On Unraveling Student Resilience and Academic Performance in Higher Education

Aldy Gunawan[1][a], Lim Ee-Peng[1][b], Audrey Tedja Widjaja[1], William Tov[2][c], James Foo[3][d] and Lieven Demeester[4]

[1]*School of Computing and Information Systems, Singapore Management University, 80 Stamford Road, Singapore*

[2]*School of Social Science, Singapore Management University, 10 Canning Rise, Singapore, Singapore*

[3]*Centre for Teaching Excellence, Singapore Management University, 81 Victoria Street, Singapore, Singapore*

[4]*Lee Kong Chian School of Business, Singapore Management University, 50 Stamford Road, Singapore, Singapore*

{*aldygunawan, eplim, audreyw, willliamtov, jamesfoo, ldemeester*}*@smu.edu.edu*

Keywords: Resilience, Learning Experience, Academic Performance, User Study, Prediction Model.

Abstract: The transition period from pre-tertiary to higher education levels is critical. We explore the role of resilience by conducting a survey to investigate students' resilience and the relationship with overall academic performance, learning experience, and well-being. This effort is part of an initiative to develop strategies for better student engagement in the academic program, enhance their resilience, and prepare them for a competitive job market. We conclude that (i) high-resilience students are associated with better life satisfaction and are likely to perform well academically, (ii) a favorable learning environment supports students to study and perform well in the university, and (iii) academic program experience can contribute to students' resilience. Additionally, we demonstrate that a grade prediction model, developed using students' historical performance, resilience strength, learning experiences, and well-being, can accurately forecast their overall academic performance, with an average prediction error as low as one letter grade difference from the actual grades.

1 INTRODUCTION

Students transitioning from pre-tertiary to higher education levels face various new challenges that come along with a very different academic environment and greater emphasis of both breadth and depth of knowledge. How a student responds to these academic challenges can be estimated through their resilience (Pathak and Lata, 2018). Resilience is defined as the capacity to show successful adaptation despite challenging circumstances, such as stressful events or adversity (Wu et al., 2013). In the academic context, it allows students to adapt to university life and to persist through academic challenges (Eisenberg et al., 2016). Most of the academic community believes that resilient students demonstrate knowledge proficiency and often perform well on assessments (Crawford-Garrett, 2018).

To evaluate the impact of resilience on academic results, previous research has focused on first-year student grades as measured academic results (Prickett et al., 2020). While those are indeed more directly related to the academic transition from pre-tertiary to higher educations, little is known about the resilience's impact on longer-term academic outcomes. Therefore, understanding our students' resilience strength and providing initiatives to further promote their resilience, so as to help them make good progress in their studies and to produce high-quality graduates are important. As resilience is believed to be positively associated with favorable psychological outcomes (i.e. lower risk of depression, greater life satisfaction, and better lifestyle behavior) (MacLeod et al., 2016), understanding resilience is important to strengthen their subjective well-being.

We investigate factors that influence undergraduate student success, measured by the grade point average (GPA). We avoid using self-reported academic success, which often involves subjective judgement. Rather than limiting ourselves to the grades obtained in the first-year academic study (Prickett et al., 2020), we focus more on the overall GPA of the students, as it is seen as the measure of student success in higher

[a] https://orcid.org/0000-0003-0697-8619
[b] https://orcid.org/0000-0003-0065-8665
[c] https://orcid.org/0000-0002-4306-8860
[d] https://orcid.org/0009-0007-0878-286X

Gunawan, A., Lim, E.-P., Widjaja, A. T., Tov, W., Foo, J. and Demeester, L.
On Unraveling Student Resilience and Academic Performance in Higher Education.
DOI: 10.5220/0013197500003932

In *Proceedings of the 17th International Conference on Computer Supported Education (CSEDU 2025) - Volume 2*, pages 208-215
ISBN: 978-989-758-746-7; ISSN: 2184-5026

education programs (York et al., 2015). Furthermore, as university students are likely to spend more time in their own academic program, student experience has been shown to positively correlate with their intention to persevere in the major (Barker et al., 2014). In addition, we assess the relationship between student experience and academic success.

We summarize the key novelties of our work here. Firstly, we analyze the relationship between (i) student resilience and academic performance, (ii) student resilience and their subjective well-being, and (iii) student experience and academic performance across different terms. Secondly, we use students' *actual grades* (i.e. extracted from their transcript data) as the measure of academic performance to improve both accuracy and efficiency of measurement, instead of subjective ratings (i.e. perceived performance or opinion) (Rodríguez-Fernández et al., 2018). Thirdly, we build a grade prediction model to predict students' overall academic performance based on their historical performance, resilience, experience, and well-being. The model can also be used to analyse importance of factors that affect students' overall academic performance. Lastly, we show (i) a positive correlation between resilience and academic performance, (ii) a positive correlation between resilience and students' well-being, (iii) favorable environment supports good learning and academic performance in the university, and (iv) good academic program experience can contribute to students' resilience.

2 RELATED WORK

Several studies have focused on linking resilience with academic performance. The positive association between students' resilience and academic performance was also found in (Allan et al., 2014). (Prickett et al., 2020) evaluated the relationship between students' resilience and academic performance. While the above works used student's actual grade as the measure of academic performance, there are other research works using different measurements, such as the quotient between the number of recognized academic ECTS (European Credit Transfer System) and the number of registered ECTS of first-year students (Ayala and Manzano, 2018), and the score of three assessment items (Kwek et al., 2013).

The education research community has always been interested in predicting students' academic performance. Academic performance prediction can take many forms, including the prediction of course grades (Okubo et al., 2017), prediction of term-specific course grades (Widjaja et al., 2020), and the cumulative GPA in the last term (Asif et al., 2017).

3 OUR STUDY DESIGN

To determine the relationship between students' resilience and their overall academic performance, we distributed questionnaires that assessed students' general and academic resilience, well-being, and sentiments regarding their academic program. We also requested participants to share their most recent academic transcript.

We surveyed undergraduate students from the Computing and Business schools of a university in Asia from four cohorts (Academic Years (AYs) 2017 to 2020). A web-based user study interface has been specially developed to minimize the effort required for study participation. Our study consists of five main steps (Figure 1). Step 1 collects the student profile information and their latest academic transcripts

In Step 2, the study requires students to complete *Nicholson McBride Resilience Questionnaire (NMRQ)* that measures their general resilience scores. NMRQ (Clarke and Nicholson, 2010) measures resilience strength using 12 statements on the five-point likert scale from "strongly disagree (1)" to "strongly agree (5)". A high (or low) score indicates high (or low) resilience. As high-resilience individuals could experience better life satisfaction (Abolghasemi and Varaniyab, 2010), we also include a *Overall well-being* questionnaire to measure overall well-being of students in Step 3 (Stephen et al., 2013) that comprises two survey items (VanderWeele et al., 2020): 1) Item 1 (Overall, how satisfied are you with your life as a whole these days?) and 2) Item 2 (Overall, to what extent do you feel the things you do in life are worthwhile?). The agreement towards each statement is expressed in a 0 to 10 likert scale score where 0 means "not at all" (or worst well-being) and 10 means "completely" (or best well-being).

In Step 4, the study measures students' resilience in the academic context using *Academic Resilience Scale-30 (ARS-30)*. We used both NMRQ and ARS-30 resilience measurements to investigate the relationship between student's resilience and his/her academic performance. ARS-30 (Cassidy, 2016) measures academic resilience based on students' adaptive cognitive-affective and behavioral responses towards academic adversity. The ARS-30 survey consists of 30 items categorized under three factors (i.e., "Perseverance", "Reflecting and adaptive-help-seeking", and "Negative affect and emotional response") and each item is answered on the five-point likert scale

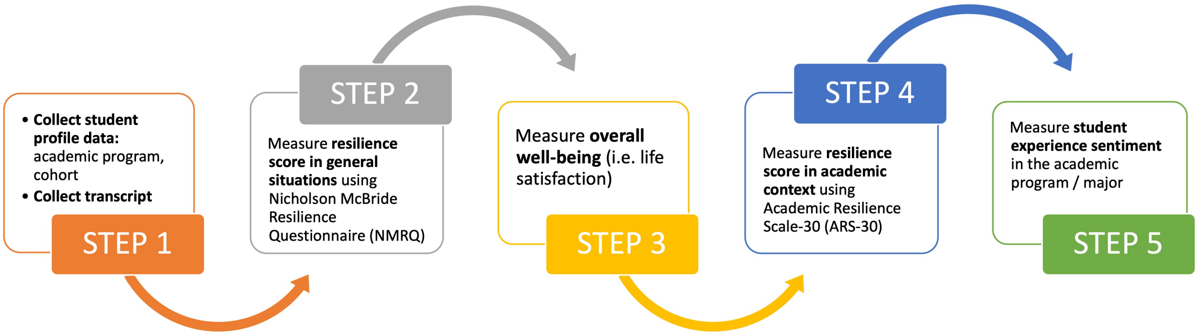

Figure 1: Methodology.

from "likely (1)" to "unlikely (5)". To compute the overall ARS-30 resilience score, we reverse the scores of positively phrased items and sum the scores of all items together. A high overall score indicates high resilience. ARS-30 consists of three factors (Cassidy, 2016), namely:

- *Perseverance*: This factor reflects hard work and trying, not giving up, sticking to plans and goals, accepting and utilising feedback, imaginative problem solving, and treating adversity as an opportunity to meet challenges and improve as central themes.
- *Reflecting and adaptive-help-seeking*: This factor includes reflecting on strengths and weaknesses, adjusting study approaches, seeking help, support, and encouragement, monitoring effort and achievements, and administering rewards and consequences.
- *Negative affect and emotional response*: This factor includes anxiety, catastrophizing, avoiding negative emotional responses, pessimism. If a student has a low score in this factor, it shows setbacks have a negative effect on him/her.

Finally, Step 5 of the study considers students' external environment. It measures student experience in the academic program as students' perceptions towards school environment. We adopt the *Student Experience of the Major* questionnaire (NCWIT, 2021). It evaluates 10 dimensions of a student's academic and social experiences within their academic program or major. There are 65 items are from the original SEM (NCWIT, 2021) and the remaining six items are newly added by modifying two original SEM items to measure the availability of social support in the academic program. We list the newly added items in Table 1 and the respective original SEM items.

The measurement adopts a four-point scale of 1 to 4, where the higher score corresponds to more positive experience sentiment. The overall experience

Table 1: Newly added SEM items.

Original SEM item (NCWIT, 2021)	New SEM item derived from the original SEM item
The **TAs** for my courses or labs are good at helping me learn	The **students in my class** are good at helping me learn
	Other students who previously took the same class as mine are good at helping me learn
	The **professors** of my courses are good at helping me learn
I got enough help from **TAs** during scheduled lab time	I got enough help from the **students in my class**
	I got enough help from **other students** who previously took the same class as mine
	I got enough help from **professors** during class time

sentiment (SEM score) is defined by the average of all dimension scores. We managed to get 223 students from the Computing and Business respectively. Table 2 presents the average and standard deviation values of all surveyed measures (i.e., NMRQ, ARS-30, Well-being, and SEM). It is shown that in every academic program, the average measurement scores are always greater than the mid score of the respective theoretical range. The students are relatively resilient, as the NMRQ and ARS-30 scores are generally close to their respective maximum scores of 60 and 150. Students also generally enjoy good well-being, as most of their well-being scores are well above the minimum score of 10, and they exhibit a positive experience sentiment in their academic program, with SEM scores approaching the maximum value of 4.

4 STUDY 1: STUDENTS' RESILIENCE

As students progress through university, spending most of the time in their academic programs and interacting primarily with peers, we examine the effects

Table 2: Survey statistics.

	Statistics (mean ± standard deviation)			Theoretical range
	Computing program	Business program	Both programs	[min, max]: mid
NMRQ	39.45 ± 5.63	40.59 ± 6.04	40.03 ± 5.86	[12, 60]: 36
ARS-30	112.03 ± 14.65	113.61 ± 13.0	112.84 ± 13.82	[30, 150]: 90
Well-being	13.74 ± 3.49	13.88 ± 3.13	13.81 ± 3.3	[0, 20]: 10
SEM	2.97 ± 0.3	2.94 ± 0.28	2.95 ± 0.29	[1, 4]: 2.5
	Cronbach's alpha			Acceptable alpha
	Computing program	Business program	Both programs	(Abraham and Barker, 2015)
NMRQ	0.726	0.758	0.745	> 0.7
ARS-30	0.890	0.859	0.875	> 0.7
Well-being	0.851	0.818	0.836	> 0.7
SEM	0.874	0.868	0.868	> 0.7

of differences in academic programs and cohorts on students' resilience. Understanding how these external factors impact resilience can inform the design of targeted interventions for specific student groups. In addition to external factors, we examine the relationship between internal factors—such as students' well-being and their perceived experiences during their academic program—and their resilience, referred to as the internal effect. If students' resilience positively correlates with their well-being, it underscores the importance of fostering well-being among students. If specific dimensions of students' experiences are found to correlate with resilience, academic institutions can implement activities designed to enhance these dimensions, thereby promoting greater resilience among students.

4.1 External Effect

We investigate whether students from different academic programs and cohorts exhibit similar levels of resilience. We performed a Mann–Whitney U test on the NMRQ score distributions of students from two different academic programs. There is no difference on general resilience distributions between students from these two programs. Similarly, we found no significant difference in ARS-30 score distributions between students in computing and business programs.

To better assess resilience differences between cohorts, we conducted statistical tests on NMRQ and ARS-30 scores (Table 3). The test results reveal no significant differences in resilience between student cohorts across different academic programs.

4.2 Internal Effect

We hypothesize that positive correlations among general resilience, academic resilience, and well-being will reinforce personal characteristics and contribute to better physical and mental well-being. We use the overall NMRQ score to measure general life resilience, the ARS-30 score for academic resilience, and the overall well-being score to assess life satisfaction. We find positive correlations among all three. These suggest that people who manage daily challenges (such as financial problems, relationship problems, and family problems) effectively are also likely to handle academic challenges (such as exam failures or assignments difficulties) well. Furthermore, the ability to cope with both daily and academic adversities contributes to greater life satisfaction. This underscores the importance of fostering resilience in students to enhance their overall life satisfaction, subjective well-being, and positive emotions.

To evaluate the relationship between students' resilience and their experience sentiment in the academic program, we measure the correlation between each ARS-30 factor and SEM dimension pair. We use the top five correlations common to both Computing and Business programs to highlight the most important relationships.

- *rflcting_adptve_help_seek* and *fclty_stu_intrctn*: Enriching interactions between faculty members and students can enhance students' awareness and encourage them to reflect and proactively seek help when facing academic challenges.
- *perseverance* and *rel_mngful_assgmnt*: Relevant and meaningful class assignments appear to have a significant positive impact on students' perseverance. This suggests that assignments connect to real-world concepts, problems, or that are personally meaningful to students encourage them to persist and not easily give up when facing challenges.

In the Computing program, we found that *class_pdgogy* and *commit* are significantly positively correlated with all ARS-30 factors. This suggests that effective classroom pedagogy and commitment to the major positively impact various aspects of academic

Table 3: Statistical test for resilience score difference between cohorts: p-value (Confidence Interval).

Overall NMRQ score

Computing program			
	2018	2019	2020
2017	0.283(-2, 7)	0.556(-3, 5)	0.487(-3, 6)
2018		0.336(-4, 1)	0.607(-5, 3)
2019			0.843(-2, 3)
2020			

Business program			
	2018	2019	2020
2017	0.914(-3, 4)	0.109(-1, 6)	0.422(-2, 7)
2018		0.083(0, 5)	0.310(-2, 5)
2019			0.601(-4, 3)
2020			

Overall ARS-30 score

Computing program			
	2018	2019	2020
2017	0.670(-10, 14)	0.209(-4, 14)	0.524(-8, 14)
2018		0.356(-4, 11)	0.876(-9, 12)
2019			0.494(-10, 5)
2020			

Business program			
	2018	2019	2020
2017	0.808(-5, 8)	0.237(-2, 11)	0.135(-3, 18)
2018		0.343(-3, 9)	0.234(-4, 16)
2019			0.504(-6, 13)
2020			

resilience. In the Business program, *coll_lrning* is significantly positively correlated with all ARS-30 factors. This suggests that increased opportunities for collaborative learning enhance overall academic resilience.

5 STUDY 2: FACTORS AFFECTING ACADEMIC PERFORMANCE

We analyze the correlation between our resilience/SEM measures and FinalGPA, which represents the student's cumulative GPA in their last observed term. We then conduct a statistical test with α = 5%, as shown in Table 4. The results indicate that general resilience is significantly positively correlated with FinalGPA in both academic programs. High-resilience students are more likely to excel academically. Interestingly, the NMRQ shows a higher correlation with FinalGPA compared to the ARS-30. This may be because the NMRQ captures resilience from a broader range of perspectives. A significant correlation is observed between *FinalGPA* and *ARS-30_neg_effct_emtional_rsponse* for Computing students, indicating that a better emotional response to setbacks is associated with improved academic performance. For Business students, a significant positive correlation between *FinalGPA* and *well-being* suggests that greater life satisfaction is linked to better academic performance.

Next, we investigate how students' experiences are correlated with their academic performance. We find that Computing students have more experience dimensions strongly correlated with their academic performance compared to Business students. Specifically, in the Computing program, *FinalGPA* is significantly correlated with *SEM_rel_mngful_assgmnt, SEM_class_pdgogy, SEM_stu_stu_intrctn, SEM_commit, SEM_fclty_stu_intrctn,* and *SEM_ovrll_stsfcn*. In contrast, in the Business program, a significant correlation is found only between *FinalGPA* and *SEM_class_pdgogy*.

In addition to evaluating the impact of individual resilience and SEM measures on students' academic performance, we aim to use these factors as features to predict students' final GPA. Furthermore, we incorporate students' historical performance as an additional predictor. This study aims to demonstrate: (i) the impact of students' historical performance on their future performance, and (ii) the features that are important determinants of FinalGPA.

Given a student's i resilience strength, experience in the major, and cumulative GPA (cumGPA) in the k^{th} term, we predict the students's FinalGPA in the last term (which occurs after the k^{th} term). k can be different values (i.e., $k = 1, 2, \ldots, 5$) depending on the cohort the student belongs to. For each k, we only involve students whose final term is later than k. For the prediction accuracy evaluation, we split these students into training and testing sets using stratified 10-fold or *LeaveOneOut* (LOO) method for the number of students more than and less than 80 respectively (Table 5).

In addition to using all NMRQ, ARS-30, SEM, well-being, and cumulative GPA at term k as features, we also include the cohort year to determine the cohort of a student. We train a **positive linear regression (PLR)** for predictions. The training data is denoted by $\{\mathbf{x}_i, y_i\}_{i=1}^{N}$ where y_i is the FinalGPA of student i and $\mathbf{x}_i$ represents the p features of student i, i.e., ($\mathbf{x_i} \in \mathbb{R}^p$). PLR learns the weight $\mathbf{w}$ of each feature vector ($\mathbf{w} \in \mathbb{R}^p$) to minimize the residual sum of squares between y_i and $\hat{y}_i$, the predicted FinalGPA of student i. The trained PLR has $\mathbf{w} \geq 0$. We add a L1 regularization term to the objective function, weighted by λ. Formally, PLR minimizes

Table 4: Correlation coefficients and p-values between NMRQ/ARS-30/SEM survey measure and academic performance.

FinalGPA versus Measure	Computing program	Business program
FinalGPA − NMRQ	0.23 (0.016)*	0.219 (0.019)*
FinalGPA − Well-being	0.118 (0.223)	0.195 (0.038)*
FinalGPA − ARS-30	0.135 (0.16)	0.048 (0.61)
FinalGPA − ARS-30_perseverance	0.052 (0.59)	0.007 (0.942)
FinalGPA − ARS-30_neg_effct_emtional_rsponse	0.189 (0.049)*	0.056 (0.551)
FinalGPA − ARS-30_rflcting_adptve_help_seek	0.13 (0.178)	0.052 (0.581)
FinalGPA − SEM_rel_mngful_assgmnt	0.218 (0.023)*	-0.034 (0.723)
FinalGPA − SEM_pace_wrkld_exp	-0.089 (0.359)	0.086 (0.361)
FinalGPA − SEM_coll_lrning	0.082 (0.397)	0.017 (0.857)
FinalGPA − SEM_class_pdgogy	0.232 (0.015)*	0.231 (0.013)*
FinalGPA − SEM_stu_stu_intrctn	0.253 (0.008)*	0.168 (0.075)
FinalGPA − SEM_stu_ta_intrctn	0.061 (0.528)	0.096 (0.313)
FinalGPA − SEM_commit	0.246 (0.01)*	0.114 (0.226)
FinalGPA − SEM_fclty_stu_intrctn	0.23 (0.016)*	0.09 (0.342)
FinalGPA − SEM_prejdc_free_env	-0.133 (0.168)	0.025 (0.792)
FinalGPA − SEM_ovrll_stsfcn	0.24 (0.012)*	0.112 (0.236)

Table 5: Student distribution over k's.

k	Computing program	
	Total num. of students	Trg/Test Split
1	109	10-fold
2	90	10-fold
3	90	10-fold
4	40	LOO
5	40	LOO
k	Business program	
	Total num. of students	Trg/Test Split
1	114	10-fold
2	101	10-fold
3	100	10-fold
4	63	LOO
5	50	LOO

$$\frac{1}{2N}||y - X\mathbf{w}||_2^2 + \lambda||\mathbf{w}||_1$$

The features used are 1) *nmrq* is the overall NMRQ score of the student, 2) *ars*30 is a multi-hot vector (vector size = 3), where each vector element represents a specific ARS-30 score factor, 3) *wellbeing* is the overall well-being score of the student, 4) *sem* is a multi-hot vector (vector size = 10), where each vector element represents a specific experience dimension (i.e., relevant and meaningful assignments, pace and workload experience, collaborative learning, etc.), 5) *cum_gpa* is the cumulative GPA of the student up to (including) term k, and 6) *cohort* is a one-hot vector that represents the student's cohort.

We introduce two baseline methods for comparison, namely: 1) **Historical performance (HP)** that predicts student i FinalGPA using the cumulative GPA up to term k, and 2) **linear regression (LR)** that uses the same set of features as PLR, but without forcing the weights to non-negative values. We use Mean Absolute Error (MAE) to evaluate the prediction's accuracy, which returns the average prediction grade error against the ground truth.

To achieve the first objective, we evaluate the PLR and the baseline methods for $1 \leq k \leq 5$. Our experimental results indicate that the HP method, which simply uses the cumulative GPA at term k to predict the FinalGPA, performs surprisingly well. All MAE values are kept below 0.3, which corresponds to a one-letter grade difference (e.g., between A+ and A). LR and PLR, however, outperform HP for all k values. PLR slightly outperforms LR across all k values, likely due to reduced overfitting, as we limit the feature weights to be non-negative. Finally, we observe that MAE decreases as k increases, consistent with our earlier intuition that prediction becomes easier with larger k.

To understand the impact of students' historical performance, resilience, well-being, and sentiment on their future performance, we analyze the learned weights $\mathbf{w}$ from the PLR model, averaged across all folds. For one-hot and multi-hot features with more than one vector (e.g., *ars*30, *cohort*, and *sem*), we aggregate the vectors by summation. In this context, a feature with a higher weight signifies greater importance in predicting students' future performance (i.e., FinalGPA). In both academic programs, *cum_gpa* has the highest weight, indicating that students' future performance strongly depends on their earlier performance. This is particularly sensible because students in earlier terms typically take foundational courses that prepare them for more advanced courses in later terms.

The next important feature is *cohort*. The cohort information proves to be useful for this prediction

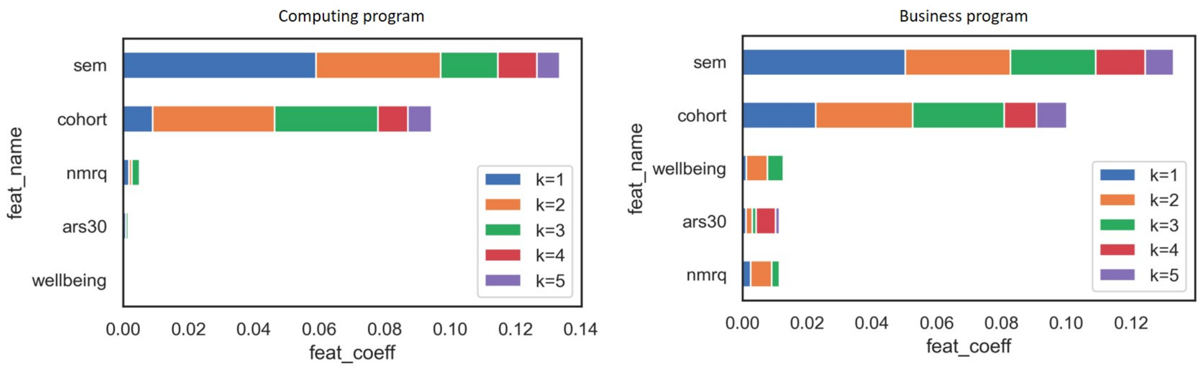

Figure 2: Features' weight from PLR model.

task, as it helps differentiate students when predicting their FinalGPA. For instance, the FinalGPA for students in the 2017 cohort is based on their grades from terms 1 to 8, while for students in the 2019 cohort, it is based on grades from terms 1 to 4. The remaining features do not receive large weights, which are less important. However, we observe that FinalGPA is more influenced by the academic program's environmental dimension of SEM than by the students' resilience and well-being.

6 DISCUSSION

The study on students' resilience reveals a positive correlation between academic resilience, general resilience, and overall well-being. This suggests that students who demonstrate high resilience in their daily lives also exhibit high resilience in an academic context, and that high-resilience students tend to have better life satisfaction. Support systems help students recognize when they need help and encourage them to seek it, while meaningful assignments motivate students to persist because they see the value in what they're learning. Creating a comfortable classroom environment supports resilience in Computing students, whereas providing more opportunities for group work helps Business students build resilience. These differences arise because Computing courses focus more on individual work in classes and labs, while Business courses involve more group projects. Thus, comfort in class is more important for Computing students, while collaboration is more crucial for Business students.

The second study demonstrates that a positive learning experience and high resilience are associated with better academic performance. This finding is consistent with existing research (Prickett et al., 2020), which indicates that resilience benefits both first-year and long-term students' performance. Effective classroom practices, such as strong interactions between instructors and students and providing early, consistent feedback on assignments, also contribute to improved student performance. The regression models indicate that students' overall academic performance is positively influenced by their historical performance, resilience, experience sentiment, and well-being. However, when all these attributes are included in the regression model, resilience has a lower impact on overall academic performance compared to SEM (Student Experience Measures). This suggests that SEM might account for some of the effects of resilience. It may be beneficial to focus on enhancing learning experiences to improve resilience. This can be achieved by providing relevant and meaningful assignments while considering the curriculum's pace and workload, increasing opportunities for collaborative learning, ensuring a prejudice-free teaching environment, and offering strong support systems from faculty, teaching assistants, and peers.

As this study focuses primarily on evaluating students' academic performance, we also assessed whether our student participants are representative of the entire student population by comparing their final GPAs to those of the broader student body. We found that, except for the 2017 cohort in the Computing program and the 2020 cohort in the Business program, our participants generally have significantly higher academic abilities. This suggests that the findings of this study are more applicable to students with relatively high academic performance. To address this discrepancy, recruiting more participants could help bridge the gap between the two groups.

7 CONCLUSION

A user study was conducted to analyze the impact of student resilience and experience on long-term academic performance. The study concluded that high-resilience students tend to have greater life satisfaction and are more likely to excel academically. Additionally, a supportive environment enhances students' ability to study effectively and perform well at university. Academic programs can implement various initiatives to improve students' perceived experiences and strengthen their resilience.

The findings can inform curriculum design and the learning environment in academic programs. Follow-up studies should be conducted to evaluate their impact. This could involve implementing initiatives as academic interventions and measuring students' resilience and academic performance before and after the interventions. Further research on student experiences and changes in resilience during and after the COVID period would also be valuable.

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