REGISTERED REPORT

Stage 1 Report

Academic motivation-achievement cycle and the behavioural pathways: a short-timeframe experiment with manipulated perceived achievement

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Abstract

The present research investigates the relations between motivation and academic achievement in educational contexts. The first main question is whether motivation is reciprocally related to achievement and a cyclic loop of motivation and achievement is formed over time. The second objective is to study a possible behavioural mediating pathway between motivation and achievement by measuring objective effort spent on learning. Third, we examine the causality of these relations by investigating the dynamics between motivation and achievement (rather than the individual constructs) when perceived achievement is experimentally manipulated. The study is a short-timeframe experiment in which undergraduate Dutch students learn new English vocabulary and their motivation, effort, and achievement is measured at multiple time points within one hour. Roughly halfway in the experiment, participants receive rigged feedback that their achievement has dropped, which is expected to influence their subsequent motivation, effort, and actual achievement. To study these dynamics, we will model how one construct affects another construct over time under a random-intercept cross-lagged panel framework. Planned analyses, expected (narrative) results, and simulated data are provided.

Keywords: motivation, effort, academic achievement, reciprocal, random-intercept cross-lagged modelling.

Introduction

Many theoretical and empirical studies have concluded that there are close relations between motivation and academic achievement (Eccles & Wigfield, 2002; Gottfried et al., 2013; Valentine et al., 2004; Winne & Nesbit, 2010), with recent literature suggesting that these relations are reciprocal or cyclical (Huang, 2011; Marsh & Martin, 2011; Möller et al., 2011; Niepel et al., 2014a, 2014b; Sewasew & Koester, 2019; Sewasew & Schroeders, 2019). Various motivation theories (Eccles & Wigfield, 2002) generate conceptualizations of motivation that encompass beliefs and behaviours. However, motivation in the majority of studies is measured with self-reports, neglecting the behavioural pathway leading from motivation to achievement. Certain motivation theories suggest that effort investment is the most plausible pathway (Cleary & Zimmerman, 2012; Feldon et al., 2019; Keller, 2008; Kuhl, 1984), yet this is a hypothesis to be tested because objective effort (rather than self-reported subjective effort) is rarely measured. Moreover, the causality of this reciprocal relationship between motivation and achievement is still an open question. Few studies have taken an experimental approach in which reciprocal effects through time are investigated and a construct is manipulated. The present research is an one-hour experiment to study the cyclical relationship of motivation and academic achievement in Dutch undergraduate students. We measure motivation and achievement at eight time points, with an emphasis on measuring effort expenditure objectively. The experiment also includes a manipulation to tackle the question of causality where we exert an impact on perceived achievement and test if the reciprocity is still preserved.

Reciprocal relationship between motivation and achievement

There is solid theoretical and empirical support for the strong relations between students' motivation and their academic achievements (Burnette et al., 2013; Eccles & Wigfield, 2002;

Gottfried et al., 2013; Guay et al., 2003; Huang, 2011; Marsh & Craven, 2006; Marsh & Martin, 2011; Robbins et al., 2004; Seaton et al., 2014). To study motivation, many related constructs such as academic self-concepts, achievement goals, self-efficacy, and so forth have been used (Eccles & Wigfield, 2002). Much empirical research in the reciprocal motivation-achievement relationship operationalizes motivation as *academic self-concept* (ASC), which is students' perception of their ability in a certain academic domain, most often in mathematics and verbal subjects (Gottfried et al., 2013; Guay et al., 2003; Seaton et al., 2014; for meta-analyses and reviews, see Burnette et al., 2013; Eccles & Wigfield, 2002; Marsh & Craven, 2006; Marsh & Martin, 2011; Robbins et al., 2004). Motivation such as these constructs are related to achievement because theoretically having a positive self-concept should lead to being engaged in self-affirmative and self-regulatory behaviours such as to exert effort, demonstrate more persistence, select adaptive goals, and make behavioural choices that are congruent with academic goals (Valentine et al., 2004).

Previous findings indicated that, in educational contexts, motivation not only affects academic achievement but that the relation is bidirectional in nature and achievement also boosts motivation (Huang, 2011; Marsh & Craven, 2006; Marsh & Martin, 2011; Möller et al., 2011). A common view is that both the “motivation → achievement” or “achievement → motivation” links exist because motivation and achievement influence each other in a reciprocal manner over time (Arens et al., 2017; Guay et al., 2003; Huang, 2011; Marsh et al., 2016; Marsh & Craven, 2006; Marsh & Martin, 2011; Möller et al., 2011; Murayama et al., 2013; Niepel et al., 2014a, 2014b; Seaton et al., 2014). Yet, empirical research not has not reached a full consensus. Recently, there are some doubts about the robustness of the reciprocal relationship between motivation and achievement when testing under different statistical models. Specifically,

methodologists pointed out a flaw in the widely used CLPM in earlier research: the conflation of between- and within-person variations (Hamaker et al., 2015). Newer studies contrasting the results from CLPM and RI-CLPM - the latter can distinguish these two sorts of variations - found that when fitting RI-CLPM to the same data, the reciprocal effects were either not found (Ehm et al., 2019) or only the achievement → motivation (ASC) link was apparent (Burns et al., 2020).

Causality, time frame, and behavioural consequences

To our knowledge, several aspects of the relations between motivation and achievement are still to be further investigated. First, even when extant research has demonstrated longitudinal relations between the constructs, a *causal interpretation* remains difficult because of the shortage of studies that have both a longitudinal design *and* an experimental manipulation of either motivation or achievement independently (Marsh et al., 2018; Mega et al., 2014). In other words, experimentally manipulating one of the components *within the cyclical loop* between motivation and achievement has been rarely done in previous research. As a consequence, direct evidence about causality is largely lacking. Unsurprisingly, in almost every longitudinal study investigating the reciprocal relations between motivation and achievement, the discussion section mentions the need for experimental designs that can tackle this issue (Marsh et al., 2016, 2018; Mega et al., 2014; Pinxten et al., 2014).

Second, much research on the reciprocity between motivation and achievement was conducted at large time intervals, which reflect changes that happen over a long period of time such as a school year or semester (e.g., Harackiewicz et al., 2008; Marsh et al., 2005, 2016; Nuutila et al., 2018). However, theories of motivation are often framed in terms that suggest that motivation constructs fluctuate in wide-ranging timeframes. For instance, within expectancy-

value theory and self-efficacy theory, ASC and self-efficacy are expected and found to shift indeed over a school semester (Eccles & Wigfield, 2002). Yet, according to self-determination theory (Ryan & Connell, 1989, p. 750), intrinsic motivation are "reasons for action where the behaviour is done simply for its inherent enjoyment", which seems to suggest that this motivation construct operates on a much shorter timeframe than self-concepts. An emerging body of research in achievement emotions also suggests that motivation can be fast-changing (Pekrun, 2006). A related issue is that data collection at large intervals might not be able to capture the ebbs and flows of the relations between constructs over time. Taken together, future studies with a special attention to motivation constructs of short time frames and in an intensive manner therefore should be highly valuable for both theories and applications.

Third, previous reciprocity studies have also left an unanswered question concerning the behavioural mediating pathway from motivation to achievement. Although motivation theories in educational psychology generate many ways of conceptualizing and operationalizing motivation (Eccles & Wigfield, 2002), the majority of empirical studies studying the reciprocity has operationalized motivation as academic self-concept, achievement goals, self-efficacy, and the likes (Gottfried et al., 2013; Guay et al., 2003; Seaton et al., 2014; for meta-analyses and reviews, see Burnette et al., 2013; Eccles & Wigfield, 2002; Marsh & Craven, 2006; Marsh & Martin, 2011; Robbins et al., 2004). These constructs often tap into students' *beliefs or perception* about their competence and efficacy, their *expectations* of success or failure, and *sense* of control (Eccles & Wigfield, 2002). Whereas, in theoretical models of general motivation, motivation is usually associated with *behaviours* that are employed to reach an outcome (Berridge & Robinson, 2016; Weiner, 2010). In fact, many empirical studies cite the

rationale that motivation leads to active and effortful commitment to learning, implying that motivation influences achievement by inducing what could be called effort (see Figure 1).

Figure 1. The cyclical relations between motivation and achievement, mediated by effort. The red arrows represent the cross-lagged parameters and the green arrows auto-regressive parameters similar to those in Figure 4 (see below).

In the few longitudinal motivation-achievement studies that have investigated effort, the findings differed as a function of whether subjective or objective measures of effort were used. Pinxten et al.(2014) were among the first, to our knowledge, to conduct a longitudinal study on

the motivation-achievement relations that also included a measure of effort. They found that although motivation and achievement had positive reciprocal effects on each other, they had *negative* effects on subsequent effort. Marsh et al.(2016) actually found the ASC → effort links to be non-significant in most of their statistical models. Note that Marsh et al.(2016) and Pinxten et al.(2014) measured *subjective* effort - i.e., students were asked to rate their own effort expenditure. Students might perceive that having to try hard (i.e., expending a great deal of effort) is indicative of a lack of academic ability (Baars et al., 2020). Subjective effort, as opposed to objective effort, might therefore have a very different relation to motivation and achievement. We concur with Pinxten et al. (2014)'s and Marsh et al. (2016)'s hunch that the most feasible pathway for motivation, such as academic self-concept, to relate to achievement is via *objective* effort put into learning.

Studies that do include objective measures of effort also depict a complex picture. There is some evidence for a positive link between academic achievement and effort when *quality* of effort is measured (e.g. adopting effective learning strategies) (Trigwell et al., 2013). For example, in vocabulary learning, a meta-analysis concluded that higher-quality strategies that make use of contextual information (e.g. example sentences) yielded higher achievement than a lower-quality strategy in which students only study the definition of the words (Stahl & Fairbanks, 1986). However, when effort is measured as *quantity* of learning (e.g. study time), the effort-achievement relationship turns out to be negative (Koriat et al., 2006; Nelson & Leonesio, 1988; Undorf & Ackerman, 2017) or only significant after controlling for quality of effort (Cury et al., 2008; Doumen et al., 2014; Plant et al., 2005). Together, these findings suggest that to really understand the behavioural pathways of the mutual influences between motivation and

achievement it is necessary to look at objective (and not subjective) measures of effort and to examine both quantity and quality of effort expenditure.

Furthermore, a large volume of previous research suggests that students form implicit theories about their intelligence which are on a continuum between two extremes: incremental and entity theories. These implicit theories may affect students' quantity and quality of effort (Burnette et al., 2013; Dweck, 2012) as they have been shown to be associated with students' academic motivation in terms of achievement goals (Burnette et al., 2013), and are theorized to influence effort expenditure and beliefs about effort (Blackwell et al., 2007; Tempelaar et al., 2014). Students who hold an incremental perspective (or have a growth mindset) believe that their intelligence is malleable and therefore, can be changed through effort. In contrast, those who are entity theorists (or have a fixed mindset) see intelligence as a fixed entity which cannot be improved much (Dweck, 2012). Incremental theorists often focus on learning goals and employ mastery-oriented strategies to reach their goals. In contrast, entity theorists more often focus on performance goals and employ helpless-oriented strategies when facing challenges (but see very recent research by Yu & McLellan, 2020 for a more nuanced picture where differences in goal orientation are found even within a mindset). This means that when there are setbacks (e.g., low perceived achievement) the differences in terms of effort expenditure and goal orientation between entity and incremental theorists will be revealed as these students will have dissimilar changes in their subsequent effort. Yet, there has also been little empirical research on the moderating role of implicit theory of intelligence (or mindset), by experimentally introducing setbacks, in the reciprocal relationship between motivation, effort, and achievement.

The present research

The present research is motivated by the gaps identified above and its theoretical and practical aims are threefold. The **first** is to replicate the findings of previous research that the relationship of motivation and achievement is a cyclical loop, each construct leading to changes in the other in the subsequent time point (**Hypothesis 1**). We focus on a motivation construct that is expected to fluctuate in a short time frame, that is intrinsic motivation. Additionally, while looking into the loop over time, we can estimate the relative magnitude of each of the “motivation → achievement” and “achievement → motivation” links.

The **second aim** is to investigate the mechanism underlying the reciprocal relationship by **measuring the proposed behavioural pathway between motivation and achievement**: effort spent on learning. Intrinsic motivation is hypothesized to be associated with quantity and quality of objective effort, which in turn is related to achievement which again is linked with subsequent motivation and so on (**Hypothesis 2**, see Figure 1).

Third, we examine the causality of the relations between motivation, effort, and achievement by manipulating perceived achievement, which is expected to have an impact on the entire cycle rather than on individual constructs (**Hypothesis 3a**). Specifically, we expect that when experiencing setbacks, learners’ levels of motivation, effort, and achievement will be affected yet the relationships between these constructs remain reciprocal.

Next, we predict this effect to depend on a learner’s theory of intelligence. A growth mindset is expected to be associated with smaller changes in effort after a drop in perceived achievement, while a fixed mindset be linked with larger and negative changes in effort after the drop, which would have corresponding effects on the participants’ achievement and subsequent motivation (**Hypothesis 3b**). As explained above, mindset theory also postulates implications for

achievement goal orientation and effort beliefs of learners, we include questionnaires to measure them but will only analyze these additional constructs exploratorily.

To reach these three aims, the present research has several innovations. First, to understand the unfolding dynamics between motivation and achievement, we will make use of random-intercept cross-lagged panel models (RI-CLPM). An RI-CLPM includes a cross-lagged parameter that reflects the effect of the previous score in one variable on the change score in another variable in the subsequent time point. Yet, unlike CLPM, this relatively new modelling technique takes into account stable individual differences or initial levels in constructs (Usami et al., 2019). This means that the RI-CLPM enables uncovering possible reciprocal relations between these variables temporally and ascertaining the relative magnitude of each link while taking into account potential confounds that are unrelated to the temporal dynamics. Second, the present study is a one-hour experiment that has a short-time frame, multiple-time point design. Over eight time points, the motivation, effort, and achievement of students who learn new vocabulary are measured (McNeish & Hamaker, 2019). The use of multiple time points has the advantage of capturing the ebbs and flows of the relations between constructs over time that might be missed if measured by relatively lengthy intervals (Duff et al., 2015; McNeish & Hamaker, 2019). Finally, our experiment has a manipulation of perceived achievement. Longitudinal studies with data collected at schools (which are mostly non-experimental designs) are informative because they provide a comprehensive overview of the multiple factors that are related to motivation and achievement. Yet, conclusions that can be drawn from non-experimental designs are limited to associations and confounding variables that may play a role in observed effects cannot be ruled out. Therefore, experiments are the gold standard for inferring causal relations between manipulated variables and dependent ones.

Methods

Sample characteristics

The sample will be 300 Dutch college students (see sample size determination below) recruited from a research university [masked for blind review], who are non-native speakers of English and are expected to be between 16 and 25 years old. Participants who complete the experiment will be remunerated with course credits.

Participant recruitment and exclusion

As we study motivation, we hope to align participation in the experiment with participants' own interests. The experiment will be advertised as a vocabulary learning study for non-native speakers of English with the hope to attract participants whose motivation is in line with the experimental task.

Recruitment will be done through an online booking system of the university (called SONA). Students who are required to earn credits will browse this website where our experiment is advertised. To participate, they can click on a URL which leads them to the Pavlovica server hosting the experiment. Only complete data files and questionnaires without missing data for the main variables of interest (i.e., motivation, effort, achievement, and mindset) will be used for analyses. To comply with the guidelines of ethics and privacy protection of the university, participants will be allowed to skip demographic questions. Therefore, missing data in the demographic questionnaire will be considered acceptable. We will stop data collection as soon as we know that the target sample size has been reached. Due to conservative overbooking, we might slightly exceed the target sample size. To make sure that we have reached the target

sample size even after having to remove some participants, we will check the completeness of the data files during data collection. However, only after having stopped data collection will we analyze the data.

We will apply for an ethical review at the research ethical committee of the university before conducting data collection, where an important consideration will be that our experiment contains minor deception (see Achievement below). The committee will also receive the final Stage 1 Report, the consent and debriefing forms.

Pilot

While waiting for the review of the first version of this Stage 1 Report, we ran a pilot. The modifications to the design described in this version of the report reflect both our response to the feedback of the reviewers and insights from this pilot. If the current report receives in-principle acceptance, we will proceed by first running another pilot with 20 participants. The purpose of the new pilot is to identify and fix any programming issues or unclear instructions (which might lead to non-optimal data organization in data files, potential loss of data, participant attrition, etc.).

Experimental design and procedure

The experiment consists of a one-hour session in which participants learn new English words. Participants are tested on English words they do not know and receive feedback on their performance which is experimentally manipulated to rank them first as above peer-average, and later below peer-average.

Due to the COVID19-related restrictions, the experiment will be fully computerized and conducted online. Participants will be required to participate using a computer, a mouse and a keyboard. The experiment is programmed in Python-based open-sourced PsychoPy (Peirce et al., 2019) and is hosted online by Pavlovia (<https://pavlovia.org/>). First, after being directed to Pavlovia, participants will read and sign the informed consent form which includes general information about the experiment. If consent is given, participants will proceed to read general instructions and will be told that the goal of their task in this experiment is to enrich their English vocabulary. Then they will answer a number of pre-task questionnaires.

Pre-task Questionnaires (see Appendix A)

General Theory of Intelligence questionnaire (general TOI). The general TOI consists of four statements about fixed mindset (e.g., "*To be honest, I don't think I can really change how intelligent I am*") and four statements about growth mindset (e.g., "*I believe I can always substantially improve how intelligent I am*"). Participants indicate their responses on a 6-point Likert scale ranging from 1 (*completely disagree*) to 6 (*completely agree*).

Specific Theory of Intelligence questionnaire (specific TOI). Given that someone's mindset can be different depending on the subject (Burnette et al., 2013), we added a specific subscale to measure beliefs about the malleability of language learning. In this version of the TOI, the term "intelligence" is adapted into "foreign language aptitude". Again, this TOI consists of four statements about the growth mindset and four statements about the entity mindset. Participants indicate their responses on a 6-point Likert scale ranging from 1 (*completely disagree*) to 6 (*completely agree*).

Goal-Orientation questionnaire. Goal orientation will be measured by the 2x2 Achievement Goal Questionnaire (AGQ) which has four subscales (mastery-approach goal, mastery-avoidance goal, performance-approach goal, and performance-avoidance goal) and consists in total of 12 items (e.g., “*I am striving to do well compared to other students*”) (Elliot & McGregor, 2001; Elliot & Murayama, 2008).

Effort Belief questionnaire. This questionnaire consists of five items of positive attitude (e.g., “*The harder you work at something, the better you will be at it.*”) and five items of negative attitude about effort (e.g., “*If you're not good at a subject, working hard won't make you good at it.*”) (Blackwell, 2002). Participants indicate their response on a 6-point Likert scale ranging from 1 (*completely disagree*) to 6 (*completely agree*).

Academic Self-Concept questionnaire. Since our experimental task taps into verbal ability (see below), we will administer the subscale of Verbal Self-Concept (and not the other subscales) of the widely used Self-Description Questionnaire III (Marsh & O’Neill, 1984; Marsh, 1990). The Verbal subscale consists of ten items (e.g., “*I have a poor vocabulary.*”). Participants indicate their response on a 6-point Likert scale ranging from 1 (*not true*) to 6 (*true*). Although in the present research ASC is not our focus, given the importance of ASC in previous research, we include this measure for exploratory investigation.

Word Selection Phase

In this phase, participants see the words that they will potentially learn (see the section Stimuli below). From a total pool of 1305 items (see Stimuli below), words are presented one by one on the screen and participants indicate whether they already know the meaning of each word by answering “Yes”, “Kind of”, and “No”. This phase ends when the participant indicates a total

of 325 words as unknown (i.e., to which they answer “No”) which will be used in the subsequent phases (for that particular participant). Participants who do not reach 325 unknown words will not be asked to continue to the next phases of the experiment and will be reimbursed with half the study credits. An overview of the experimental design is in Figure 2.

Figure 2. Schematic presentation of the experimental design and trial structure. Each block consists of multiple trials depending on the speed of individual participants. Note that for the purpose of illustration, the number of blocks in each round is four. Yet, in the experiment, the number of blocks within a round differs across participants, i.e. participants experience the achievement drop/setback at different moments in the task. The total number of blocks is always eight for all participants.

Learning and Testing Phase

Round structure. Participants will then enter the next phase which starts with a practice round followed by two experimental rounds. The trials in the practice round are identical to those in the experimental rounds, but the practice round only consists of ten trials and five words. Participants are informed that the practice round is to familiarize them with the task and their scores are not calculated until the “real experiment” starts. To ensure that participants understand the task well, participants will have to practice until they have an accuracy rate of 60% or above and demonstrate at least a total of three seconds of the quantity of effort measure (see Effort below). Only then they can proceed to the experimental rounds.

Each experimental round consists of multiple blocks (see Block Structure below and Figure 2), each block consists of multiple trials (see Trial Structure below). The two experimental rounds are identical to each other except for the feedback (actual and manipulated achievement) that appears at the end of each *block*.

Achievement (actual and manipulated). At the end of each block, participants see their score and the scores of “other participants” of that block. This feedback thus includes *two* pieces of information: *score*, i.e. actual achievement, and *rank*, i.e. manipulated achievement. Crucially, there are two variants of the manipulated achievement: above-average and below-average. This manipulation concerns the rank, but not the score. The first round consists of blocks that end with “above-average” rank and the second round consists of blocks with “below-average” rank. A normal distribution of scores of 19 “other participants” (fake participants) are generated on the fly from the score of the real participant in that block. In the *above*-average round, the “other participants” and their scores are selected from the distribution so as the participant is randomly

either ranked the 3rd, or 4th, or 5th in the list that displayed a total of 20 participants. In the *below-average* round, the “other participants” and their corresponding scores are selected from the same distribution in a way that the rankings of the real participant will be either the 13th, or 14th, or 15th in the list of 20 participants. The order of the rounds is fixed, to create an achievement drop (or a setback) from above to below average. The ranking positions of the fake participants are created using an inverse sigmoid function with the score and ranking of the participants in each block as input (see Appendix B) to create a believable change in achievement. See Figure 3 for examples of the two variants of feedback manipulation.

Importantly, the number of blocks within a round differs across participants, i.e. participants experience the achievement drop/setback at different moments in the task. One third of the participants have four above-average and four below-average blocks (like in Figure 2). Another third has two above-average and six below-average blocks and the last third has six above-average and two below-average blocks (currently not illustrated in Figure 2). Participants will be randomly assigned to these “conditions”. This feature is not a focus of the experimental design. It only allows us to rule out the possibility that the drop in motivation and effort is a result of fatigue and not of the feedback manipulation. If fatigue was the cause then motivation and effort might wane generally at the later blocks regardless of the conditions. If not, motivation and effort should just follow the feedback manipulation.

Trial structure. In each trial, after the 500-ms fixation cross, one out of the participant’s individual pool of 325 unknown words will be randomly drawn for presentation. Its meaning (i.e. correct Dutch translation) together with three incorrect alternatives (thus, four Dutch words in total) will be presented on the screen and participants are prompted to click and choose an

option. If they choose a correct response, then a “Correct!” screen will pop up and the next trial will begin. If their response is incorrect, then the “Incorrect!” screen will pop up and subsequently, participants will be asked to choose: either to view only the meaning of the word (i.e. effort of lower quality) or the meaning of the word *and* an example sentence (i.e. effort of higher quality) (Stahl & Fairbanks, 1986). The choice of the participant is our measure of *quality* of effort. Whichever option they choose, they will have to press a mouse button for the materials to be displayed on the screen. If they don’t press, the screen will remain blank until the end of the duration of the trial. The amount of time that participants press the mouse button constitutes our measure of *quantity* of effort.

To prevent excessively large differences in the number of trials across participants (as blocks have a fixed length, but trials do not), an upper and lower limit are imposed on the duration of trial. The duration of each trial is at least four seconds (even if participants get a correct answer) and at most eight seconds (even if participants spend time viewing the materials). Pilot results show that participants never spend more than five seconds on viewing the learning materials. Words to which participants provide an incorrect response will randomly reappear in a future trial that is between two and eight trials away. This means that a majority of the words will reappear within the block. The next trial is always a word randomly drawn from the learning subset, and never the same word as in the immediately preceding two trials.

Block structure. Each word reappears until it has been answered correctly three times or the block ends. A block ends after it exceeds the total block time of four minutes, resulting in a maximum of 60 trials and minimum of 30 trials per block. A unique subset of 40 words is created for each block. When a word has been answered correctly three times, it is taken out of the learning subset of the block, to be replaced by another word from the subset. The use of a

learning subset per block is necessary to ensure that it does not take too long for a word to repeat. Words that are already used in a previous block, even when not yet learned, will not appear in subsequent blocks. After each block, participants will *first receive the achievement feedback* (both the actual, i.e. scores and the manipulated feedback, i.e. ranking) and *then* respond to the motivation measure (see Motivation below). This order (see Figure 2) is important because achievement is expected to influence their subsequent motivation and behaviours.

Example of above-average feedback

	Score
Participant D	33%
Participant I	31%
Participant C	29%
Participant K	28%
You	26%
Participant M	24%
Participant F	20%
Participant B	17%
Participant Q	16%
Participant E	15%
Participant J	14%
Participant A	13%
Participant L	12%
Participant G	11%
Participant N	10%
Participant O	9%
Participant P	8%
Participant H	7%
Participant R	6%

Example of below-average feedback

	Score
Participant O	39%
Participant R	38%
Participant C	37%
Participant A	36%
Participant G	35%
Participant J	34%
Participant B	33%
Participant N	32%
Participant I	31%
Participant F	30%
Participant K	29%
Participant L	28%
Participant M	27%
You	26%
Participant H	25%
Participant D	24%
Participant P	23%
Participant Q	22%
Participant E	21%

Figure 3. Example of the manipulation of achievement feedback used in the Learning and Testing Phase. At the end of each block, participants are shown this scoring board which contains two pieces of information: 1) their *actual achievement* (the score, i.e. the percentage of

correct answers in that block) and 2) the *manipulated achievement* (the ranking of the participant relative to “other participants” in that block). In the first round, no matter what score the participants achieve, their positions would be above average. Similarly, in the second round, regardless of their actual achievement, their positions would be below average. See details in Achievement (actual and manipulated).

Motivation. At the end of every block, a three-part question will appear on the screen: “*I am doing this task: .. because it is fun. ... because I enjoy doing it. ... because it is fun to answer hard questions.*” Participants are instructed to drag the cursor to a point that corresponds to their answer on three lines below each of these three questions (visual analogue scale) (de Boer et al., 2004; Gallagher et al., 2002). One end of each line corresponds to “*completely disagree*” and the other end “*completely agree*” (corresponding to a score between 1 and 100), with intermittent anchors at 10-score intervals. These questions are the intrinsic motivation subscale from the Academic Self-Regulation Scale (Ryan & Connell, 1989), which is a well-validated and widely used questionnaire connected to self-determination theory.

Manipulation check. After completing the Learning and Testing Phase, participants will be asked if they noticed any change in their achievement in the second round of the task. We also ask if they could guess why the change happened (without giving it away) and will discard those that correctly guess that the feedback is rigged. Additionally, participants will also be asked what they did when they press the mouse to keep the materials displayed. This is to check whether they indeed study the meanings of the words.

Demographic questionnaire. Finally, participants answer the demographic questionnaire which consists of questions regarding participants' age, gender, study track in high school and their English grade in high school.

Then they will be thanked and debriefed thoroughly about the manipulated achievement before being directed back to the SONA system to collect their study credit.

Stimuli

In this experiment, we use the pool of 1305 words from the website Exam Word (<https://www.examword.com/difficult/gre>) which provides the study materials to prepare for the Graduate Record Examinations (GRE), a standardized test for admission to graduate schools in the United States and Canada. The correct option for the meaning of each word is taken from the equivalent in Dutch provided by various English-Dutch, English-English and Dutch-Dutch dictionaries. The other (incorrect) options are Dutch translations of other words within the pool. The translations example sentences are chosen by the first author and research assistants who are native speakers of Dutch. The criteria are that the sentences must come from a dictionary (Merriam Webster or Longman), not longer than 100 letters, must independently give some clues to the meaning of the word, and there must be correspondence between the Dutch translation and the meaning of the English word in the example sentence¹. The full list of the stimuli is available upon request for now (but will be openly shared once/if we receive In-Principle Acceptance).

¹ An English word can have multiple meanings that correspond to different Dutch translations. We had to choose one Dutch translation as the correct answer. Accordingly, when we choose an English example sentence we need to make sure that this correspondence exists.

Variables

Questionnaire variables. For each subscale of the Goal Orientation (GO), Effort Belief (EB), and verbal Academic Self-Concept (vASC) questionnaires, we compute individual mean scores. Regarding general TOI, the fixed mindset statements are reversed-scored and added to the growth mindset score, so the higher a sum score (general mindset score, gTOI) it is assumed that the more of a general growth mindset the participant endorses (De Castella & Byrne, 2015; Dweck, 2012). The same treatment is used for the specific TOI subscale, resulting in specific mindset scores (sTOI).

Motivation. Motivation score is the average motivation rating on the three intrinsic motivation items that participants rate at the end of every block. There will be eight measurements of motivation corresponding to eight experimental blocks.

Effort.

Effort quality. Qualitative effort is the percentage of time per block that participants choose the option of higher-quality effort (i.e. viewing the meaning of the word and the example sentence) over the option of lower-quality effort (i.e. viewing only the meaning of the word). There will be eight measurements of quality of effort corresponding to eight experimental blocks.

Effort quantity. Quantitative effort is the average time per block that participants spend actively viewing the learning materials. There will be eight measurements of quantity of effort corresponding to eight experimental blocks.

Actual Achievement (score). The score is computed as the proportion of trials answered correctly within a block, after excluding those trials in which a word was presented the first time

(since on such trials participants can only guess). For example, consider a participant who completed 41 trials in a block, of which 11 were new words presented for the first time; out of the remaining 30, if that participant answered 12 correctly, (s)he would score 40% in that block. There will be eight measurements of achievement corresponding to eight experimental blocks.

Rank (manipulated achievement). In the *above*-average round, participants' scores are randomly either ranked the 3rd, or 4th, or 5th. In the *below*-average round, the rankings of the participants' score will be either the 13th, or 14th, or 15th. (In the pilot, we also included a version of the experiment where the rankings for the above-average round were set as the 7th, 8th and 9th and the rankings for the below-average round as the 11th, 12th and 13th. The results indicated that there were no significant differences between the two versions of the experiment in terms of motivation, effort and actual achievement. Therefore we decided to only include the version with the biggest drop in rank. There will be eight measurements of rank corresponding to eight experimental blocks.

Analysis plan

All analysis will be conducted in R (R Core Team, 2017) using the *lavaan* package (Version 5.22, Rosseel, 2012) and based on the R scripts by Usami and colleagues (2019). Full information maximum likelihood with robust standard errors to account for missingness and non-normality will be used. If there are violations of multivariate normality, the robust weighted least squares estimator would be used.

Modelling specifications

We will fit a series of cross-lagged panel models with random intercepts (RI-CLPM, Usami et al., 2019) and follow Usami and colleagues' (2019)'s modelling framework and rationale (paraphrased in the following text). First, RI-CLPM has two classes of parameters that can serve our purposes: the autoregressive parameter (β) and the cross-lagged parameter (γ). The latter is the parameter for inferring reciprocal relations between the variables. They represent a simple partial regression coefficient from the predictor (e.g. motivation) to the outcome variable (e.g. achievement) after controlling for the effect of the outcome variable at the previous time point. Crucially, the RI-CLPM framework allows us to directly model (within-person) changes over time as a function of structural parameters. The second (and third) domains of interest are measured on the same number of occasions as the first domain. This allows for the investigation of "cross-domain" or cross-lagged relations, that captures the extent to which change in one domain (actual achievement) is a function of the level of the second domain (motivation), whose change is in turn a function of the third domain (qualitative or quantitative effort). These dynamics will be investigated in a series of RI-CLPM models (see Model Comparisons below). Likelihood ratio tests of these dynamic parameters furnish evidence for, or against, models that represent unilateral or bidirectional hypothesized causal influences.

Second, the RI-CLPM differs from the CLPM (whose flaws were discussed in the previous research reviewed in the Introduction) in that it explicitly models stable between-person differences over time. The measurements of variables Motivation and Achievement at time t for individual i is a combination of temporal group means, an invariant component of a variable in an individual over time and residuals. The RI-CLPM then separates stable between-person differences (i.e. the invariant component) from within-person fluctuations over time and the regression coefficients represent the amount of within-person carry-over. In addition, our pilot

data showed large individual differences in all three key variables of interest (namely motivation, effort, and achievement); therefore, the random intercepts in RI-CLPM are also useful in this respect.

Finally, the RI-CLPM model can capture at least four different motivation-effort-achievement relationships. First, we have motivation-effort covariance and the effort-achievement covariance at time point 1. Second, we have motivation-effort and effort-achievement cross-lagged parameters (shown in red in Figure 4). Third, we have a rate, or degree, of change over time of the domains (autoregressive parameters, shown in green). Finally, we have an estimate of correlated changes (currently not shown yet in Figure 4), reflecting the degree to which the domains' changes co-occur after taking into account the cross-lagged pathways.

Note that we model the rankings (manipulated achievement) as observed variables that influence motivation directly. Therefore, the achievement-related cross-lagged parameters we refer to from this point on are linked to the latent variables of *actual* achievement, not manipulated achievement. Qualitative and quantitative effort will be modelled separately (see details at Hypothesis 2 below).

Figure 4. Illustration of the planned trivariate RI-CLPM models. Here the three main groups of variables of interest are Motivation, Effort, and Achievement ones. M_t (and m_t) are the Motivation variables, e_t the effort variable, A_t (and a_t) the actual Achievement variables, and R_t the rankings (manipulated achievement), with t indicating the time point (block). Circles indicate latent variables and rectangles indicate observed variables. I_a , I_e , I_m are the random intercepts of the Achievement, Effort and Motivation variables. Note that a^* , m^* , and e^* are the latent variables where the mean and intercepts are removed, reflecting the dissociation of between-person differences (i.e. the invariant component) from within-person fluctuations over time (see Model Specifications below). The arrows denoting the cross-lagged parameter are in red and the autoregressive parameter in green. For visual clarity, variances and covariances are not included in the figure. For the same reason, we only include the latent variable structure for e^* but in the analysis, observed variables of effort will be modelled using the same structure as a^* (see further

details in Model Specifications). The rankings (manipulated achievement) are modelled as observed variables that influence motivation directly. Qualitative and quantitative effort will be modelled in separate series of models.

Model comparisons and parameter estimates

The RI-CLPM model as specified in Figure 4 will be fitted separately for the first round and second round. In case these models reach an acceptable fit, we will proceed to test our hypotheses.

Hypothesis 1 is that the relationship of motivation and achievement is a cyclical loop, each link leading to changes in the other in the subsequent time point on a short time frame. To test this hypothesis, we examine bivariate models that exclude the Effort variables (see Figure 5). These bivariate models are the core of the trivariate models presented in Figure 4. The only difference is that the bivariate models do not include the Effort variables which are not relevant for Hypothesis 1.

The testing steps are as follows:

In Model 1 (“free” model): both directional pathways are freely estimated (i.e. the cross-lagged parameters are freely estimated), assuming that the relationship between motivation and achievement is reciprocal.

In Model 2a (“unilateral” model): the cross-lagged parameter from motivation to achievement is fixed to 0, assuming that the relationship is unilateral in the motivation → achievement direction.

In Model 2b (“unilateral” model): the reverse path (the cross-lagged parameter from achievement to motivation) is fixed to 0, assuming that the relationship is unilateral in the achievement → motivation direction.

In Model 3 (“full” model): both directional cross-lagged parameters are fixed to 0, assuming that there is no relationship between motivation and achievement.

If Model 3 or 2a is the best model then we stop the confirmatory analyses.

If Model 2b or 1 is the best model then we move to the next test.

Apart from model comparisons, we will also estimate the relative magnitude of each of the “motivation → achievement” and “achievement → motivation” links by examining their standardized effects (i.e. the coefficients when estimating the parameters).

In building these models we will consider changes to model parameters based on modification indices aiming for a good model fit. These changes such as restrictions, linking factors to variables, and correlations between error terms will be stated explicitly in the Stage 2 paper and their effects on model comparison will be investigated and reported.

Figure 5. Illustration of the planned bivariate RI-CLPM models to test Hypothesis 1. Here the two main variables of interest are Motivation and Achievement. This figure is largely identical to Figure 4; the only difference is that the Effort variables are not included here.

Hypothesis 2 is that the underlying behavioural pathway from motivation to achievement is effort spent on learning. Intrinsic motivation is expected to lead to changes in quantity and quality of objective effort, which in turn lead to changes in achievement which again feeds in subsequent motivation and so on.

To test this hypothesis, we examine trivariate models that *do* include the Effort variables (see Figure 4). Yet qualitative and quantitative effort will be modelled in separate series of models. Henceforth, we use the term “effort” to refer to qualitative and quantitative effort collectively for the sake of brevity.

The testing steps are as follows:

In Model 4: All cross-lagged parameters (motivation-effort, effort-achievement, achievement-motivation) are freely estimated.

Model 5, 6, and 7: These versions of models only differ in terms of constraints (i.e., one of the cross-lagged parameters between the constructs being fixed to 0 at a time), which enables us to identify which cross-lagged effect factor loading(s) can be fixed.

Model 8a: is the final model with the free and fixed cross-lagged parameters based on the results of the models 5, 6, and 7.

Model 8b: is Model 8a plus allowing the motivation-achievement cross-lagged parameter (direct path) to be freely estimated.

Then we conduct a Model 8a vs. Model 8b comparison to test if the coefficient of the motivation-achievement direct path is significant. It can be significant or non-significant, but if it is lower than that path in Model 1 of the first test, then it suggests that including effort downgrades the relation between motivation and achievement. In sum, with these tests, we can search for support that effort indeed mediates the motivation-achievement path.

Hypothesis 3a & 3b is about causality of the relations between motivation, effort, and achievement. When introducing the experimental manipulation of perceived achievement, we expect this to have an impact on the cycle rather than on individual constructs (**Hypothesis 3a**).

To test Hypothesis 3a, we will compare the values of the key parameters and mean scores in the first round of the task with those in the second round of the task. The expectations of the changes in the parameters and scores are presented in the table below.

In the second round of the experimental task, compared to the first round	
Autoregressive parameter	Would not change
Cross-lagged parameter	Would not change
Means of scores	Means of motivation, effort and actual achievement decrease (3a), and the change would be even larger when the mindset score decreases (as lower score indicates more of a fixed mindset) (3b)

To test the role of mindset (**Hypothesis 3b**), the gTOI and sTOI scores will be regressed separately on the motivation, effort, and achievement scores.

Previous research has also demonstrated that the item-specific difficulty of the task (or the item-specific knowledge level) may moderate the pathway from motivation to effort choice (Koriat et al., 2006; Undorf & Ackerman, 2017). Given that each participant will work with their unique stimuli set (see the Word Selection phase in Figure 2) where each item has been judged by the participant him/herself to be completely unknown (and therefore possibly of relative difficulty) we do not expect this to have a systematic impact on the dynamics between the variables of interests. However, to be 100% certain, since we cannot rule out any effect of similarity based on previously incorrect answers, we will conduct an extra multilevel model with random intercepts across stimuli to check for any potential effects due to the potential differences in perceived difficulty across stimuli.

All other analyses will be labeled as exploratory.

Statistical criteria for model comparison

We will assess overall model fit via the chi-square test, the root-mean-square error of approximation (RMSEA; acceptable fit: $< .08$, good fit: $< .05$), the comparative fit index (CFI; acceptable fit: $.95-.97$, good fit: $> .97$), and the standardized root-mean-square residual (SRMR; acceptable fit: $.05-.10$, good fit: $< .05$; (Schermelleh-Engel et al., 2003). We compared the models in three ways: overall model fit (cf. (Schermelleh-Engel et al., 2003), information criteria (Akaike's information criterion, AIC, and Bayesian information criterion, BIC), and Akaike weights (Wagenmakers & Farrell, 2004), which use differences in AICs and BICs to quantify the relative likelihood of a model being the best among the set of competitors, given the data. To ease parameter comparisons, we will always ask for standardized coefficients in the analyses.

Data simulation, sample size determination and model complexity

A set of data is simulated and the codes are provided in Supplemental Materials. For the sake of sample size estimate, the data simulation is based on a bivariate model (Figure 5) which is the core of the trivariate model (Figure 4). Hereby, we assume that if there is a reciprocal relationship between motivation and achievement then the effect is mediated by effort. Hence, to find a mediator effect by effort we should be certain to find cross-lagged effects between motivation and achievement in the two-variable model. In other words, data simulation is constructed to be sufficient for conducting the test if Hypothesis 1 (see above), leaving the Effort variables out of the equation. Using the RI-CLPM framework, we modelled the change scores on two domains (motivation and achievement) as the function of two processes: an autoregressive process (β) and a cross-lagged process (γ), as explained above (see Modelling Specifications).

Since we don't have strong expectations of the effect size we studied the power of the most important model comparison for a large range of possible values of cross-lagged parameters. We set the possible values of the cross-lagged parameters to be 0, 0.025, 0.05, 0.1, 0.2, 0.2 and 0.3. The sample size is 300 and the number of replicated datasets is 500. The key question is with the sample size of 300 as informed by the rule of thumb, how the power of the study would vary when the real effect sizes vary. In each replication we fit models to the simulated data and then compared the models by the differences between the BIC information criteria (Wagenmakers & Farrell, 2004). As can be seen in Figure 6, when the cross-lagged parameter is of interest and of a magnitude similar to what is found in previous studies, the data simulation shows that, with the sample size of 300 we would achieve desirable power (> 0.75).

Figure 6. Plots showing estimated power given various possible values of cross-lagged parameters capturing how the change in one construct of interest is determined by another in the previous time point (and vice versa). Power is estimated with regards to the three different model comparisons, based on the BIC differences. “Free” is the model where both cross-lagged parameters are freely estimated (Model 1). “Unilateral” is where a unidirectional relationship (i.e. either one pathway) is freely estimated and the other constrained to zero (Model 2a and 2b, which are identical from the perspective of data simulation). “Full” is the fully constrained model where both directions are constrained to zero (Model 3). The simulation shows that with a sample size of 300 participants, we have the power greater than 0.75 to detect the reciprocal relationship of effect size of 0.1.

Open resources

The codes to build the experiment are hosted at GitLab and will be made freely accessible after we finish collecting our data.

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Appendix A

Pre-task questionnaires

General Theory of Intelligence questionnaire

Entity subscale:

I don't think I personally can do much to increase my intelligence.

My intelligence is something about me that I personally can't change very much.

To be honest, I don't think I can really change how intelligent I am.

I can learn new things, but I don't have the ability to change my basic intelligence.

Incremental subscale:

With enough time and effort I think I could significantly improve my intelligence level.

I believe I can always substantially improve on my intelligence.

Regardless of my current intelligence level, I think I have the capacity to change it quite a bit.

I believe I have the ability to change my basic intelligence level considerably over time.

Specific Theory of Intelligence questionnaire

Entity subscale:

I don't think I personally can do much to increase my foreign language aptitude .

My foreign language aptitude is something about me that I personally can't change very much.

To be honest, I don't think I can really change my foreign language learning aptitude.

I can learn new things, but I don't have the ability to change my basic foreign language aptitude.

Incremental subscale:

With enough time and effort I think I could significantly improve my foreign language aptitude level.

I believe I can always substantially improve on my foreign language aptitude.

Regardless of my current foreign language aptitude level, I think I have the capacity to change it quite a bit.

I believe I have the ability to change my basic foreign language aptitude level considerably over time.

Achievement Goal Questionnaire

Mastery-approach subscale:

My aim is to completely master the material presented in this class.

My goal is to learn as much as possible.

I am striving to understand the content as thoroughly as possible.

Performance-approach subscale:

I am striving to do well compared to other students.

My aim is to perform well relative to other students.

My goal is to perform better than the other students.

Mastery-avoidance subscale:

My aim is to avoid learning less than I possibly could.

My goal is to avoid learning less than it is possible to learn.

I am striving to avoid an incomplete understanding of the course material.

Performance-avoidance subscale:

My goal is to avoid performing poorly compared to others.

I am striving to avoid performing worse than others.

My aim is to avoid doing worse than other students.

Effort Beliefs

Positive belief subscale:

When something is hard, it just makes me want to work more on it, not less.

If you don't work hard and put in a lot of effort, you probably won't do well.

The harder you work at something, the better you will be at it.

If an assignment is hard, it means I'll probably learn a lot doing it.

Negative belief subscale:

To tell the truth, when I work hard at my schoolwork, it makes me feel like I'm not very smart.

It doesn't matter how hard you work--if you're not smart, you won't do well.

If you're not good at a subject, working hard won't make you good at it.

If a subject is hard for me, it means I probably won't be able to do really well at it.

If you're not doing well at something, it's better to try something easier.

Verbal Academic Self-Concept

I have trouble expressing myself when trying to write something.

I can write effectively.

I have a poor vocabulary.

I am an avid reader.

I do not do well on tests that require a lot of verbal reasoning ability.

Relative to most people, my verbal skills are quite good.

I often have to read things several times before I understand them.

I am good at expressing myself.

In school I had more trouble learning to read than most other students.

I have good reading comprehension.

Appendix B

Codes to generate the scores of rankings of the fake participants

```
# Define sigmoid and inverse sigmoid
def sigmoid(x):
    return 100/(1 + 2*np.exp(-3.5*x/100))**2

def inverse_sigmoid(y):
    return -100/3.5*np.log((np.sqrt(100/y) - 1)/2)

# Shuffle the participant names, but only within their categories
for sublist in [pBest, pGood, pAverage, pBad, pWorst]:
    np.random.shuffle(sublist)

# Create different versions of the manipulation
if Block == "AAF":
    rank_max = 7
    rank_min = 9
else:
    rank_max = 11
    rank_min = 13
rank = np.random.randint(rank_max, rank_min + 1)
thisExp.addData('Participant_rank', rank)

# Concatenate the participant names and the participant in the correct position
pName_shuffled = np.concatenate((pBest, pGood, pAverage, pBad, pWorst))
pName_shuffled = np.insert(pName_shuffled, rank-1, 'You:      ')

# Create sample of scores
inverse_correct_percentage = inverse_sigmoid(correct_percentage)
sample = np.random.normal(loc=inverse_correct_percentage, scale=20, size=500)

higher_scores = sigmoid(sample[sample > inverse_correct_percentage][:rank - 1])
lower_scores = sigmoid(sample[sample < inverse_correct_percentage][:20 - rank])

scores = np.concatenate((higher_scores, lower_scores))
scores = np.around(np.sort(np.append(scores, correct_percentage)), decimals=1)[::-1]
```

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Supplemental Materials

MODEL ESTIMATIONS

#free model = all gamma's are estimated

```
est_free_model <- '
```

```
a1~mua1*1
```

```
m1~mum1*1
```

```
a2~mua2*1
```

```
m2~mum2*1
```

```
a3~mua3*1
```

```
m3~mum3*1
```

```
a4~mua4*1
```

```
m4~mum4*1
```

```
a5~mua5*1
```

```
m5~mum5*1
```

```
a6~mua6*1
```

```
m6~mum6*1
```

```
a7~mua7*1
```

```
m7~mum7*1
```

```
a8~mua8*1
```

```
m8~mum8*1
```

```
a1~~0*a1
```

```
m1~~0*m1
```

```
a2~~0*a2
```

```
m2~~0*m2
```

```
a3~~0*a3
```

```
m3~~0*m3
```

```
a4~~0*a4
```

```
m4~~0*m4
```

```
a5~~0*a5
```

$$m5 \sim 0 * m5$$

$$a6 \sim 0 * a6$$

$$m6 \sim 0 * m6$$

$$la \sim 0 * FFa1$$

$$la \sim 0 * FFm1$$

$$lm \sim 0 * FFa1$$

$$lm \sim 0 * FFm1$$

$$la = 1 * a1 + 1 * a2 + 1 * a3 + 1 * a4 + 1 * a5 + 1 * a6 + 1 * a7 + 1 * a8$$

$$lm = 1 * m1 + 1 * m2 + 1 * m3 + 1 * m4 + 1 * m5 + 1 * m6 + 1 * m7 + 1 * m8$$

$$la \sim 0 * 1$$

$$lm \sim 0 * 1$$

$$la \sim \tau_{ua} * la$$

$$lm \sim \tau_{um} * lm$$

$$la \sim \tau_{uam} * lm$$

$$FFa1 \sim 0 * 1$$

$$FFm1 \sim 0 * 1$$

$$FFa1 \sim \phi * FFa1$$

$$FFm1 \sim \phi_m * FFm1$$

$$FFa1 \sim \phi_{iam} * FFm1$$

$$FFm2 \sim \beta_m * FFm1 + \gamma_m * FFa2$$

$$FFa2 \sim \beta_a * FFa1 + \gamma_{aa} * FFm1$$

$$FFm3 \sim \beta_m * FFm2 + \gamma_m * FFa3$$

$$FFa3 \sim \beta_a * FFa2 + \gamma_{aa} * FFm2$$

$$FFm4 \sim \beta_m * FFm3 + \gamma_m * FFa4$$

$$FFa4 \sim \beta_a * FFa3 + \gamma_{aa} * FFm3$$

$FFm5 \sim \text{betam} * FFm4 + \text{gammam} * FFa5$
 $FFa5 \sim \text{betaa} * FFa4 + \text{gammaa} * FFm4$
 $FFm6 \sim \text{betam} * FFm5 + \text{gammam} * FFa6$
 $FFa6 \sim \text{betaa} * FFa5 + \text{gammaa} * FFm5$
 $FFm7 \sim \text{betam} * FFm6 + \text{gammam} * FFa7$
 $FFa7 \sim \text{betaa} * FFa6 + \text{gammaa} * FFm6$
 $FFm8 \sim \text{betam} * FFm7 + \text{gammam} * FFa7$
 $FFa8 \sim \text{betaa} * FFa7 + \text{gammaa} * FFm7$

$FFa2 \sim \sim \text{Omegaa} * FFa2$
 $FFa3 \sim \sim \text{Omegaa} * FFa3$
 $FFa4 \sim \sim \text{Omegaa} * FFa4$
 $FFa5 \sim \sim \text{Omegaa} * FFa5$
 $FFa6 \sim \sim \text{Omegaa} * FFa6$
 $FFa7 \sim \sim \text{Omegaa} * FFa7$
 $FFa8 \sim \sim \text{Omegaa} * FFa8$

$FFm2 \sim \sim \text{Omegam} * FFm2$
 $FFm3 \sim \sim \text{Omegam} * FFm3$
 $FFm4 \sim \sim \text{Omegam} * FFm4$
 $FFm5 \sim \sim \text{Omegam} * FFm5$
 $FFm6 \sim \sim \text{Omegam} * FFm6$
 $FFm7 \sim \sim \text{Omegam} * FFm7$
 $FFm8 \sim \sim \text{Omegam} * FFm8$

$\# FFa2 \sim \sim \text{Omegaam} * FFm2$
 $\# FFa3 \sim \sim \text{Omegaam} * FFm3$
 $\# FFa4 \sim \sim \text{Omegaam} * FFm4$
 $\# FFa5 \sim \sim \text{Omegaam} * FFm5$

```
# FFa6~~Omegaam*FFm6
# FFa7~~Omegaam*FFm7
# FFa8~~Omegaam*FFm8
```

```
FFm1 =~ 1*m1
FFm2 =~ 1*m2
FFm3 =~ 1*m3
FFm4 =~ 1*m4
FFm5 =~ 1*m5
FFm6 =~ 1*m6
FFm7 =~ 1*m7
FFm8 =~ 1*m8
```

```
FFa1 =~ 1*a1
FFa2 =~ 1*a2
FFa3 =~ 1*a3
FFa4 =~ 1*a4
FFa5 =~ 1*a5
FFa6 =~ 1*a6
FFa7 =~ 1*a7
FFa8 =~ 1*a8
```

```
# introduce the rigged feedback variable
FFm1 ~ delta*RF1 #regress FFm1 on RF1 with factor loading to be estimated
FFm2 ~ delta*RF2
FFm3 ~ delta*RF3
FFm4 ~ delta*RF4
FFm5 ~ delta*RF5
FFm6 ~ delta*RF6
FFm7 ~ delta*RF7
```

```
FFm8 ~ delta*RF8
```

```
,
```

```
#fully constrained model = all gamma's are set to 0
```

```
est_full_cons_model <- '
```

```
a1~mua1*1
```

```
m1~mum1*1
```

```
a2~mua2*1
```

```
m2~mum2*1
```

```
a3~mua3*1
```

```
m3~mum3*1
```

```
a4~mua4*1
```

```
m4~mum4*1
```

```
a5~mua5*1
```

```
m5~mum5*1
```

```
a6~mua6*1
```

```
m6~mum6*1
```

```
a7~mua7*1
```

```
m7~mum7*1
```

```
a8~mua8*1
```

```
m8~mum8*1
```

```
a1~~0*a1
```

```
m1~~0*m1
```

```
a2~~0*a2
```

```
m2~~0*m2
```

```
a3~~0*a3
```

```
m3~~0*m3
```

```
a4~~0*a4
```

```
m4~~0*m4
```


$a5^{00}a5$

$m5^{00}m5$

$a6^{00}a6$

$m6^{00}m6$

$la^{00}FFa1$

$la^{00}FFm1$

$lm^{00}FFa1$

$lm^{00}FFm1$

$la = 1a1 + 1a2 + 1a3 + 1a4 + 1a5 + 1a6 + 1a7 + 1a8$

$lm = 1m1 + 1m2 + 1m3 + 1m4 + 1m5 + 1m6 + 1m7 + 1m8$

la^{01}

lm^{01}

$la^{\tau}la$

$lm^{\tau}lm$

$la^{\tau}am^{\tau}lm$

$FFa1^{01}$

$FFm1^{01}$

$FFa1^{\phi}FFa1$

$FFm1^{\phi}FFm1$

$FFa1^{\phi}FFm1$

$FFm2 \sim \beta_m FFm1 + 0 FFa2$

$FFa2 \sim \beta_a FFa1 + 0 FFm1$

$FFm3 \sim \beta_m FFm2 + 0 FFa3$

$FFa3 \sim \beta_a FFa2 + 0 FFm2$

$FFm4 \sim \beta_m FFm3 + 0 FFa4$

$FFa4 \sim \text{betaa} * FFa3 + 0 * FFm3$

$FFm5 \sim \text{betam} * FFm4 + 0 * FFa5$

$FFa5 \sim \text{betaa} * FFa4 + 0 * FFm4$

$FFm6 \sim \text{betam} * FFm5 + 0 * FFa6$

$FFa6 \sim \text{betaa} * FFa5 + 0 * FFm5$

$FFm7 \sim \text{betam} * FFm6 + 0 * FFa7$

$FFa7 \sim \text{betaa} * FFa6 + 0 * FFm6$

$FFm8 \sim \text{betam} * FFm7 + 0 * FFa7$

$FFa8 \sim \text{betaa} * FFa7 + 0 * FFm7$

$FFa2 \sim \sim \text{Omegaa} * FFa2$

$FFa3 \sim \sim \text{Omegaa} * FFa3$

$FFa4 \sim \sim \text{Omegaa} * FFa4$

$FFa5 \sim \sim \text{Omegaa} * FFa5$

$FFa6 \sim \sim \text{Omegaa} * FFa6$

$FFa7 \sim \sim \text{Omegaa} * FFa7$

$FFa8 \sim \sim \text{Omegaa} * FFa8$

$FFm2 \sim \sim \text{Omegam} * FFm2$

$FFm3 \sim \sim \text{Omegam} * FFm3$

$FFm4 \sim \sim \text{Omegam} * FFm4$

$FFm5 \sim \sim \text{Omegam} * FFm5$

$FFm6 \sim \sim \text{Omegam} * FFm6$

$FFm7 \sim \sim \text{Omegam} * FFm7$

$FFm8 \sim \sim \text{Omegam} * FFm8$

$\# FFa2 \sim \sim \text{Omegaam} * FFm2$

$\# FFa3 \sim \sim \text{Omegaam} * FFm3$

$\# FFa4 \sim \sim \text{Omegaam} * FFm4$

$\# FFa5 \sim \sim \text{Omegaam} * FFm5$

```
# FFa6~~Omegaam*FFm6
# FFa7~~Omegaam*FFm7
# FFa8~~Omegaam*FFm8
```

```
FFm1 =~ 1*m1
FFm2 =~ 1*m2
FFm3 =~ 1*m3
FFm4 =~ 1*m4
FFm5 =~ 1*m5
FFm6 =~ 1*m6
FFm7 =~ 1*m7
FFm8 =~ 1*m8
```

```
FFa1 =~ 1*a1
FFa2 =~ 1*a2
FFa3 =~ 1*a3
FFa4 =~ 1*a4
FFa5 =~ 1*a5
FFa6 =~ 1*a6
FFa7 =~ 1*a7
FFa8 =~ 1*a8
```

```
# introduce the rigged feedback variable
FFm1 ~ delta*RF1 #regress FFm1 on RF1 with factor loading to be estimated
FFm2 ~ delta*RF2
FFm3 ~ delta*RF3
FFm4 ~ delta*RF4
FFm5 ~ delta*RF5
FFm6 ~ delta*RF6
FFm7 ~ delta*RF7
```

```
FFm8 ~ delta*RF8
```

```
,
```

```
#unilaterally constrained model = gamma's of one way (doesnt matter which) are set to 0
```

```
est_uni_cons_model <- '
```

```
a1~mua1*1
```

```
m1~mum1*1
```

```
a2~mua2*1
```

```
m2~mum2*1
```

```
a3~mua3*1
```

```
m3~mum3*1
```

```
a4~mua4*1
```

```
m4~mum4*1
```

```
a5~mua5*1
```

```
m5~mum5*1
```

```
a6~mua6*1
```

```
m6~mum6*1
```

```
a7~mua7*1
```

```
m7~mum7*1
```

```
a8~mua8*1
```

```
m8~mum8*1
```

```
a1~~0*a1
```

```
m1~~0*m1
```

```
a2~~0*a2
```

```
m2~~0*m2
```

```
a3~~0*a3
```

```
m3~~0*m3
```

```
a4~~0*a4
```

```
m4~~0*m4
```

$$a5^{00}a5$$

$$m5^{00}m5$$

$$a6^{00}a6$$

$$m6^{00}m6$$

$$la^{00}FFa1$$

$$la^{00}FFm1$$

$$lm^{00}FFa1$$

$$lm^{00}FFm1$$

$$la = 1a1 + 1a2 + 1a3 + 1a4 + 1a5 + 1a6 + 1a7 + 1a8$$

$$lm = 1m1 + 1m2 + 1m3 + 1m4 + 1m5 + 1m6 + 1m7 + 1m8$$

$$la^{01}$$

$$lm^{01}$$

$$la^{taua}la$$

$$lm^{taum}lm$$

$$la^{tauam}lm$$

$$FFa1^{01}$$

$$FFm1^{01}$$

$$FFa1^{phi}FFa1$$

$$FFm1^{phim}FFm1$$

$$FFa1^{phiam}FFm1$$

$$FFm2 \sim \text{betam} * FFm1 + 0 * FFa2$$

$$FFa2 \sim \text{betaa} * FFa1 + \text{gammaa} * FFm1$$

$$FFm3 \sim \text{betam} * FFm2 + 0 * FFa3$$

$$FFa3 \sim \text{betaa} * FFa2 + \text{gammaa} * FFm2$$

$$FFm4 \sim \text{betam} * FFm3 + 0 * FFa4$$

$FFa4 \sim \text{betaa} * FFa3 + \text{gammaa} * FFm3$
 $FFm5 \sim \text{betam} * FFm4 + 0 * FFa5$
 $FFa5 \sim \text{betaa} * FFa4 + \text{gammaa} * FFm4$
 $FFm6 \sim \text{betam} * FFm5 + 0 * FFa6$
 $FFa6 \sim \text{betaa} * FFa5 + \text{gammaa} * FFm5$
 $FFm7 \sim \text{betam} * FFm6 + 0 * FFa7$
 $FFa7 \sim \text{betaa} * FFa6 + \text{gammaa} * FFm6$
 $FFm8 \sim \text{betam} * FFm7 + 0 * FFa7$
 $FFa8 \sim \text{betaa} * FFa7 + \text{gammaa} * FFm7$

$FFa2 \sim \sim \text{Omegaa} * FFa2$
 $FFa3 \sim \sim \text{Omegaa} * FFa3$
 $FFa4 \sim \sim \text{Omegaa} * FFa4$
 $FFa5 \sim \sim \text{Omegaa} * FFa5$
 $FFa6 \sim \sim \text{Omegaa} * FFa6$
 $FFa7 \sim \sim \text{Omegaa} * FFa7$
 $FFa8 \sim \sim \text{Omegaa} * FFa8$

$FFm2 \sim \sim \text{Omegam} * FFm2$
 $FFm3 \sim \sim \text{Omegam} * FFm3$
 $FFm4 \sim \sim \text{Omegam} * FFm4$
 $FFm5 \sim \sim \text{Omegam} * FFm5$
 $FFm6 \sim \sim \text{Omegam} * FFm6$
 $FFm7 \sim \sim \text{Omegam} * FFm7$
 $FFm8 \sim \sim \text{Omegam} * FFm8$

$\# FFa2 \sim \sim \text{Omegaam} * FFm2$
 $\# FFa3 \sim \sim \text{Omegaam} * FFm3$
 $\# FFa4 \sim \sim \text{Omegaam} * FFm4$
 $\# FFa5 \sim \sim \text{Omegaam} * FFm5$

```
# FFa6~~Omegaam*FFm6
# FFa7~~Omegaam*FFm7
# FFa8~~Omegaam*FFm8
```

```
FFm1 =~ 1*m1
FFm2 =~ 1*m2
FFm3 =~ 1*m3
FFm4 =~ 1*m4
FFm5 =~ 1*m5
FFm6 =~ 1*m6
FFm7 =~ 1*m7
FFm8 =~ 1*m8
```

```
FFa1 =~ 1*a1
FFa2 =~ 1*a2
FFa3 =~ 1*a3
FFa4 =~ 1*a4
FFa5 =~ 1*a5
FFa6 =~ 1*a6
FFa7 =~ 1*a7
FFa8 =~ 1*a8
```

```
# introduce the rigged feedback variable
FFm1 ~ delta*RF1 #regress FFm1 on RF1 with factor loading to be estimated
FFm2 ~ delta*RF2
FFm3 ~ delta*RF3
FFm4 ~ delta*RF4
FFm5 ~ delta*RF5
FFm6 ~ delta*RF6
FFm7 ~ delta*RF7
```

```
FFm8 ~ delta*RF8
```

```
,
```

SIMULATION OF POPULATION MODEL

```
#where we assign a constant to the parameters of interest
```

```
#here are the gamma's (the coupling parameters)
```

```
pop_model <- function(gammaa, gammam) {
```

```
  mod <- paste(
```

```
    'a1~mua1*1
```

```
m1~mum1*1
```

```
a2~mua2*1
```

```
m2~mum2*1
```

```
a3~mua3*1
```

```
m3~mum3*1
```

```
a4~mua4*1
```

```
m4~mum4*1
```

```
a5~mua5*1
```

```
m5~mum5*1
```

```
a6~mua6*1
```

```
m6~mum6*1
```

```
a7~mua7*1
```

```
m7~mum7*1
```

```
a8~mua8*1
```

```
m8~mum8*1
```

```
a1~~0*a1
```

```
m1~~0*m1
```

```
a2~~0*a2
```

```
m2~~0*m2
```

```
a3~~0*a3
```


$m_3 \sim m_3$

$a_4 \sim a_4$

$m_4 \sim m_4$

$a_5 \sim a_5$

$m_5 \sim m_5$

$a_6 \sim a_6$

$m_6 \sim m_6$

$l_a \sim F_{Fa1}$

$l_a \sim F_{Fm1}$

$l_m \sim F_{Fa1}$

$l_m \sim F_{Fm1}$

$l_a = a_1 + a_2 + a_3 + a_4 + a_5 + a_6 + a_7 + a_8$

$l_m = m_1 + m_2 + m_3 + m_4 + m_5 + m_6 + m_7 + m_8$

$l_a \sim 1$

$l_m \sim 1$

$l_a \sim \tau_a l_a$

$l_m \sim \tau_m l_m$

$l_a \sim \tau_{am} l_m$

$F_{Fa1} \sim 1$

$F_{Fm1} \sim 1$

$F_{Fa1} \sim \phi F_{Fa1}$

$F_{Fm1} \sim \phi F_{Fm1}$

$F_{Fa1} \sim \phi F_{Fm1}$

$F_{Fm2} \sim .1 F_{Fm1} + \gamma_m, F_{Fa2}$

$F_{Fa2} \sim .1 F_{Fa1} + \gamma_a, F_{Fm1}$

$\text{FFm3} \sim .1 * \text{FFm2} + ', \text{gammam}, ' * \text{FFa3}$
 $\text{FFa3} \sim .1 * \text{FFa2} + ', \text{gammaa}, ' * \text{FFm2}$
 $\text{FFm4} \sim .1 * \text{FFm3} + ', \text{gammam}, ' * \text{FFa4}$
 $\text{FFa4} \sim .1 * \text{FFa3} + ', \text{gammaa}, ' * \text{FFm3}$
 $\text{FFm5} \sim .1 * \text{FFm4} + ', \text{gammam}, ' * \text{FFa5}$
 $\text{FFa5} \sim .1 * \text{FFa4} + ', \text{gammaa}, ' * \text{FFm4}$
 $\text{FFm6} \sim .1 * \text{FFm5} + ', \text{gammam}, ' * \text{FFa6}$
 $\text{FFa6} \sim .1 * \text{FFa5} + ', \text{gammaa}, ' * \text{FFm5}$
 $\text{FFm7} \sim .1 * \text{FFm6} + ', \text{gammam}, ' * \text{FFa7}$
 $\text{FFa7} \sim .1 * \text{FFa6} + ', \text{gammaa}, ' * \text{FFm6}$
 $\text{FFm8} \sim .1 * \text{FFm7} \# + ', \text{gammam}, ' * \text{FFa7}$
 $\text{FFa8} \sim .1 * \text{FFa7} + ', \text{gammaa}, ' * \text{FFm7}$

$\text{FFa2} \sim \sim \text{Omegaa} * \text{FFa2}$
 $\text{FFa3} \sim \sim \text{Omegaa} * \text{FFa3}$
 $\text{FFa4} \sim \sim \text{Omegaa} * \text{FFa4}$
 $\text{FFa5} \sim \sim \text{Omegaa} * \text{FFa5}$
 $\text{FFa6} \sim \sim \text{Omegaa} * \text{FFa6}$
 $\text{FFa7} \sim \sim \text{Omegaa} * \text{FFa7}$
 $\text{FFa8} \sim \sim \text{Omegaa} * \text{FFa8}$

$\text{FFm2} \sim \sim \text{Omegam} * \text{FFm2}$
 $\text{FFm3} \sim \sim \text{Omegam} * \text{FFm3}$
 $\text{FFm4} \sim \sim \text{Omegam} * \text{FFm4}$
 $\text{FFm5} \sim \sim \text{Omegam} * \text{FFm5}$
 $\text{FFm6} \sim \sim \text{Omegam} * \text{FFm6}$
 $\text{FFm7} \sim \sim \text{Omegam} * \text{FFm7}$
 $\text{FFm8} \sim \sim \text{Omegam} * \text{FFm8}$

$\text{FFa2} \sim \sim \text{Omegaam} * \text{FFm2}$

```
FFa3~~Omegaam*FFm3
# FFa4~~Omegaam*FFm4
# FFa5~~Omegaam*FFm5
# FFa6~~Omegaam*FFm6
# FFa7~~Omegaam*FFm7
# FFa8~~Omegaam*FFm8
```

```
FFm1 =~ 1*m1
FFm2 =~ 1*m2
FFm3 =~ 1*m3
FFm4 =~ 1*m4
FFm5 =~ 1*m5
FFm6 =~ 1*m6
FFm7 =~ 1*m7
FFm8 =~ 1*m8
```

```
FFa1 =~ 1*a1
FFa2 =~ 1*a2
FFa3 =~ 1*a3
FFa4 =~ 1*a4
FFa5 =~ 1*a5
FFa6 =~ 1*a6
FFa7 =~ 1*a7
FFa8 =~ 1*a8
```

```
# introduce the rigged feedback variable
```

```
FFm1 ~ delta*RF1 #regress FFm1 on RF1 with factor loading to be estimated
FFm2 ~ delta*RF2
FFm3 ~ delta*RF3
FFm4 ~ delta*RF4
```

```
FFm5 ~ delta*RF5  
FFm6 ~ delta*RF6  
FFm7 ~ delta*RF7  
FFm8 ~ delta*RF8')
```

```
  return(mod)  
}
```

SIMULATION

```
library(lavaan)
library(tidyverse)

source("sim_pop_model.R")
source("est_model.R")

# -----
# approach 1: assume the coupling effects (gammaaa/a, gammab/b) to be of certain values (e.g., 0.1)
# then calculate power for the possible N = 50, 100, 150, 200, 250, 300

set.seed(1)

nruns <- 100
bics <- matrix(NA, nruns, 4)
all_bics <- matrix(NA, 1, 4)
a <- 0.1
b <- 0.1
for (n in c(50, 100, 150, 200, 250, 300)) {
  for (s in 1:nruns) {
    modx <- pop_model(gammaaa = a, gammab = b)

    d <- simulateData(modx, sample.nobs = n)

    fit_free <- cfa(est_free_model, data = d, missing='fiml')
    fit_uni_cons <- cfa(est_uni_cons_model, data = d, missing='fiml')
    fit_full_cons <- cfa(est_full_cons_model, data = d, missing='fiml')
    bics[s,] <- c(n, BIC(fit_free), BIC(fit_uni_cons), BIC(fit_full_cons))
  }
}
```

```

all_bics <- rbind(all_bics, bics)
cat(n, s, '\n')
}

```

```

all_bics <- all_bics[-1, ]
all_bics <- as.data.frame(all_bics)
names(all_bics) <- c('n', 'free', 'unilateral', 'full')
all_bics$diff1 <- all_bics$free - all_bics$unilateral
all_bics$diff2 <- all_bics$free - all_bics$full
all_bics$diff3 <- all_bics$unilateral - all_bics$full

```

```

all_bics %>% ggplot(aes(x = as.factor(n), y = diff1)) +
  geom_boxplot() +
  theme_bw()

```

```

all_bics %>%
  group_by(n) %>%
  summarise(
    m1 = mean(free - unilateral < 0),
    m2 = mean(free - full < 0),
    m3 = mean(unilateral - full < 0))

```

```

# -----

```

```

# approach 2: make a list of possible coupling effects (gammaa/a, gammab/b) = 0, .025, .05, 0.1, .2, .3
# then calculate power for N = 300

```

```

nruns <- 100

```

```

bics_2 <- matrix(NA, nruns, 4)

```

```

all_bics_2 <- matrix(NA, 1, 4)

as <- bs <- c(0, .025, .05, 0.1, .2, .3)

for (n in 1:length(as)) {
  for (s in 1:nruns) {
    modx <- pop_model(gammaa = as[n], gammam = as[n])
    d <- simulateData(modx, sample.nobs = 300)
    fit_free <- cfa(est_free_model, data = d, missing='fiml')
    fit_uni_cons <- cfa(est_uni_cons_model, data = d, missing='fiml')
    fit_full_cons <- cfa(est_full_cons_model, data = d, missing='fiml')

    bics_2[s,] <- c(as[n], BIC(fit_free), BIC(fit_uni_cons), BIC(fit_full_cons))
  }

  all_bics_2 <- rbind(all_bics_2, bics_2)
  cat(n, s, '\n')
}

all_bics_2 <- all_bics_2[-1, ]
all_bics_2 <- as.data.frame(all_bics_2)
names(all_bics_2) <- c('as', 'free', 'uni', 'full')
all_bics_2$diff1 <- all_bics_2$free - all_bics_2$uni
all_bics_2$diff2 <- all_bics_2$free - all_bics_2$full
all_bics_2$diff3 <- all_bics_2$uni - all_bics_2$full

all_bics_2 %>% ggplot(aes(x = as.factor(as), y = diff1)) +
  geom_boxplot() +
  theme_bw()

```

```

x <- all_bics_2 %>%
  group_by(as) %>%
  summarise(
    m1 = mean(free - uni < 0),
    m2 = mean(free - full < 0),
    m3 = mean(uni - full < 0))

xx <- data.frame(as = x$as,
  comparison = rep(c('free - unilateral', 'free - full', 'unilateral - full'), each = nrow(x)),
  m = c(x$m1, x$m2, x$m3))

xx %>% ggplot(aes(x = as, y = m, colour = comparison)) +
  geom_line(size = 2, alpha = .5) +
  geom_point(size = 4, alpha = .5) +
  labs(y = "Estimated power", x = "Possible values of cross-lagged parameters") +
  theme_bw()

```