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On Analysing Student Resilience in Higher Education Programs using a Data-Driven Approach

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***Abstract*—Analysing student resilience is important as research has shown that resilience is related to students' academic performance and their persistence through academic setbacks. While questionnaires can be conducted to assess student resilience directly, they suffer from human recall errors and deliberate suppression of true responses. In this paper, we propose ACREA, ACademic REsilience Analytics framework which adopts a data-driven approach to analyse student resilient behavior with the use of student-course data. ACREA defines academic setbacks experienced by students and measures how well students overcome such setbacks using a quasi-experimental design. By applying ACREA on a real world student-course dataset, we analyse different types of effects on future term and course performance due to earlier setbacks. We found that setbacks in early academic term significantly affect more subsequent academic results. We also analyse the multiplier and redemption effects due to the resilience-driven behavior. The insights from the analysis contribute to a better understanding of student resilience using their performance after some academic setbacks. When the recovery of post-setback academic performance is not satisfactory, one can consider introducing new measures to strengthen student resilience. Students may also benefit from the findings when they can be better guided to recover from academic setbacks.**

***Keywords*—data-driven framework, academic resilience, quasi-experimental design, pairwise analysis**

I. INTRODUCTION

Motivation. Resilience is a personality trait that enables a person to persist in challenging physical and mental settings. High-resilience individuals have been associated with favorable psychological outcomes, including lower depression risk, greater life satisfaction, and better lifestyle behavior [1]. As such, it has gained much attention across many sectors of study, for example resilience in the workplace [2], [3], academic [4], [5], and also medical [6], [7]. In the academic context, resilience has been shown as an important determinant of academic performance that allows students to persist through and bounce back from academic challenges [8], such as poor performance in specific terms or courses. Moreover, as most students graduating from higher education institutes will enter the job market next, it is utmost important to ensure that they are resilient against the competitive job market as well as stresses and setbacks in their career.

One can measure student resilience by using specially designed questionnaires [9], [10] and user experiments [11], [12]. These traditional approaches have been effective in detecting resilience related personality traits, and determining resilience strengths among students, especially for some academic programs requiring high resilience students, e.g., medical and nursing programs [13]. These measurements have also been effectively used as a proxy of effective learning and academic success in a particular course [14]. As such, many have attempted to investigate factors that influence resilience [15] and to find strategies that strengthen resilience [16].

Nevertheless, past research on student resilience has largely focused on resilience measurement and related-behavior for a small group of individuals. To the best of our knowledge, a large-scaled data-driven approach to study students resilience against academic setbacks has not been attempted. Student and course data, which are easily found in today's databases of schools and universities, capture students' progress and setbacks during their learning journey. To determine if students are coping well with resilience at scale, a data-driven framework to measure and analyse student resilience will be necessary. Unlike the traditional approaches which only focus on a particular group of targeted students (i.e. those who are participating in the surveys or user experiments), our proposed approach allows schools and universities to make use all of their students' academic data to evaluate their resilience related-behavior in wider scope. The insights from such assessment contribute to a better understanding of student resilience and to initiate programs that can strengthen student resilience when the recovery of post-setback academic performance is not satisfactory. Students may also benefit from the findings when they can be better guided to recover from their academic setbacks.

Objectives. In this paper, our research objective is to:

- Introduce ACREA as a data-driven framework to evaluate students' resilience strength in a university program using the academic setbacks the students had experienced. The data-driven approach has advantages to capture actual academic performance, including students' progress and setbacks during their learning journey, and can be conducted in a larger scale to study larger group of students.
- Determine the various research components of the above framework and propose to use quasi-experiments to anal-

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yse academic setbacks and their impact to subsequent terms and courses.
- Conduct data science study on a real world university student-course dataset. We then learn the following findings: (1) as students become more mature, academic setbacks have lesser impact on them, (2) the more severe the setbacks, the harder it is to recover, and (3) setbacks in pre-requisite courses have more negative impact on follow-up courses than non-requisite courses.

Paper Outline. The rest of the paper is organised as follows. Section II presents ACREA framework and details on the input data. Sections III and IV present the fine-grained analysis on the impact of academic setbacks. Section V discusses how ACREA overcomes various threats of validity. Finally, Section VI concludes this study.

II. ACREA Framework

ACREA is developed based on a data-driven approach performed on a student-course dataset. The framework consists of a series of steps to conduct resilience analysis using academic setbacks during the course programs. Instead of conducting a randomized controlled experiment to infer the causal relationship of academic setbacks and students' future academic performance (which is deem to be infeasible in this education scenario), ACREA uses a *quasi-experimental design* (QED) on an observational real world data.

A. Student-Course Dataset

The ACREA framework assumes that a student-course dataset providing detailed observed real world data of multiple cohorts of students and the grades they received from courses throughout their academic programs. Every course has its title, credits and description. We assume that an academic program consists of a series of academic terms: 1 to n_{term}. For each course taken by a student, a grade is given ranging from A+ to F. To analyse the student grades numerically, we map the grades A+, A, A-, B+, B, B-, C+, C, C-, D+, D, and F to 4.3, 4.0, 3.7, 3.3, 3.0, 2.7, 2.3, 2.0, 1.7, 1.3, 1.0, and 0.0 respectively.

When a course c_j has a prerequisite course c_i, we denote their relationship by $c_i \Rightarrow c_j$. To keep the prerequisite relationships simple, we remove redundant prerequisite relationships from the dataset. For example, $c_i \Rightarrow c_k$ is known to be *redundant* if $c_i \Rightarrow c_j$ and $c_j \Rightarrow c_k$ already exist and should be removed.

We formally represent a student s_i's course data as a set of (s_i, c, t) tuples that represents course c taken by student s_i in term t. The grade in numeric value received by student s_i for course c in term t is denoted by $g(s_i, c, t)$. When s_i took the same course c more than once in different terms, we will use only the grade result of c in the earliest term, and remove the latter grade record(s).

Data preprocessing. We remove student outliers including those who join in the middle of program (e.g., students switching from one program to another, incoming visiting

TABLE I
DATASET STATISTICS

Cohort	Computing Program		Business Program	
	#students	n_{term}	#students	n_{term}
1	273	8	694	8
2	273	8	745	8
3	258	8	740	8
4	261	8	708	8
5	269	8	756	8
6	270	8	751	8
7	304	6	740	6
8	405	4	779	4
9	489	2	831	2

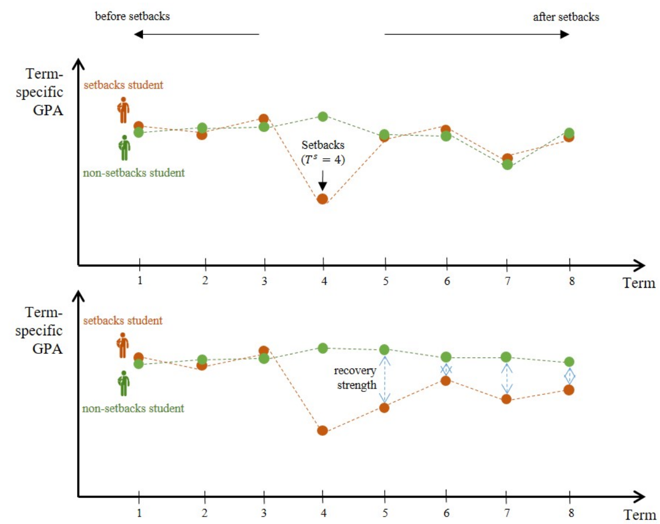

Fig. 1. Concept for matching setbacks and non-setbacks students to measure recovery strength: top figure illustrates setbacks student is able to recover after setbacks, while bottom figure illustrates the opposite

students), and those who stay beyond the expected number of academic terms.

To illustrate the ACREA framework in the remaining parts of the paper, we use a student-course dataset from an autonomous university in Asia. This dataset covers 9 cohorts of students, where the recorded academic data used is between mid of 2011 until mid of 2020. This includes 2,802 students from Computing undergraduate program and 6,744 students from Business undergraduate program as summarized in Table I. Both programs require 8 terms for students to graduate. Cohorts 7 to 9 however involve fewer terms as students from these cohorts have not yet completed their programs. Subsequently, the recovery strength of the setbacks students is measured based on the future terms / courses performance difference against the non-setbacks students, as illustrated in Figure 1. Finally, we define several metrics, as presented in Sections III-A and IV, to perform fine-grained analysis on the outcome measurements.

B. Term-Specific Setbacks

We introduce **term-specific setback** in term T^s to be the first academic setback a student had experienced in the term.

An *academic setback* is the event when a student receives a poor grade. In our experiment, we use 'C' to be the grade threshold[1]. A student receiving 'C' or below will be regarded as experiencing an academic setback. We care about the first term with setback because it ensures that the setback is not the effect of another earlier setback.

When a student encounters a term-specific setback, we anticipate that the setback may affect his or her future term's academic performance. If the setback propagates to the subsequent terms, we may observe poorer grades in these terms. On the other hand, it may also happen that the student instead "recovers" from the setback and demonstrates his or her resilience.

Nevertheless, such "observed" recovery may not be correctly determined unless the future term performance of students with term-specific setback is compared against other students without the same term-specific setback. Following the QED, we perform **pairwise comparison** pair evaluation on s_i, a student experiencing term-specific setback in term T^s, with another student s_i' who is not experiencing term-specific setback in term T^s. s_i and s_i' are expected to be similar before s_i experiences setback in T_s. We then evaluate s_i's performance in term T^s+k ($k \geq 1$ and $T^s+k \leq n_{term}$), against that of s_i'. If the former is lower than latter with statistical significance, we may conclude the negative impact of setback in term T^s to the performance in term T^s+k. To conduct this analysis, we define several recovery strength metrics in Section III-A.

We also determine s_i and s_i' to be similar by:

- *Cohort matching*: s_i and s_i' belonging to the same cohort.
- *Course credits matching*: s_i and s_i' take equal course credits at T^s.
- *Comparable historical performance*: s_i and s_i' having similar historical academic performance: they registered equal number of course credits and have not more than one letter grade level difference in cumulative GPA (grade point average) up to T^s-1. To have at least one term for implementing this matching criteria, T^s is restricted to be $2 \leq T^s \leq (n_{term}-1)$.

Table II shows the distribution of (s_i, s_i') student pairs over different T^s's. We observe that most students experienced their first setbacks in their second term, i.e., $T^s = 2$. This may be attributed to several possible reasons, including more intellectually challenging terms in the first year than later years, and fewer students already experiencing their first setbacks in the later terms. The former is supported by 387 Computing students (or 29% of all Computing students) and 648 Business students (or 13% of all Business students).

Unless stated otherwise, we use a *minimum support* of 10 matched student pairs in our subsequent analysis. Hence, we rule out the term-specific setback of Computing students in $T^s = \{6,7\}$ which involves only 8 and 1 student pairs.

[1]Another lower threshold could also be used but it will result in fewer students involved in setbacks.

TABLE II
DISTRIBUTION OF (s_i, s_i') PAIRS FOR DIFFERENT T^s'S

T^s	Computing Program		Business Program	
	Students with setbacks	Matched (s_i, s_i') pairs	Students with setbacks	Matched (s_i, s_i') pairs
2	387 (29%)	319	648 (13%)	607
3	50 (5%)	32	473 (11%)	436
4	55 (8%)	43	239 (7%)	213
5	21 (4%)	14	88 (3%)	71
6	11 (3%)	8	43 (3%)	32
7	6 (3%)	1	35 (3%)	26

C. Course-Specific Setbacks

A course-specific setback in a course c is an academic setback a student experienced when he or she completed the course c. Here, we adopt the same academic setback definition given in Section II-B.

Following a QED approach, we analyse the effects of course-specific setbacks by identifying for a given course c, the set of students who had experienced academic setback in course c and proceeded to complete another course c' in some future term. We pair each of these students with another similar student who completed course c without setbacks and also went on to complete course c'. When among the matched student pairs (s_i, s_i')'s, the grade received by student s_i in course c' is worse than that received by student s_i' in course c', we may conclude the negative impact of course-specific setbacks of c on c'.

Here, we determine s_i and s_i' to be similar by:

- *Cohort matching*: s_i and s_i' belonging to the same cohort.
- *Course credits matching*: s_i and s_i' take equal course credits when taking course c.
- *Course completion order compliance ($c \rightarrow c'$)*: both s_i and s_i' completed c before c'.
- *Comparable historical performance*: s_i and s_i' having similar historical academic performance before taking course c: they registered equal number of course credits and have not more than one letter grade level difference in cumulative GPA before taking course c. To have at least some courses for implementing this matching criteria, c is restricted to be taken in term 2 to $n_{term}-1$.

Instead of considering all $c \rightarrow c'$ course completion order pairs, we also restrict our analysis to course pairs with prerequisite relationships and course pairs with implicit order relationships. The former are $c \rightarrow c'$ such that c is the prerequisite of c'. The latter are those with sufficient support, i.e., having at least 500 student pairs taking c before c'.

We say that a student experiences a **course-specific setback** in course c if the student receives a grade that is below majority of the other students taking the course c. Let μ_c and σ_c denote the mean and standard deviation of grades received by students in course c. A grade is below majority if $g(s,c,t) < \mu_c + z \times \sigma_c$, where z is the cutoff point where k% of the population lies below it. For k =5%, $z = -1.645$. With this definition, we observe that most of the grade setback threshold lies around C-, C, C+ for both Computing and Business programs, which

TABLE III

TOP COURSE PAIRS WITH MOST NUMBER OF STUDENTS WITH COURSE-SPECIFIC SETBACKS ON c (COURSE TITLES ARE ABBREVIATED.)

Type	$c \rightarrow c'$	Students with setback on c	(s_i, s_i') pairs
Computing Program			
Prereq	Process Model. $\rightarrow$ Ent. Integration	125	90
	OOAD $\rightarrow$ S/w Engineering	97	78
	OOAD $\rightarrow$ Ent. Integration	95	73
	S/w Engineering $\rightarrow$ IS Appln. Proj.	61	45
	Data Mgt. $\rightarrow$ Process Model.	55	36
Implicit order	Process Model. $\rightarrow$ Interact. Design	126	74
	Process Model. $\rightarrow$ IS Appln. Proj.	124	72
	Process Model. $\rightarrow$ Info. Security	117	75
	Info. Security $\rightarrow$ IS Appln. Proj.	99	53
	OOAD $\rightarrow$ Process Model.	96	76
Business Program			
Prereq	Strategy $\rightarrow$ Business Capstone	180	130
	Marketing $\rightarrow$ Cons. Behavior	165	117
	Marketing $\rightarrow$ Marketing Research	136	84
	Operations Mgt. $\rightarrow$ Svc. Processes	82	56
	Operations Mgt. $\rightarrow$ Sup. Ch. Mgt.	75	47
Implicit order	Marketing $\rightarrow$ Strategy	340	203
	Marketing $\rightarrow$ Spreadsheet Model.	296	193
	Marketing $\rightarrow$ Operations Mgt.	267	177
	Mgt. Accounting $\rightarrow$ Strategy	266	112
	Marketing $\rightarrow$ Mgt. Accounting	257	173

is close to the grade threshold used in Section II-B. Courses with unrealistically high grade threshold, e.g., A or B, due to very few students completing them, are excluded from our analysis.

In our dataset, we observe a total of 51 and 40 $c \rightarrow c'$ course pairs with prerequisite relationships for Computing program and Business program, respectively, with course-specific setbacks in c. There are also 157 and 363 $c \rightarrow c'$ course pairs with implicit order for Computing program and Business program, respectively with course-specific setback in c. Table III summarizes the top $c \rightarrow c'$ course pairs with course-specific setbacks on c. The table shows that OOAD and Process Model. are two courses that may affect several other courses under the Computing program when students experiences course-specific setbacks in the two courses. For Business program, Marketing and Operation Mgt are the two courses that may affect other courses. For each $c \rightarrow c'$ pair with course-specific setback on c, we subsequently develop metrics to measure course-specific setbacks in Section IV.

III. TERM-SPECIFIC SETBACKS ANALYSIS

A. Recovery Strength Metrics

We derive the following metrics to evaluate the impact of term-specific setbacks.

Overall recovery strength (ORS). This metric evaluates s_i general ability to recover after experiencing a term-specific setback in term T^s. It measures s_i future performance difference compared to s_i' in all terms ahead simultaneously. Formally, ORS is defined by:

$$ORS(s_i, s_i', T^s) = cGPA(s_i, [T^s+1, n_{term}]) - cGPA(s_i', [T^s+1, n_{term}]) \quad (1)$$

TABLE IV

OVERALL RECOVERY AFTER TERM-SPECIFIC SETBACKS

T^s	Computing Program		Business Program	
	#pairs	P-value(confidence interval)	#pairs	P-value(confidence interval)
2	319	p=0.000(-0.278, -0.195)	607	p=0.000(-0.25, -0.19)
3	32	p=0.011(-0.337, -0.034)	436	p=0.000(-0.188, -0.124)
4	43	p=0.000(-0.35, -0.127)	213	p=0.000(-0.206, -0.108)
5	14	p=0.542(-0.18, 0.162)	71	p=0.015(-0.191, -0.02)
6	8	-	32	p=0.015(-0.32, -0.037)
7	1	-	26	p=0.354(-0.317, 0.117)

where $cGPA(s, [T^s+1, n_{term}])$ is student s's cumulative GPA from terms T^s+1 to n_{term}. The cumulative GPA is computed by averaging course grades weighted by course credits for all courses taken by student s from target term T^s+1 to term n_{term}.

Term recovery strength (TRS). This metric evaluates a student s_i's *recovery strength* in term T^s+k after a term-specific setback in term T^s compared with student s_i' who did not have term-specific setback. Formally, TRS is defined by:

$$TRS(s_i, s_i', T^s+k) = termGPA(s_i, T^s+k) - termGPA(s_i', T^s+k) \quad (2)$$

where $termGPA(s,t)$ is student s's GPA at term t. For example, $TRS(s_i, s_i', 5) = -0.5$ indicates that s_i performs worse than s_i' about two letter grade levels in term 5 (say, $termGPA(s_i, 5) = B-$ and $termGPA(s_i', 5) = B+$). We then perform statistical tests on ORS and TRS of (s_i, s_i') pairs to determine if s_i performs significantly worse than s_i' in future terms or in term T^s+k. This will allow us to assess both overall effect and term-effect of term-specific setbacks.

B. Overall Recovery after Term-Specific Setbacks

We first present our findings on the overall performance recovery of students after term-specific setbacks. Given a setback term T^s, we analyse the ORS of student pairs defined in Equation 1 and conduct a statistical test. Table IV shows the results for both Computing and Business programs with different setback term T^s. It shows that most confidence intervals of ORS values fall within the negative range (as highlighted in yellow) except for $T^s = 5$ and $T^s = 7$ for Computing and Business programs respectively. This indicates that there are long-term negative performance impact for students experiencing term-specific setbacks. Moreover, the small P-values show that this findings is generally significant. As the above findings however does not focus on the amount of impact a term-specific setback caused to the different upcoming terms, we conduct the next analysis on specific future terms.

C. Term Recovery after Term-Specific Setbacks

Given the above findings that term-specific setbacks have long term effect, our intuition suggests that a term-specific setback should have stronger impact to the next term than to the much later terms. This means that performance recovery should be harder in the near-by terms than in the later terms. Hence, we next analyse the term GPA in each future term

TABLE V
MULTIPLIER EFFECT ANALYSIS

c^s	Computing Program			
	$T^s = 2$			
	#students/#pairs	P-value(CI)		
1	282/238	p=0.000(-0.241, -0.153)		
2	68/55	p=0.027(-0.35, -0.018)		
3	30/23	p=0.004(-0.31, -0.071)		
c^s	Business Program			
	$T^s = 2$		$T^s = 3$	
	#students/#pairs	P-value(CI)	#students/#pairs	P-value(CI)
1	519/491	p=0.000(-0.223, -0.157)	388/357	p=0.000(-0.182, -0.109)
2	101/91	p=0.000(-0.398, -0.22)	73/68	p=0.000(-0.268, -0.124)
3	25/23	p=0.000(-0.754, -0.366)	11/10	p=0.037(-0.386, -0.012)

*CI = confidence interval

TABLE VI
REDEMPTION EFFECT ANALYSIS

$g(T^s)$	Computing Program			
	$T^s = 2$			
	#students/#pairs	P-value(CI)		
C	192/158	p=0.000(-0.323, -0.204)		
C-	126/106	p=0.000(-0.296, -0.163)		
D+	116/89	p=0.000(-0.371, -0.188)		
D	27/20	p=0.000(-0.593, -0.234)		
F	25/17	p=0.000(-0.798, -0.341)		
$g(T^s)$	Business Program			
	$T^s = 2$		$T^s = 3$	
	#students/#pairs	P-value(CI)	#students/#pairs	P-value(CI)
C	362/340	p=0.000(-0.2, -0.122)	292/271	p=0.000(-0.174, -0.095)
C-	197/179	p=0.000(-0.319, -0.209)	133/126	p=0.000(-0.243, -0.129)
D+	131/122	p=0.000(-0.425, -0.293)	90/83	p=0.000(-0.271, -0.128)
D	52/47	p=0.000(-0.566, -0.288)	24/19	p=0.008(-0.465, -0.056)
F	15/14	p=0.000(-0.646, -0.238)	0/0	-

*CI = confidence interval

$T^s + k$ of students experiencing setback in term T^s against students without setback using Equation 2.

Figure 2 summarizes the term impact of term-specific setbacks. The two points shown for each term t (between 3 and 8) shows upper and lower ends of the confidence interval of term GPA difference indicating the impact of setbacks in term T^s on term $t = T^s + k$. The number in parentheses indicates the number of student pairs involved in the analysis. The results show that in both Computing and Business programs, term-specific setbacks in $T^s = 2$ have negative performance impact to much later terms. Specifically, once students experienced setbacks in $T^s = 2$, they were unlikely to perform well in any future term. We further show the term recovery strength for setbacks in term $T^s = 3$ for Business students as it shows poor term recovery in all future terms. For Computing students, this setbacks only significantly affect terms 4 and 8 which therefore we leave out from the illustration. This shows that Computing students may exhibit greater future term grade recovery than Business students. To understand what had contributed to this difference, we shall leave it to our future work that involves a user study evaluation.

D. Multiplier Effect of Term-Specific Setbacks

Next, we analyse performance recovery after term-specific setbacks of different degree. We measure the *degree of term-specific setbacks* by the number of courses in term T^s that a student receives poor grades, as denoted by $c(T^s)$. The distribution of students with different $c(T^s)$ values is summarized in Table V. We observe that most students have $c(T^s) = 1$, i.e., they experienced setbacks in only one course. Subsequently, for any student pairs (s_i, s'_i) found in every $c^s(T^s)$, we calculate ORS, their future performance differences, using Equation (1), and perform a statistical test on the differences.

Due to limited student pairs for analysis, we only show the analysis results for $T^s = 2$ for both Computing and Business programs, and $T^s = 3$ for Business program only. As depicted in Table V, we observe that for a given T^s, the confidence interval of term-GPA difference shifts towards negative direction, indicating that higher degree of term-specific setbacks contribute to more negative impact to the overall future performance. In other words, students suffering from more poor grades in the early terms found it harder to recover and may thus give up.

E. Redemption Effect of Term-Specific Setbacks

Finally, we analyse the impact of term-specific setbacks based on a poor grade at different levels instead of number of courses receiving a poor grade. Let $g(T^s)$ denote a letter grade at term T^s and $g(T^s) \leq$ 'C'. We first present the distribution of students receiving grade of $g(T^s)$ or lower for at least one course in term T^s, and the corresponding student pairs for quasi-experiment analysis in Table VI. As the number of student pairs for several T^s are too few for this analysis, we will focus on $T^s = 2$ for Computing students, and $T^s = 2$ and 3 for for Business students.

Among the different $g(T^s)$ grades, the most popular $g(T^s)$ among students is 'C', and the popularity decreases as we go down the lower grades. This distribution of students and student pairs is reasonable as we expect fewer students to receive lower grades. For each $g(T^s)$, we examine the impact using ORS in Equation (1).

As shown in Table VI, there appears to be a small redemption effect for Computing students with $g(T^s)$='C-' compared with those with $g(T^s)$ ='C' as the confidence interval shifts upwards from $(-0.323, -0.204)$ to $(-0.296, -0.163)$. For other $g(T^s)$ values, there is no redemption effect from the students. It seems that the students are not able to redeem themselves from any poor grades in general. This findings is interesting and consistent with the multiplier effect results. It suggests that students require more assistance in the early stage of the academic program to redeem themselves.

IV. COURSE-SPECIFIC SETBACKS ANALYSIS

Recovery Strength Metrics. We use **course recovery strength (CRS)** to evaluate s_i recover ability in course c' after experiencing setbacks in course c. It measures the performance difference in course c' between a setback student s_i and non-setback student s'_i in c such that c is completed before c', i.e., $c \rightarrow c'$. Formally, CRS is defined as:

$$CRS(s_i, s'_i, c \rightarrow c') = g(s_i, c', t) - g(s'_i, c', t') \quad (3)$$

where t and t' are the terms s_i and s'_i completed c' respectively.

Analysis of Course Relationship Effect. We determine if two types of course relationships could affect students' performance recovery, namely: *prerequisite relationship* and *implicit*

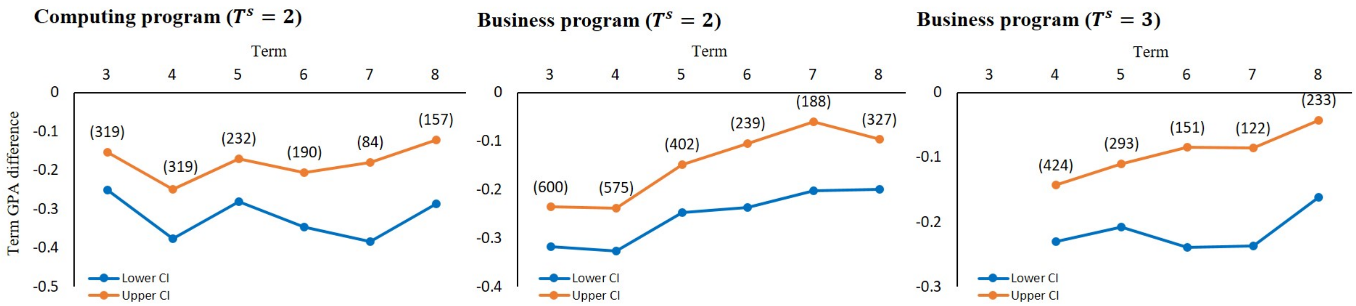

Fig. 2. Term Recovery in term $t = T^s + k$ after Term-Specific Setbacks in $T^s = 2$ and $T^s = 3$

TABLE VII
COURSE-SPECIFIC EFFECT

	Computing Program		Business Program	
	Prereq	Implicit order	Prereq	Implicit order
$c \to c'$ pairs ≥ 10	15	129	19	304
Pairs with $-$ve diff.	7 (46.7%)	42 (32.6%)	9 (47.4%)	138 (45.4%)

order relationship, as defined in Section II-C. Intuition says that setback in a prerequisite course should make a student harder to recover in the course that has it as the prerequisite. We then used Equation (3) to measure how well s_i students are able to recover in course c' after experiencing setbacks in course c.

Out of 51 and 40 course pairs with prerequisite relationships on Computing and Business programs respectively, we derive 15 and 19 course pairs with sufficient student pairs for analysis. Similarly, we obtain 129 and 304 course pairs with implicit order relationships. Note that the prerequisite and implicit order relationships are mutually disjoint. Table VII shows that prerequisite relationship shows more significant negative effect than implicit order relationship, although the effect size is smaller for Business program.

Interestingly, the results also show that there are non-negligible proportions of course prerequisite relationships that do not see the negative performance effect of course-specific setbacks. This suggests that students may be able to easily catch up their performance in these cases.

V. DISCUSSION

As ACREA uses a QED from the observational data, we need to address the systematic bias due to the confounding variables that are threats to a causal conclusion [17]. We hereby discuss how the validity threats [18], [19] are addressed in ACREA.

Construct validity. This refers to the confidence in metrics used to measure the targeted variables (i.e. recovery strength). The threat can be caused by the different of difficulty levels over terms / courses that may lead to a false conclusion when measuring students' recovery strength by direct comparison between his pre- and post-setbacks performances. ACREA measures the setbacks effect based on the performance difference between two groups, setback students (treatment group) and non-setback students (control group), in the same target term / course. It ensures a fair measurement by exploiting specific characteristic of the target term / course to establish the causal relationship.

Internal validity. This refers to the confidence that the causal relationship established in the study is credible and trustworthy. For example, without any proper control, our analysis may select the non-setback students to be academically stronger students and hence leading us to wrongly conclude the negative effect of setbacks. Here, in our ACREA framework, we match two students who were initially have similar performances before setback term T^s before analysing their performances in the future target term / course. It eliminates the possible discrimination caused by the above-mentioned issues. We also consider other matching criteria (see Sections II-B and II-C) to better eliminate confounding variables.

Statistical conclusion validity. This refers to the confidence in the statistical methods used to establish the causal relationship. One of the threats is adopting the wrong statistical test assumptions for small data samples [20]. We mitigate this by not assuming that the data follows a specific distribution. Instead, we adopt the non-parametric test (i.e. Wilcoxon) in our analysis.

External validity. This refers to the confidence in generalisation of the established causal relationship. To address this external validity, we replicate our analysis on two academic programs, Computing and Business programs, and show the consistency in the findings derived from each program.

VI. CONCLUSION AND FUTURE RESEARCH

This paper introduces ACREA as a framework to analyse students resilience using a data-driven approach. While resilience is often measured by using specially designed questionnaires, ACREA uses student-course data as input as it captures actual academic performance. ACREA can be used to analyse term-specific setbacks and course-specific setbacks with newly proposed metrics and student pairing to address confounding factors.

By applying ACREA framework on a real world student-course dataset, we are able to derive interesting findings, including: (1) students show different recovery strength depending on the term in which setbacks occur; (2) students have different recovery strengths depending on the severity of the setbacks they experienced; and (3) setbacks in pre-requisite courses have more negative impact on follow-up courses than non-requisite courses. It should be noted that these findings might be limited to the dataset-specific observation and thus, not meant to be generalised in all situations. Instead, we show that ACREA can be adopted by other academic institutions when the student-course data are available, with regard to the personal data protection regulations whenever applies, to derive some insights on their students' resilience related-behavior. It is then can be used to initiate programs that promote student resilience, especially when the recovery of post-setback academic performance is not satisfactory.

As part of future work, we will extend ACREA to determine the underlying factors that explain the discovered findings. This could be an extended user study that allows us to combine students' feedback and course performance data in the analysis. Furthermore, the use of intelligent method, such as to learn students' feedback (i.e. the measured resilience) to predict their academic performance, is yet to explore. Such approach can be used to further analyse student resilience-related behavior and examine its relationship towards academic performance. This will hopefully improve the design of higher-education curriculum in the long term.

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References

[1] S. MacLeod, S. Musich, K. Hawkins, K. Alsgaard, and E. R. Wicker, "The impact of resilience among older adults," *Geriatric Nursing*, vol. 37, no. 4, pp. 266–272, 2016.

[2] P. C. Winwood, R. Colon, and K. McEwen, "A practical measure of workplace resilience: Developing the resilience at work scale," *Journal of occupational and environmental medicine*, vol. 55, no. 10, pp. 1205–1212, 2013.

[3] S. Hartmann, M. Weiss, A. Newman, and M. Hoegl, "Resilience in the workplace: A multilevel review and synthesis," *Applied Psychology*, vol. 69, no. 3, pp. 913–959, 2020.

[4] M. T. Hartley, "Investigating the relationship of resilience to academic persistence in college students with mental health issues," *Rehabilitation Counseling Bulletin*, vol. 56, no. 4, pp. 240–250, 2013.

[5] T. L. Hanson, G. Austin, and J. Lee-Bayha, "Student health risks, resilience, and academic performance," *Los Alamitos, CA: WestEd*, 2003.

[6] N. McKinley, P. N. Karayiannis, L. Convie, M. Clarke, S. J. Kirk, and W. J. Campbell, "Resilience in medical doctors: a systematic review," *Postgraduate medical journal*, vol. 95, no. 1121, pp. 140–147, 2019.

[7] M. Mealer, J. Jones, J. Newman, K. K. McFann, B. Rothbaum, and M. Moss, "The presence of resilience is associated with a healthier psychological profile in intensive care unit (icu) nurses: results of a national survey," *International journal of nursing studies*, vol. 49, no. 3, pp. 292–299, 2012.

[8] D. Eisenberg, S. K. Lipson, and J. Posselt, "Promoting resilience, retention, and mental health," *New Directions for Student Services*, vol. 2016, no. 156, pp. 87–95, 2016.

[9] S. Cassidy, "The academic resilience scale (ars-30): A new multidimensional construct measure," *Frontiers in psychology*, vol. 7, p. 1787, 2016.

[10] M. Turner, S. Holdsworth, and C. M. Scott-Young, "Resilience at university: The development and testing of a new measure," *Higher education research & development*, vol. 36, no. 2, pp. 386–400, 2017.

[11] D. S. Yeager and C. S. Dweck, "Mindsets that promote resilience: When students believe that personal characteristics can be developed," *Educational psychologist*, vol. 47, no. 4, pp. 302–314, 2012.

[12] L. I. Mayor-Silva, M. Romero-Saldaña, A. G. Moreno-Pimentel, Á. Álvarez-Melcón, R. Molina-Luque, and A. Meneses-Monroy, "The role of psychological variables in improving resilience: Comparison of an online intervention with a face-to-face intervention. a randomised controlled clinical trial in students of health sciences," *Nurse education today*, vol. 99, p. 104778, 2021.

[13] J. C. Houpy, W. W. Lee, J. N. Woodruff, and A. T. Pincavage, "Medical student resilience and stressful clinical events during clinical training," *Medical Education Online*, vol. 22, no. 1, p. 1320187, 2017.

[14] T. Prickett, J. Walters, L. Yang, M. Harvey, and T. Crick, "Resilience and effective learning in first-year undergraduate computer science," in *Proceedings of the 2020 ACM Conference on Innovation and Technology in Computer Science Education*. Association for Computing Machinery, 2020, pp. 19–25.

[15] A. Robbins, E. Kaye, and J. Catling, "Predictors of student resilience in higher education." *Psychology Teaching Review*, vol. 24, no. 1, pp. 44–52, 2018.

[16] J.-E. Russell, A. Smith, and R. Larsen, "Elements of success: Supporting at-risk student resilience through learning analytics," *Computers & Education*, p. 103890, 2020.

[17] S. S. Krishnan and R. K. Sitaraman, "Video stream quality impacts viewer behavior: inferring causality using quasi-experimental designs," *IEEE/ACM Transactions on Networking*, vol. 21, no. 6, pp. 2001–2014, 2013.

[18] H. Oktay, B. J. Taylor, and D. D. Jensen, "Causal discovery in social media using quasi-experimental designs," in *Proceedings of the First Workshop on Social Media Analytics*. Association for Computing Machinery, 2010, pp. 1–9.

[19] W. R. Shadish, T. D. Cook, and D. T. Campbell, *Experimental and quasi-experimental designs for generalized causal inference*. Houghton Mifflin Boston, MA, 2002.

[20] M. A. García-Pérez, "Statistical conclusion validity: Some common threats and simple remedies," *Frontiers in psychology*, vol. 3, p. 325, 2012.