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Research Notes

Influence of anticipated and actual grades on studying intentions

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ABSTRACT

This study explores two questions regarding differences between students' anticipated and actual grades in university courses: what factors contribute to those differences arising, and which of those differences influence students' subsequent studying? The research surveyed 278 students in a first-year undergraduate business course. Students with stronger academic abilities tended to have smaller (less negative) gaps between their grades and goals, while students with higher personal control scores tended to have wider (more negative) gaps. These gaps narrowed later in the course as students' goals decreased to match their actual grades more closely. Students increased their studying if their actual grades were lower than their original goals, and/or lower than their updated goals. By contrast, the difference between students' subjective grade goals and their objectively forecast final grades did not influence their studying intentions.

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1. Introduction

1.1. Background

Feedback is an integral part of education (Hattie & Timperley, 2007; Mory, 2003; Schartel, 2012; Shute, 2008). Ramaprasad (1983: 4) defines feedback as "information about the gap between the actual level and the reference level of a system parameter which is used to alter the gap in some way". The *self-regulated learning model* (Thurlings, Vermeulen Bastiaens, and Stijnen, 2013), for example, supposes that students establish goals for each course (reference level), assess the grades they get as feedback on their progress (actual level), and adjust their effort as needed to achieve their goals (Butler & Winne, 1995; Nicol & Macfarlane-Dick, 2006).

Students' behaviour in this context can be affected by their sense of *control*; i.e., their perceived ability to influence a process to obtain an outcome. A sense of control has been related to many outcomes, including achievement, motivation, and success (Skinner, 1996).

Students' behaviour may also be affected by their perceived performance. Unfortunately, students' self-assessments often only approximate their actual learning (Nowell & Alston, 2007; Sitzmann, Ely, Brown, & Bauer, 2010), despite their receiving

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outcome feedback such as test grades. Students tend to over-estimate their learning progress and likely course outcomes, with weaker students being more prone to this tendency (Kruger & Dunning, 1999). This over-estimation could impede students' success by making it less likely they will recognize the need to adjust their studying.

Instructors can reduce this problem by helping students make better self-assessments. For instance, they can ask students to keep journals in which they reflect on their learning challenges (Finch, Peacock, Lazdowski, & Hwang, 2014). Instructors can also provide *cognitive feedback* to encourage good study practices and more self-awareness (Feys, Anseel, & Wille, 2011). For example, Purdue University's Signals system displays color-coded dashboards on students' cell phones to indicate whether they are following good study habits (Pistilli & Arnold, 2010). These tools inform students about their past or current status in a course.

By contrast, some experiments have offered students *predictive* or *prognostic feedback* about their future status: where they are heading, rather than where they have been. Armstrong (2013) gave undergraduate business students a spreadsheet that enabled them to forecast their own final course grades while the course was ongoing. In that experiment, 29% of students said the quantitative forecast was lower than expected, versus only 6% who said it was higher. After the exercise, 47% said they were studying more than previously intended, while only 3% reported studying less. An informal study by Swenson (2015) obtained similar results with grade forecasting in an undergraduate mathematics course. Rahal and Zainuba (2016) included a grade forecasting spreadsheet along with several other innovations in their undergraduate business course. Their combined changes helped average and above-average students obtain better marks, but had less impact on below-average students.

Armstrong (2013) seems to have been the first study of quantitative grade forecasting done by students for their own use. Some previous research had students "predicting" their own course grades, in the sense of simply asking them what grade they expect to receive, without providing them with any quantitative tools (e.g., Nowell & Alston, 2007). Other studies involved quantitative forecasts for use by university staff. For example, Beck and Davidson (2001) used orientation surveys and high school marks to predict first-year university grades, so that counsellors could identify the students most likely to fail. The only prior research where the students themselves received the forecasts was Beyer (1971). He gave new university students forecasts of their first-semester grade point averages. Half of these forecasts were biased upward, to see whether that manipulation would affect student performance. No significant impact on end-of-semester grades was found.

One surprise in Armstrong (2013) and Swenson (2015) was that the difference between participants' objective grade forecasts and their own prior subjective grade expectations did not seem to influence studying intentions. For example, students whose forecast grade was lower than they had expected did not increase their studying; instead, students studied more after receiving a low forecast, even if it matched their prior expectations. This presents a puzzle. If students do not react to differences between the forecast grades and their prior expectations, as predicted by various learning theories, then to what do they react?

1.2. Which grade differences influence studying?

Our first objective in this study is to explore which grade differences cause students to adjust their studying. We primarily do this by examining a larger set of potential triggers for increased studying than what Armstrong (2013) and Swenson (2015) considered. Those studies surveyed students at only one point, near the end of the course; they compared each student's own subjective grade expectation at that time to an objective grade forecast. Our study surveys students twice, in the second and eighth week of the course, to collect two subjective goals and two objective grades. This enables us to look for responses to three differences in grades:

- (a) Between the target grade the student set at the beginning of the course, and their actual current grade as of week eight;
- (b) Between their current grade in week eight, and the grade they say at that time that they expect to achieve by the end of the course; and,
- (c) Between that final grade that they expect, and the final grade that they quantitatively forecast.

We measure the goals of only the students, as opposed to those of their instructors or parents. As Sadler (1989) argues, only when the learner takes ownership of the goal can it play a significant role in self-regulation. Since goals are frequently dynamic (Ramaprasad, 1983), measuring them twice also reveals how they change as the course progresses.

In addition to examining a wider set of grade differences, we also collect more precise data about grades and participants than the earlier studies did. We ask students to report specific numerical values for their grades (e.g., "76%"), instead of the broad categories (e.g., "70–79%") that Armstrong (2013) collected. This allows us to calculate exact differences between grades, and thereby make the analysis more sensitive. Students also report their gender and high school location (i.e., foreign or domestic) so that we can control for those factors.

Our experiment differs from previous work in several other respects. The earlier studies involved courses whose content was mostly (Armstrong, 2013; Rahal & Zainuba, 2016) or entirely (Swenson, 2015) quantitative, whereas the course material in our study is about 97% qualitative. The earlier studies involved students in a second-year (Armstrong, 2013; Swenson, 2015) or third-year (Rahal & Zainuba, 2016) course. By contrast, we study students in a first-year course, who have much less experience with university-level work. Finally, we ask students for their reactions immediately after the forecasting

experience using online survey software, rather than several days later using a paper form as in [Armstrong \(2013\)](#). These differences help to generalize the experimental results related to grade forecasting, by ensuring they are not merely artefacts of one particular choice of course content, program level, or survey design.

1.3. What factors influence grade differences?

Our second objective is to explore which factors contribute to the differences that occur between grade goals and actual grades. The first factor we consider is academic ability, as measured by students' reported high school averages. Previous research (Kruger & Dunning, 1999) has shown that weaker students are more prone to overestimating their grades; this implies they are likely to have larger grade differences in our context.

We also have students complete a short personality test to assess their sense of *personal control*. We chose personal control as it indicates "individuals' beliefs about their capacities to exercise control in their lives" ([Gurin, Gurin, & Morrison, 1978](#), p. 275). This metric emerged from [Rotter's \(1966\)](#) seminal work on locus of control, which refers to general beliefs about the internality or externality of causality, and which has been extensively researched in the management literature.

Finally, because we survey students twice during the course, we can see whether grade differences evolve over time. Such differences presumably should diminish over time as students respond to feedback; they may adjust their efforts to change their performance ([Thurlings, Vermeulen Bastiaens, and Stijnen, 2013](#)), or they may adjust their goals to reflect their performance ([Ramaprasad, 1983](#)).

1.4. Research context

This study is part of a larger research program that aims to help students better understand their current progress and likely outcomes, both within individual courses and across overall degree programs. We believe this will help them to make better decisions related to, e.g., course selection, time allocation, and course withdrawal.

2. Hypotheses

2.1. Responding to feedback

Student response to feedback is a key component of many learning theories. [Hattie \(2009\)](#) argues that feedback plays a significant role in *behaviourism*, through *cognitivism*, *social cultural theory*, *meta-cognitivism*, and *social constructionism*. *Self-regulated learning* theory suggests that students should respond to feedback that indicates differences between their goals and their actual progress (e.g., [Nicol & Macfarlane-Dick, 2006](#); [Sitzmann et al., 2010](#)). *Achievement goal* theory (e.g., [Nicholls, 1984](#); [Dweck, 1986](#)) suggests those goals may involve *mastery* (e.g., improving their ability by learning challenging material) and/or *performance* (e.g., demonstrating their ability by obtaining high grades). *Metacognition* and *self-monitoring* are also relevant here (e.g., [Ben-Eliyaju & Bernacki, 2015](#)). *Meta-cognitivism* suggests that students can develop themselves as self-regulated learners, as feedback can help them "learn to learn" ([Brown, 1987](#); [Garner, 1987](#)).

Given these theories, when students' actual learning fails to meet their goals, they presumably should increase their studying to compensate. However, this does not always happen. For example, [Armstrong \(2013\)](#) found that differences between expected grades (a subjective goal) and forecast grades (an objective metric) did not affect studying intentions. He speculated that students might have reacted to some other difference instead. The environment can also complicate response to feedback. For example, transitions between schools (e.g., from primary to secondary, or secondary to university) place extra demands on learning strategies, while also disrupting them ([Grolnick & Raftery-Helmer, 2015](#)).

In our study, we explore three differences between grade goals and actual grades, to see which one(s) might be influential in the context of an undergraduate course.

Hypothesis 1a. *The difference between current and target grades, i.e., [current – target], will be negatively associated with studying intentions. E.g., students will study more when current grades are lower than target grades.*

Hypothesis 1b. *The difference between expected and current grades, i.e., [expected – current], will be positively associated with studying intentions. E.g., students will study more when expected grades are higher than current grades.*

Hypothesis 1c. *The difference between forecast and expected grades, i.e., [forecast – expected], will be negatively associated with studying intentions. E.g., students will study more when forecast grades are lower than expected grades.*

2.2. Grades and differences over time

Students' self-assessments often only approximate their actual learning ([Nowell & Alston, 2007](#); [Sitzmann et al., 2010](#)), and tend to be overly optimistic. Consequently, we expect grade targets set by students early in a course to be higher than what they actually achieve mid-way. Similarly, when surveyed mid-way through the course, the final grades students expect to receive should be higher than both their current grades at that point and the final grades forecast for them.

Weaker students are more prone to over-estimate their learning (Kruger & Dunning, 1999). We therefore would expect that the most overly optimistic students initially also will be the most overly optimistic later in the course as well. However, theories such as self-regulated learning (Thurlings, Vermeulen Bastiaens, and Stijnen, 2013) argue that students will adjust their effort to close any gaps between goals and achievements (Butler & Winne, 1995; Nicol & Macfarlane-Dick, 2006). This would imply that grade differences later in a course could instead differ considerably from earlier ones.

We word our hypotheses under the assumption that grade differences at different points in time will be positively associated.

Hypothesis 2a. *The difference between current and target grades will be positively associated with the difference between forecast and expected grades. E.g., students with current grades below their initial targets will have forecast grades below their later expectations.*

Hypothesis 2b. *The difference between current and target grades will be negatively associated with the difference between expected and current grades. E.g., students with current grades below their initial targets will have expected grades above their current ones.*

Hypothesis 2c. *The difference between forecast and expected grades will be negatively associated with the difference between expected and current grades. E.g., students with current grades below their expectations will have forecast grades below their expectations.*

2.3. Personal control

Many studies have examined the idea that some people (“internals”) feel more in-control of their lives. There has been a surprising heterogeneity among the terms used, such as *personal control*, *locus of control*, *sphere of control*, and *outcome control*, among others (Skinner, 1996). Control, variously measured, has been associated with affective, cognitive, and behavioural outcomes (e.g., Anderson, Hellriegel, & Slocum, 1977; Bandura, 1986) across several age categories (e.g., Abel & Hayslip, 2001; Finn & Rock, 1997). Internals have stronger beliefs that their effort will lead to better performance (Mitchell, Smyser, & Weed, 1975), and they place greater value on goal attainment (Hollenbeck & Brief, 1987). Yukl and Latham (1978) found that internals have a stronger need for achievement and often set harder goals. Gregory (1978) showed that internals produce greater effort and have better performance. The meta-analyses of Findley and Cooper (1983), Judge and Bono (2001), and Kalechstein and Nowicki (1997) likewise found that internals perform better.

In our study, we include what Paulhus and Van Selst (1990) called *personal control*, one of three dimensions in their *sphere of control* construct. The studies listed above make it clear that higher personal control should be associated with higher initial target grades, higher current grades, and higher expected final grades. However, the net effect of personal control on the differences between these grades is unclear. To the extent that students with higher personal control set harder goals, their anticipated grades may be higher than their actual ones. By contrast, to the extent that they perform better, their anticipated grades may be lower than their actual ones. Our hypotheses’ wording assumes that goals will exceed achievements.

Hypothesis 3a. *Higher personal control scores will be negatively associated with the difference between current and target grades. E.g., students with higher personal control are more likely to have current grades below their target grades.*

Hypothesis 3b. *Higher personal control scores will be positively associated with the difference between expected and current grades. E.g., students with higher personal control are more likely to have expected grades above their current grades.*

Hypothesis 3c. *Higher personal control scores will be negatively associated with the difference between forecast and expected grades. E.g., students with higher personal control are more likely to have forecast grades below their expected grades.*

2.4. Academic ability

Our study, like many others (e.g., Armstrong & Biktimirov, 2013; Richter, 2006), uses high school averages to indicate university students’ general academic ability. Higher averages therefore should be associated with higher initial target grades, higher current grades, and higher expected final grades. The interesting question is how differences in grades might vary by ability. Students who have learned the least in a course seem to overestimate their learning the most, while stronger students may underestimate it (see, e.g., Armstrong, 2013; Kruger & Dunning, 1999; Nowell & Alston, 2007). Therefore, we should see a corresponding relationship between high school grades and each of the three grade differences.

Hypothesis 4a. *The difference between current and target grades will be positively associated with high school average. E.g., students with higher high school averages are more likely to have current grades above their target grades.*

Hypothesis 4b. *The difference between expected and current grades will be negatively associated with high school average. E.g., students with higher high school averages are more likely to have expected grades below their current grades.*

Hypothesis 4c. *The difference between forecast and expected grades will be positively associated with high school average. E.g., students with higher high school averages are more likely to have forecast grades above their expected grades.*

2.5. Combined path model

Fig. 1 shows the path model that results from combining Hypotheses 1, 3, and 4. To avoid confusion, it omits the grade difference correlations described in Hypothesis 2.

3. Method

3.1. Student population

This study took place at a Canadian university accredited by the Association to Advance Collegiate Schools of Business. The university has about 1600 students enrolled in its 4-year undergraduate business degree programs. These students must take a 1-semester business principles course, normally during their first year. The course contains 5 assessment components that each account for 20% of the total course grade: exam #1, a writing proficiency test, exam #2, an essay assignment, and exam #3. Grades are recorded on a scale from 0 to 100: 0–49 is a failure or “F”, 50–59 is a “D,” 60–69 is a “C,” 70–79 is a “B,” and 80–100 is an “A.” The average overall course grade is typically about 60. Almost 20% of students fail the course, and another 20% withdraw before completion; most of those students retake the course in a later semester.

3.2. Data collection

We ran the experiment during the fall semesters of 2012 and 2013, during which 721 students finished the course. Each semester we administered 2 student surveys; to encourage participation, we held 2 prize draws for either a free textbook or a bookstore gift certificate.

We administered the first survey in class in the 2nd week of the 12-week semester. The paper survey form asked students for their high school average, the target grade they had in mind for the course, their gender, and whether they had attended a domestic or foreign high school.

The survey also included 10 Likert-type questions about personal control (see appendix). We used the revised scale recommended by Paulhus and Van Selst (1990), as it is parsimonious, has established reliability, and has face validity in our study’s context. To prevent order effects, we made 3 versions of the scale with the questions in different random sequences. Half of the questions were worded to be reverse-scored.

We administered the second survey online in the 8th week of the semester, when the students knew their marks for exam #1, the writing test, and exam #2. The online survey asked students to input these 3 actual marks, and also the final course grades they subsequently expected to receive. The software then calculated and displayed their current course grade (i.e., the average of the 3 assessments), along with their minimum and maximum possible final grades.

For half of the students (the “full feedback” group), the software also displayed a forecast of their final course grade. The other students (the “partial feedback” group) were not shown the forecast. This division allowed us to check whether students reacted to the forecast grade itself, or to the feedback exercise in general. After seeing the full or partial feedback, the students were asked whether they were planning to increase their studying (see appendix). The survey did not define “studying”, but instead left that term open for students to apply in their own contexts.

We created the forecasting equations for the full-feedback group using linear regression on grades from a previous offering of the course, as in Armstrong (2013). This produced point and interval estimates of the final course grades. The best-fitting regression equation was $Forecast = 11.20 + 0.334 Exam1 + 0.217 Writing + 0.278 Exam2$.

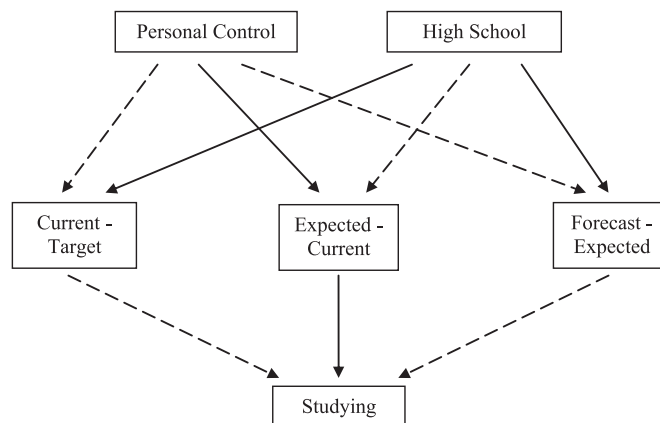


Fig. 1. Original path model showing hypothesized regression links. Solid lines indicate positive influences and dashed lines represent negative ones. Correlations are not shown.

For example, suppose a student has marks of 70 on exam #1, 50 on the writing test, and 60 on exam #2. After typing those marks into the online form, the student would see that their current average is 60, and that their final grade must fall between 36 and 76. A student in the full-feedback group would also see that their forecast final grade is 62, with a 50% chance of getting between 59 and 65, and a 95% chance of getting between 54 and 70.

A research assistant collected the responses from both surveys each semester, matched them by student name, and then removed the names. We analysed the anonymized data using Minitab statistics software and Amos structural equation modelling (SEM) software.

4. Results

4.1. Forecast accuracy for the entire class

For the two semesters combined, the actual final grades averaged 57.40, whereas the forecasts averaged 59.11. The average forecasting error therefore was 1.71, indicating a slight tendency for the forecast to overestimate. The standard deviation of the error was 5.70 and the mean absolute deviation was 4.64; that is, the distance between actual and forecast grades averaged 4.64 marks.

4.2. Descriptive data for the participants

Of the 721 students, 278 (38.6%) responded to both surveys. The mean forecast grade for the 278 respondents was 62.24, whereas that of the 443 non-respondents was 57.15, or 5.09 marks lower. A *t*-test showed this difference was statistically significant ($p < 0.001$), confirming (as in Armstrong, 2013) that students with higher grades are more likely to try forecasting.

Of the 278 respondents, 57.2% were male and 42.8% were female; 89.6% had come from domestic high schools, versus 10.4% from high schools in other countries. Their personal control scores ranged from 29 to 70 (within a possible range from 21 to 70), with a mean of 53.8, median of 54, and standard deviation of 6.58. Cronbach's alpha for the personal control questionnaire results was 0.774, indicating good reliability (Nunnally, 1978).

Table 1 shows mean reported grades for the full sample and for several subsamples. These grades include the student's high school average; the target grade they indicated on the first survey; their actual average grade, as of the second survey; the final grade they expected, as reported on the second survey; and the final grade that the formula forecast.

The students' initial target grades averaged 6.1 marks lower than their high school grades, but 13.9 marks higher than their subsequent actual grades; both differences were statistically significant (*t*-test $p < 0.001$). The tendency towards over-estimation was smaller on the second survey: students expected their grades to rise 2.3 marks by the end of the course, whereas the forecast projected they would fall 0.7 marks. Both differences were statistically significant (*t*-test $p < 0.001$). The rest of Table 1 breaks down the data by year, gender, and feedback type. While the details vary, the same tendencies appear in each subgroup.

After the forecasting exercise, students tended to report increased studying. On a scale from 1 to 7, the median response was 6, the mean was 5.50, and the standard deviation was 1.41. On average, students planned to increase their studying (*t*-test $p < 0.001$).

4.3. Correlations between survey items

Table 2 shows the Pearson correlation coefficients for all pairs of quantitative variables. Asterisks indicate statistically significant correlations ($p < 0.05$). Not surprisingly, the five grade variables are all positively correlated. Students with higher high school averages tend to set higher targets at the beginning of the course, obtain higher marks during the course, and have higher expectations and forecasts for their final grades at the end of the course.

Increased studying is negatively correlated with all of the grade measures except the initial target. Thus students with lower actual or anticipated grades are more likely to increase their studying. Personal control scores are positively correlated with target grades and expected grades, but not current grades. Thus students who feel more in control anticipate receiving higher course marks, but do not achieve them.

Table 1
Mean grades overall, and by year, gender, and feedback type.

Category	All	2012	2013	Male	Female	Partial	Full
Participants	278	170	108	159	119	134	144
High school grade	82.9	82.2	83.9	82.5	83.3	82.6	83.1
Target grade	76.8	78.2	74.6	77.2	76.1	76.7	76.8
Current grade	62.9	62.4	63.6	62.0	64.0	62.5	63.2
Expected grade	65.2	65.4	64.9	64.6	66.0	65.1	65.3
Forecast grade	62.2	61.7	63.1	61.7	63.0	61.9	62.6

Table 2
Correlations among quantitative variables, where *indicates $p \leq 0.05$.

	1	2	3	4	5	6
1. Control						
2. High school	0.109					
3. Target	0.418*	0.183*				
4. Current	0.095	0.454*	0.169*			
5. Expected	0.264*	0.405*	0.331*	0.824*		
6. Forecast	0.099	0.456*	0.159*	0.995*	0.818*	
7. Studying	0.104	-0.257*	-0.013	-0.313*	-0.184*	0.558*

4.4. Structural equation modelling (SEM)

We performed the SEM analysis in two stages. The first stage analysed the path model (Fig. 1) with all of the hypothesized links. Since students in the partial feedback group did not see the forecast and could not have been influenced by it, we set their difference [forecast – expected] equal to zero for this analysis. Table 3 shows the resulting standardized regression coefficients (i.e., scaled to fall between -1 and $+1$) and their p -values. Table 4 shows the correlations, while Table 5 shows the R-squared values.

We measured the model's fit with 3 metrics (Arbuckle, 2009: Appendix C). The chi-squared test indicates whether there is evidence to reject a model, so higher p -values are preferred. The goodness-of-fit index (GFI) gives a score where larger is better, 0.95 is suggested, and 1 is preferred. Conversely, the root mean square error of approximation (RMSEA) indicates the “badness-of-fit” where smaller is better, 0.05 is suggested, and 0 is preferred.

The initial model displayed a marginal fit (GFI = 0.984, RMSEA = 0.118) and ample evidence for rejection ($\chi^2 = 14.557$, $df = 3$, $p = 0.002$). The correlations in Table 4 are all statistically significant, but two of the regression links in Table 3 are not.

The second stage of SEM analysis refined the model by deleting the two links that were not statistically significant, and adding the one link suggested by the software's modification indices, between high school average and studying plans. This refined model (see Fig. 2) fit the data better (GFI = 0.992 RMSEA = 0.048) and was not rejected ($\chi^2 = 6.563$, $df = 4$, $p = 0.161$).

This analysis shows that the difference between current grade and target grade has a negative relationship with personal control and a positive relationship with high school average. That is, students with higher personal control scores and/or lower high school averages tend to have current grades farther below their initial targets. The opposite influences appear for the difference between expected and current grades. Students with higher personal control scores and/or lower high school averages are more likely to expect their marks to increase by the end of the course. Personal control also shows a negative influence on the difference between forecast grade and expected grade. Students with higher personal control scores tend to have forecast grades farther below their expectations.

The three grade differences are correlated as expected. In particular, the differences between current and target grades are positively correlated with the differences between forecast and expected grades. Students who set unrealistically high goals near the start of the course also tend to set unrealistically high goals near the end of the course.

There are 3 variables that show statistically significant relationships with studying plans. The difference between current and target grades displays a negative influence on studying, as does high school average. Students plan to study more if their current marks are lower than their initial targets, and/or if they did less well in high school. The difference between expected and current grade has a positive influence on studying. Students plan to study more if they expect their grade to increase by the end of the course.

4.5. Tests of categorical control variables

The SEM analysis above treated all 278 respondents as one sample. To check for differences within this set, we first reanalysed the refined model with an added grouping variable for student gender (female versus male) and compared this to the previous freely estimated model. A chi-squared test showed no statistically significant gender differences ($\chi^2_{diff} = 8.602 - 6.563 = 2.039$, $df_{diff} = 8 - 4 = 4$, $p = 0.729$). We then repeated this step using the sample year (2012 versus 2013) as the grouping variable instead; the impact was greater but still not significant ($\chi^2_{diff} = 15.336 - 6.563 = 8.773$, $df_{diff} = 8 - 4 = 4$, $p = 0.067$).

We next retested the refined model using only the 144 full feedback participants, i.e., those who saw their forecast. The model still showed a good fit (GFI = 0.989, RMSEA = 0.037) with no evidence to reject it ($\chi^2 = 4.791$, $df = 4$, $p = 0.309$). We similarly retested the refined model using only the 249 domestic students. All of the links remained significant, but the fit declined (GFI = 0.984, RMSEA = 0.090) and the model was rejected ($\chi^2 = 12.086$, $df = 4$, $p = 0.017$). Further investigation revealed that the model needed a correlation link between personal control and high school average. With this addition, the fit improved (GFI = 0.993, RMSEA = 0.052) and the model was no longer rejected ($\chi^2 = 5.029$, $df = 3$, $p = 0.170$).

Table 3
Standardized regression β weights and p -values for original and refined models.

			Original β	Original p	Refined β	Refined p
Current-Target	<-	Personal Control	-0.327	0.000	-0.324	0.000
Expected-Current	<-	Personal Control	0.230	0.000	0.227	0.000
Forecast-Expected	<-	Personal Control	-0.136	0.000	-0.132	0.000
Current-Target	<-	High School	0.721	0.000	0.696	0.000
Expected-Current	<-	High School	-0.224	0.000	-0.185	0.000
Forecast-Expected	<-	High School	0.047	0.286		
Studying	<-	Current-Target	-0.026	0.003	-0.020	0.027
Studying	<-	Expected-Current	0.045	0.031	0.035	0.017
Studying	<-	Forecast-Expected	0.021	0.424		
Studying	<-	High School			-0.052	0.002

Table 4
Correlations and p -values for original and refined models.

			Original r	Original p	Refined r	Refined p
Expected-Current	<->	Forecast-Expected	-0.568	0.000	-0.568	0.000
Expected-Current	<->	Current-Target	-0.518	0.000	-0.518	0.000
Forecast-Expected	<->	Current-Target	0.190	0.002	0.190	0.002

Table 5
 R -squared values for original and refined models.

	Original R^2	Refined R^2
Current-Target	14.4%	13.7%
Expected-Current	10.7%	9.4%
Forecast-Expected	5.9%	5.2%
Studying	10.4%	13.2%

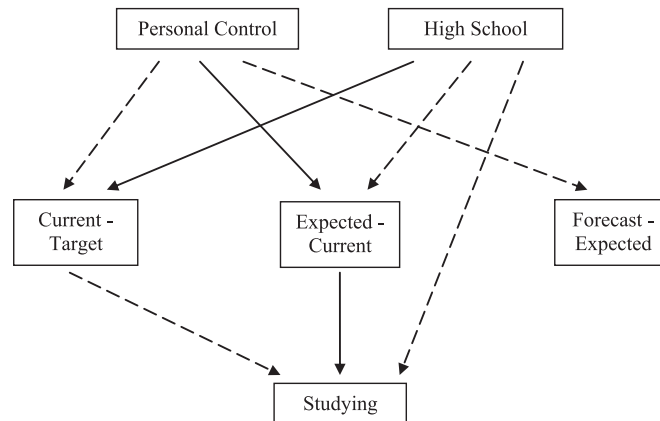


Fig. 2. Refined path model showing statistically significant regression links ($p < 0.05$).

5. Discussion

5.1. Support for hypotheses

Hypothesis 1 regarding studying is mostly (i.e., parts 1a and 1b) supported. Students are more likely to increase their studying if their current grades are lower than the target grades they initially set or the grades they later expect to achieve. However, differences between forecast and expected grades do not affect studying.

Hypothesis 2 regarding on-going grade differences is supported. Students with the most unrealistic grade expectations near the start of the course tend to have the most unrealistic expectations near the end.

Hypothesis 3 regarding personal control is supported, in that it shows significant influence on grade differences. Students with higher personal control tend to set higher goals but not achieve higher grades. Consequently, they are more prone to over-estimating their outcomes.

Hypothesis 4 regarding academic ability is mostly (i.e., parts 4a and 4b) supported. Students with higher high school averages are less prone to overestimating their outcomes. However, they are similar to other students when comparing grade expectations to forecasts.

5.2. Contributions and implications

Our first set of contributions concern student responses to differences between subjective grade goals and objective grade measures. We found that undergraduate business students do respond to differences between the target grade they initially chose and their current actual grade, as well as to differences between their current grade and the final grade they expect to achieve. They increase their planned studying if their actual grades are below their initial and/or subsequent goals. This is not surprising, as it matches the predictions of theories such as self-regulated learning (e.g., Nicol & Macfarlane-Dick, 2006; Sitzmann et al., 2010).

By contrast, students do not adjust their studying in response to differences between their subjective expectation for the final grade and the quantitative forecast of that final grade. Even when they discover that their expectations are too high, they do not study more to compensate. This confirms the results from Armstrong (2013) and Swenson (2015). Since our methodology differs in several respects from those works, it also generalizes their findings.

This non-response seems contrary to what learning theories would predict. Perhaps students disregard the forecast differences because they do not believe them. E.g., they may think the calculations are too novel or too unreliable. Alternatively, the students may consider the information redundant. E.g., they are already adjusting in response to their actual past grades, so they see no need to adjust further in response to forecast future grades.

This study's second set of contributions concerns the factors that contribute to differences arising between grade goals and actual grades. As expected, students with stronger academic ability tend to have smaller gaps between goals and performance. This fits the implications of previous work (e.g., Kruger & Dunning, 1999; Nowell & Alston, 2007).

More interestingly, students with higher personal control scores tend to have larger performance gaps. As expected, they set higher goals for their grades (Hollenbeck & Brief, 1987; Mitchell et al., 1975; Yukl & Latham, 1978). Unexpectedly, however, they do not achieve higher grades. This contrasts with previous findings on achievement (Findley & Cooper, 1983; Gregory, 1978; Judge & Bono, 2001; Kalechstein & Nowicki, 1997).

While high personal control often is a beneficial trait, in our study it was a disadvantage. This may be because our experiment involved a first-year course where students were adjusting from high school to university, a challenging transition that often leads to a performance drop (Richter, 2006). Like the transition from middle school to high school, it "... involves organizational and policy changes that may challenge children's feelings of competence and perceptions of control. Grading standards are typically higher ..." (Grolnick & Raftery-Helmer, 2015: 267). In this context, students with a high sense of control may interpret feedback and apply strategies in ways that functioned well in high school, but poorly in university. By contrast, students who feel less sense of control may be better off because their more cautious goals are better aligned, either intentionally or inadvertently, with the university environment.

The finding that the students who set their targets too high at the beginning of the course tend to continue setting them too high later in the semester is not surprising. It fits with previous work showing that weaker students are more prone to over-estimate their learning (Kruger & Dunning, 1999; Armstrong, 2013).

It is interesting that the differences between actual and anticipated grades tend to decline as the course progresses. Students initially set their targets too high, but lower than the high school grades to which they were accustomed. They seem to be trying, albeit insufficiently, to compensate for differences between university and high school grading practices. Later in the course, the students narrow the gap between actual and anticipated grades by further reducing their goals (Ramaprasad, 1983). They may also be trying to narrow the gap by increasing their efforts and thus their grades (Butler & Winne, 1995; Nicol & Macfarlane-Dick, 2006) but that effect is not apparent in our data.

We believe our results will particularly interest the instructors and advisors of undergraduate students in first- and second-year required courses. Such courses often have relatively high failure rates, causing students to repeat the courses (Armstrong & Biktimirov, 2013) or leave their programs. These negative outcomes obviously harm retention and graduation rates, which are of increasing concern to university administrators and government officials (e.g., Armario, 2012). If we can help students to set more realistic goals in their courses, and better appreciate how well (or poorly) they are truly progressing, then they may make better decisions and achieve better outcomes.

5.3. Limitations and future research

Our refined path model explains only $R^2 = 13.2\%$ of the variation in students' studying plans. This is not a high value, but we do not see it as a concern. Many factors beyond the scope of the experiment could affect studying intentions. Since we did not change course content, delivery, or assessment, the modest behavioural impact is not surprising.

Our participation rate of 38.6% is better than the 31.0% of Armstrong (2013), but the participation pattern remains a concern. In both studies, the weaker students were less likely to participate, and these are the ones who presumably could benefit most from extra feedback. This tendency may somewhat limit the applicability of our findings, making them more relevant to average and above-average students. Future research therefore should try to increase the representation of weaker students.

Future research could also collect data across multiple degree programs, universities, or countries. This could confirm whether the same behaviours are common for students in general, or instead perhaps differ based on, e.g., national or organizational culture.

Our study found that students do not react to the new information provided by forecasts that differed from their expectations, and that students with higher personal control scores do not achieve higher grades in this context. A future study, perhaps using more detailed surveys or individual interviews, could try to uncover the reasons for these intriguing results.

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Appendix. Personal sphere of control questions from Survey 1

Responses for each question range from 1 (strongly disagree) to 7 (strongly agree)

- a I can usually achieve what I want if I work hard for it.
- b Once I make plans, I am almost certain to make them work.
- c I prefer games involving some luck over games requiring pure skill.
- d I can learn almost anything if I set my mind to it.
- e My major accomplishments are mainly due to my hard work and ability.
- f I usually do not set goals because I have a hard time following through on them.
- g Bad luck has sometimes prevented me from achieving things.
- h Almost anything is possible for me if I really want it.
- i Most of what happens in my career is beyond my control.
- j I find it pointless to keep working on something that's too difficult for me.

Studying question from Survey 2

Responses range from 1 (strongly disagree) to 7 (strongly agree)

- a Now that I have completed this exercise, I plan to increase my studying for this course.

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