found a modest reciprocal association between motivation (also measures separately as self-efficacy and enjoyment) and achievement in the same sample of 9-12 year old twins. The study showed that children who are more confident and interested in reading are more likely to become more competent readers over time, and more skilled readers are also more likely to become more confident in their ability to read and interested in reading.

The Reciprocal Model of motivation and achievement was mostly not supported by the study presented in Chapter 6 that examined the longitudinal association between several aspects of motivation and achievement in the domain of second language (L2) learning. The study followed 11-year-old students over one academic year, as they were learning a second language in school for the first time. The results largely supported the Skills Development model of motivation and achievement, as the only significant longitudinal links were observed from previous achievement to later motivation, and not the other way around. Furthermore, these significant links were very weak, suggesting that motivation and achievement have a minor influence on the development of one another at this stage of L2 learning. Nevertheless, L2 achievement was found to have a small effect on the development of L2 motivation later in the academic year, whereas L2 motivation did not contribute to the development of achievement later in the school year.

Overall, the results included in Chapter 4, 5 and 6 present contrasting findings. Several factors may have contributed to the discrepancies between the results of the three studies. Firstly, it is possible that the association between motivation and achievement emerges and develops differently in different academic domains. This possibility is consistent with the different longitudinal relations that emerged from the three studies included in the present work. Secondly, the results of the investigations presented in Chapter 4 showed that the cross-lagged links were modest from achievement to later motivation and weak from motivation to later achievement. The investigation presented in Chapter 6 of the current thesis might have had insufficient statistical power to detect these weak reciprocal relations, as it included a smaller sample.

Thirdly, it may be that the relation between motivation and achievement emerges as a function of achievement and becomes reciprocal later in the learning process, perhaps due to a greater amount of feedback that students receive on their academic performance. This hypothesis is consistent with the observation that the association between motivation and achievement was unidirectional (from achievement to later motivation) during the first year of learning a second language. The hypothesis is also in line with the observation that, for those domains in which students had a greater deal of exposure to the learning process (literacy, mathematics and reading), the relations between motivation and achievement were reciprocal.

It is possible that the reciprocal links of similar effect that were observed between motivation and achievement in the domain of reading may be unique to the field of reading at that specific phase in development. As discussed in Chapter 5, the developmental period from 9 to 12 years old is a period shortly after when children make the transition from "learning to read" to "reading to learn" (Harlaar, Dale, & Plomin, 2007). Drastic improvement in children's comprehension skills during this stage may lead to better understanding and appreciation of reading activities, which in turn drives children to further refine their skills. As a result, mutual influences between reading motivation and reading achievement may be particularly evident at this unique developmental stage. Future longitudinal investigations over a more extended developmental time, which are part of our future plans, will be able to address the inconsistencies emerging from current research. Furthermore, investigations exploring the motivation-achievement association form the start of the learning process will be able to address whether the association emerges as a function of achievement and gradually becomes reciprocal over development.

The genetically informative investigations into the association between motivation and achievement support the transactional model.

The transactional model of the association between non-cognitive traits and achievement (Tucker-Drob, in press; see Chapter 1 of the present thesis) proposes that students select, evoke and experience learning environments, partly depending on their differences in non-cognitive traits (e.g. academic motivation), which are genetically influenced. Six main criteria have been identified as necessary to in order to find empirical support for the transactional model. These criteria are: (1) a correlation between the non-cognitive trait and achievement is necessary, although not sufficient; (2) Their correlation should be significant beyond their association with general cognitive ability; (3) The non-cognitive characteristics should be at least moderately heritable; (4) Non-cognitive trait and academic achievement should share a genetic correlation;

(5) The direction of effects should be significant from the non-cognitive trait to achievement; and (6) Environmental experiences should mediate the association between non-cognitive traits and achievement though a genetic pathway (Tucker-Drob, in press).

The investigations included in the five empirical chapters of the present thesis find ample support for the first five criteria. In fact, every investigation found a correlation between non-cognitive characteristics and academic achievement, supporting the first criteria. Chapter 4 showed that the associations between motivation and achievement in the domains of reading and mathematics were significant beyond *g*, finding support for the second criteria of the transactional model. Thirdly, the results of Chapter 1, 2 and 5 are in line with the third criteria, as all non-cognitive characteristics (academic anxiety measures, enjoyment and self-efficacy) were found to be moderately heritable. Fourthly, Chapters 2 and 5 of the present thesis showed that non-cognitive constructs correlated with achievement largely for genetic reasons. Additionally, the results of Chapter 5 showed that genetic factors also contribute to the longitudinal links between motivation and achievement. Lastly, the results of Chapters 4 and 5 are consistent with the fifth criteria, as the longitudinal link from non-cognitive factors to achievement was found to be significant. The results of the present thesis did not address the sixth criteria proposed by the transactional model, but this is part of our future plans. Overall, the current thesis found support for the predictions of the transactional model of the association between non-cognitive traits and educational achievement across several non-cognitive measures and multiple academic domains.

Limitations

The limitations of every study are discussed in detail in the limitation section of every experimental chapter (Chapters 2-6). More general limitations that characterize the three genetically informative studies included in the present thesis (Chapters 2, 3 and 5) are the limitations of the twin method. In fact, the twin method is based on a number of assumptions. One of these assumptions, the *equal environments assumption*, is the idea that environmental similarity is the same for monozygotic (MZ) and dizygotic (DZ) twin pairs growing up in the same family (Plomin, De Fries, Knopik, & Neiderhisser, 2013). Studies have observed that MZ twins are more likely to share analogous environmental experiences than DZ twins, for example people tend to treat them more similarly and they more often share friends. However, sharing more environmental experiences was not found to impact on the degree of their phenotypic concordance (Kendler, Kessler, Neale, Heath, & Eaves, 1993).

A further assumption of the twin method is *random mating*, the fact that people are assumed to mate at random, and not with other people that resemble them. In reality this assumption was found to be violated as people tend to mate with people who resemble them phenotypically and genetically, a concept known as assortative mating (Ask, Idstad, Engdahl, & Tambs, 2013; Ask, Rognmo, Torvik, Roysamb, & Tambs, 2012). Assortative mating has potential implications for the estimates of the twin method, as the model assumes 100% genetic similarity between MZ pairs and 50% similarity on average between DZ pairs. A greater genetic similarity between parents of DZ twins is likely to increase the genetic similarity between the DZ pairs, and to consequently increase the estimates of shared environmental influences calculated by the model (Røysamb & Tambs, 2016). However, this limitation is likely to not have had an impact on the results of the studies presented in the current thesis, as most of the shared environmental estimates in the univariate and multivariate models did not reach significance.

A further limitation of the twin method that applies to the investigations presented in the current study is the inability to disentangle the interplay between genotype and environment. The interplay of genes and environments happens through two main processes: gene-environment correlation (described in detail in Chapter 1 of the present thesis) and gene-by-environment interaction (GxE). GxE is observed when the effects of a person's genotype on a trait depend on the environment or when environmental effects depend on a person's genotype (Duncan & Keller, 2011). This interaction between genes and environments can influence the variance in a trait independently from the individual prediction that genes and environments have on that trait (Plomin et al., 2013). For example, students who have a genetic predisposition to be high achievers may thrive if they are raised in enriched environments, which provide adequate stimulation. Conversely, the same students may be less likely to achieve good grades if they grow up in less optimal environments. Therefore, limitations in the environment may constrain the “realization of genetic potential”, whereas optimal environmental inputs may facilitate the translation from genetic advantage to desirable outcomes (Taylor, Roehrig, Soden-Hensler, Connor, & Schatschneider, 2010; Tucker-Drob & Harden, 2012). The studies included in Chapters 2, 3 and 5 of the present thesis were able to assess the direct effects of genotypes and environments on the variance and co-variance of the phenotypes of interest. However, they were not able to disentangle the effects of genotype-environment interplay.

Conclusions

To conclude, the present thesis addressed several questions related to the non-cognitive correlates of educational achievement and their association with academic performance, which had been previously unexplored. The present work focused on two main non-cognitive constructs: academic anxiety and motivation. Both motivation and anxiety were found to be domain-specific, phenotypically and aetiologically. Additionally, their association with academic performance was also found to be domain-specific. Genetic and individual-specific environmental factors were found to be important contributors to the associations between anxiety, motivation and performance in different academic domains. The evidence was mixed with respect to the directionality of the association between motivation and achievement in different academic domains at different stages of the learning process. The results of these five investigations can inform future research and practice, including interventions aimed at alleviating the negative experiences associated with academic anxiety. Although the present thesis contributes a large body of knowledge, several additional unresolved questions regarding these non-cognitive correlates of academic achievement and their association with performance have been identified in this conclusive chapter. Addressing these outstanding issues is part of our future research plans.

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