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Factors associated with academic performance among computer science undergraduates: a retrospective cross-sectional study of institutional administrative data at a Chinese public university

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Abstract

Background: Universities accumulate large volumes of administrative data through routine teaching, assessment, enrolment, and student-support activity. These records offer an opportunity to describe variation in academic attainment across entire cohorts, yet learning-analytics research has largely emphasised predictive accuracy rather than the substantive interpretation of recorded characteristics. This study examined which socio-demographic, personal, and engagement-related records were associated with academic performance among computer science undergraduates at a single Chinese public university.

Methods: A retrospective cross-sectional analysis used de-identified administrative records for 1,613 undergraduates from three consecutive entry cohorts in one school of computer science. Records were drawn from the academic-affairs, student-affairs, psychological-warning, and innovation-and-entrepreneurship systems. Descriptive statistics, independent-samples t tests, one-way analysis of variance with Welch's correction where appropriate, K-means clustering of second-classroom credits, and stepwise multiple linear regression were performed.

Results: Significant differences in grade point average (GPA) were observed for gender, province and prefecture of origin, ethnicity, family economic status, psychological-warning level, political affiliation, and second-classroom performance; urban versus rural origin was not significant. GPA increased monotonically across four second-classroom engagement clusters (2.848 to 3.513), with partial eta-squared of 0.245. In the regression model, second-classroom credits showed the strongest standardised association (beta = 0.377), followed by political affiliation (0.206) and gender (0.166), whereas psychological-warning level was negatively associated with GPA (beta = -0.065). The seven retained predictors accounted for 29.7% of GPA variance (adjusted R-squared = 0.294).
Conclusions: Co-curricular engagement and psychological wellbeing are connected correlates of attainment within this institutional context. Institutional administrative data can help identify groups that may benefit from integrated academic and wellbeing support, provided that privacy safeguards are maintained. Because the data are cross-sectional and drawn from one institution, the findings are associations and do not establish causal effects.

Keywords: Academic performance; Educational data mining; Student engagement; Administrative data; Higher education; Grade point average

1 Background

Universities generate large volumes of administrative data as a by-product of routine teaching, assessment, enrolment, and student-support activity. In higher education, where curricula, teaching arrangements, and student pathways are comparatively complex, these records accumulate into databases that can be used to describe and explain differences in student outcomes [1–3]. Educational data mining and learning analytics have emerged as the principal frameworks for extracting such information, and a substantial body of work now uses institutional records to predict academic performance, identify students at risk, and inform retention interventions [4–6]. Recent reviews document both the rapid expansion of this field and its increasing methodological sophistication, including machine-learning classification, multimodal data sources, and explainable approaches designed to make predictions usable by educators rather than only accurate [7–9]. The broader diffusion of artificial intelligence in higher education has further accelerated interest in data-informed decision-making [10].

A persistent feature of this literature, however, is its emphasis on predictive accuracy. Models are typically evaluated by how well they classify or forecast an outcome, and the substantive interpretation of *which* recorded characteristics are associated with performance receives less attention. This emphasis is valuable for early-warning systems, but it leaves a gap for descriptive, institution-level evidence that can be interpreted by administrators and teachers without specialist modelling expertise [3, 5]. Moreover, much of the predictive literature draws on large-scale international assessments or on samples from a limited number of national systems. Socioeconomic status is one of the most robust correlates of academic achievement across schooling systems [11, 12], yet how such gradients appear within a single institution, and how they coexist with institutional markers and co-curricular participation, remains comparatively under-documented in Chinese higher education.

The Chinese context makes this question consequential. Expansion of higher education has widened the diversity of students' geographic, economic, and cultural backgrounds, and research has shown that rural origin and family cultural capital continue to shape how students adapt academically and socially at university [13, 14]. Qualitative work further indicates that rural students' educational aspirations and their constructions of what counts as an "ideal student" evolve through the university years in ways that are closely tied to grades [15, 16]. For professionally oriented programmes such as computer science, where cohort sizes are large and curriculum sequences are tightly structured, systematic variation in attainment has direct implications for progression, delayed graduation, and the targeting of academic support. Institutional administrative records are unusually well suited to documenting such variation because they cover entire cohorts rather than voluntary survey respondents.

A second distinctive feature is the "second classroom" system, an institutionally organised set of extracurricular, innovation, and social-practice activities for which students earn recorded credits. Unlike self-reported engagement scales, these credits

constitute an administrative trace of behavioural involvement. This is theoretically important because student involvement theory holds that outcomes depend on the amount of energy students devote to the learning environment rather than on institutional inputs alone [17, 18]. Contemporary work continues to link engagement, academic self-efficacy, and co-curricular participation with achievement [19–23], but administrative credit records have seldom been used as the operational indicator.

Against this background, the present study uses de-identified administrative records from one school of computer science at a Chinese public university to describe how academic performance varies across recorded socio-demographic, personal, and engagement characteristics, and to estimate their joint association with cumulative GPA. Three research questions guide the analysis:

1. To what extent does GPA differ across categories of gender, geographic origin, ethnicity, family economic status, psychological-warning level, political affiliation, and second-classroom performance?
2. How do students group together on the basis of second-classroom credits, and how do those groups differ in GPA?
3. Which combination of recorded characteristics is associated with GPA when considered jointly, and how much variance do they account for?

The study contributes descriptive evidence from a complete-cohort administrative dataset in a national context that is under-represented in the learning-analytics literature, and it does so with transparent, replicable group-comparison procedures rather than a black-box predictive model. All findings are reported as associations. Because the data are cross-sectional, retrospective, and drawn from a single institution, no causal claim is made.

1.1 Conceptualizing academic performance

The analysis by Lavin [24] remains a foundational statement of academic performance as a construct to be both defined and predicted. Lavin treated course grades, converted by institutional rules into a grade point average, as the observable indicator of academic performance, and proposed that performance be analysed across four domains: intellectual ability, personality, sociological factors, and the interaction of social structure with personality. A key proposition was that the relative importance of intellectual factors declines as educational level rises, so that personality and social-structural influences merit greater attention in higher education [24]. This proposition provides a direct rationale for examining recorded social and demographic characteristics alongside personal and behavioural indicators among undergraduates, rather than treating prior attainment as the sole explanatory candidate. Following this logic, the present study uses the cumulative four-year GPA exported from the institution's academic-affairs system as the outcome variable.

1.2 Student involvement and the input–environment–outcome model

Astin's input–environment–outcome (I-E-O) model and theory of student involvement shift attention from what institutions provide to what students actually do [17, 18]. Outcomes are understood as a function of student inputs, the environment encountered, and — critically — the degree of involvement with that environment; involvement is defined as the physical and psychological energy invested in the academic experience [17]. In *What Matters in College?*, Astin [18] reported that students' involvement patterns were more consequential for a wide range of college outcomes than many institutional characteristics. The theory therefore supplies a specific expectation for the present study: an administrative measure of co-curricular participation should carry explanatory weight beyond socio-demographic background.

Subsequent research has repeatedly confirmed that motivational beliefs, engagement, and persistence are associated with achievement [19–21, 25], and that co-curricular and extracurricular participation relates to student outcomes even within professionally oriented programmes [23, 26]. Work in Chinese universities likewise shows that student engagement mediates the influence of individual characteristics on achievement [13, 22]. These findings justify treating second-classroom credits as a theoretically grounded engagement indicator rather than as an incidental administrative variable.

1.3 A three-domain framework under data-availability constraints

Chinese scholarship on student development has proposed frameworks that combine students' backgrounds, institutional environments, and behavioural, cognitive, and emotional engagement. Such frameworks typically span four domains: socio-demographic characteristics, school environment, personal characteristics, and student involvement. In a single-school design, however, the institutional environment is effectively constant; it cannot explain variation within the cohort and is therefore held outside the analysis. The conceptual framework was consequently reduced to three domains — socio-demographic characteristics, personal characteristics, and student involvement — each populated only by variables that could be retrieved from extant institutional systems.

This reduction is both a design decision and a limitation. Several variables commonly included in four-domain student-development frameworks (personality traits, achievement motivation, self-efficacy, entrance-examination scores, library use, student–faculty interaction, and technology use) could not be reconstructed because the cohorts had graduated and the corresponding systems no longer retained the relevant records. Table 1 lists the domains, the retained indicators, and their source

systems. The resulting framework is deliberately modest: it asks what can be learned from records that universities actually keep, rather than from an ideal measurement design.

The retained indicators also map onto documented inequities. Family economic disadvantage is associated with material and psychological constraints on study [27]; rural origin and cultural capital shape academic adaptation in Chinese universities [14–16]; ethnic minority students may face distinct academic and linguistic challenges [28, 29]; and psychological distress is linked to poorer academic outcomes among college students, including in Chinese samples [30–32]. Political affiliation, by contrast, is an institution-specific status marker with no direct equivalent in most international datasets; it is treated here as an exploratory indicator of formal institutional participation rather than as a theoretically established predictor.

1.4 Theoretical expectations and scope

Theoretical considerations lead to three expectations that are tested descriptively rather than as causal hypotheses. First, following the framework proposed by Lavin [24], socio-demographic and personal characteristics should show measurable GPA differences. Second, following the involvement framework [17, 18], the engagement indicator should be among the strongest correlates of GPA. Third, following the literature on psychological distress and achievement [31, 33], students flagged for psychological warning should show lower average GPA. Because the analysis is exploratory and the predictors are administrative categories rather than experimentally manipulated variables, no directional causal hypotheses are advanced.

Table 1 Conceptual Domains, Retained Indicators, and Data Sources

Domain	Retained indicators	Source system
Socio-demographic characteristics	Gender; ethnicity; province of origin; urban/rural origin; family economic status	Academic-affairs system; student-affairs system
Personal characteristics	Psychological-warning level; political affiliation	Psychological-warning tracking records; Party membership records
Student involvement	Second-classroom credits	Innovation and entrepreneurship system
Outcome	Four-year cumulative GPA	Academic-affairs system

Note. School environment was treated as constant because the sample was drawn from a single school. Indicators that could not be reconstructed for graduated cohorts (personality, motivation, self-efficacy, entrance-examination score, library use, student–faculty interaction, technology use) were excluded. GPA = grade point average.

2 Methods

2.1 Study design and setting

This study used a retrospective, cross-sectional, institution-based design. De-identified administrative records were extracted for all undergraduates in three consecutive cohorts within a single school of computer science and technology at a public university in central China. The institution operates a standardised annual procedure for recognising financially disadvantaged students and an institution-wide policy governing the award of second-classroom credits for organised extracurricular, innovation, and social-practice activities. Because the school environment was common to all participants, the design isolates within-institution variation. All variables were drawn from records created for administrative purposes, not for research; no questionnaire was administered and no student was contacted.

2.2 Participants

The analytical sample comprised 1,613 undergraduates across three consecutive entry cohorts. Group sizes for the full-sample analyses were 1,613 for province of origin, prefecture of origin, urban/rural origin, ethnicity, family economic status, psychological-warning level, political affiliation, and second-classroom clustering.

Approximately 70% of students originated from the province in which the university is located, which motivated a separate within-province comparison of prefecture-level origins. The gender comparison was conducted separately by cohort.

2.3 Variables and measurement

The outcome variable was the cumulative four-year GPA recorded in the academic-affairs system on a 0–4 scale ($M = 3.001$, $SD = 0.446$ for the full sample). Predictor variables were used as recorded in the institutional systems:

- **Gender** (male, female); **ethnicity** (Han, ethnic minority); **urban/rural origin**; **province of origin** (29 categories); **prefecture of origin within the home province** (18 categories including out-of-province).
- **Family economic status**, derived from the institution's annual financial-difficulty recognition procedure (not financially disadvantaged, generally disadvantaged, specially disadvantaged).
- **Psychological-warning level**, derived from the institution's psychological-warning tracking records (no warning, Level 1, Level 2). In the full sample, 1,579 students had no warning and 17 students each were at Level 1 and Level 2.
- **Political affiliation** (Communist Party member, Communist Youth League member, unaffiliated).
- **Second-classroom credits**, the total credits recorded in the innovation and entrepreneurship system. Unlike the capped credit recognition used for graduation requirements, this administrative total has no upper bound and therefore differentiates students across a wide range.

2.4 Data sources, anonymization, and ethics

Four institutional systems contributed data: the academic-affairs system, the student-affairs system, the psychological-warning tracking records, and the innovation and

entrepreneurship system. Records were linked by an institutional identifier and then de-identified before analysis; names, student numbers, and contact information were removed, and only the variables listed in Table 1 were retained. All reported results are aggregate; no cell contains fewer than five students except where explicitly noted in Additional file 1.

The dataset contains sensitive attributes — family economic status, psychological-warning status, ethnicity, and political affiliation. The study was approved by the School of Computer Science and Technology, Wuhan University of Science and Technology, and all procedures were carried out in accordance with the relevant institutional guidelines and regulations. Permission to use the de-identified administrative records for research purposes was granted by the approving body. Because the analysis used pre-existing de-identified records and involved no direct contact with students, no individual informed consent procedure was undertaken; no identifiable personal information was extracted and no individual student can be re-identified from the reported results.

2.5 Statistical analysis

Analyses were conducted in SPSS and SPSS Modeler. Four stages were followed.

First, descriptive statistics (M, SD, n) were computed for GPA and for every grouping variable. Second, independent-samples t tests were used for two-group comparisons (gender by cohort; urban versus rural origin; ethnicity), and one-way analysis of variance (ANOVA) for comparisons involving three or more groups (province, prefecture, family economic status, psychological-warning level, political affiliation, second-classroom cluster). Where the homogeneity-of-variance assumption was not satisfied, Welch's F test was used instead of the conventional F; Welch-corrected t tests were computed for two-group comparisons. Effect sizes were reported as Cohen's d for two-group comparisons and partial η^2 and Cohen's f for ANOVAs, interpreted

against conventional benchmarks [34]. Third, K-means clustering was applied to second-classroom credits to derive empirically distinct engagement groups, following established uses of clustering for classifying student performance profiles [35]; silhouette coefficients were used to assess cluster quality, and the resulting clusters were then treated as a grouping variable in a one-way ANOVA. Fourth, a stepwise multiple linear regression was fitted with GPA as the outcome and the seven retained predictors as candidates, with variance inflation factors and the Durbin–Watson statistic used to check multicollinearity and autocorrelation.

Two methodological caveats are registered at the design stage rather than deferred. Stepwise selection is known to capitalise on sample-specific variation, produce biased coefficients, and overstate model fit, and methodological guidance recommends theory-driven entry or cross-validation instead [36, 37]. The stepwise results are therefore reported as an exploratory summary and interpreted with corresponding caution; they are not presented as confirmatory evidence. In addition, all tests are cross-sectional group comparisons: statistically significant differences establish association, not causation, and the direction of any relationship between engagement and attainment cannot be determined from these data. Significance was evaluated at $\alpha = .05$.

2.6 Use of generative artificial intelligence

A generative artificial intelligence assistant was used to support translation of the original Chinese draft into English, restructuring of the manuscript, and verification of reference metadata. All retrieved references, numerical results, and interpretations were checked by the authors against the original sources and the institutional dataset. The authors take full responsibility for the accuracy and integrity of the content; no artificial intelligence tool is listed as an author.

3 Results

3.1 Descriptive overview

Across the full sample (N = 1,613), cumulative GPA averaged 3.001 (SD = 0.446). Approximately 70% of students originated from the province in which the university is located, and 497 students (30.8%) were recognised as financially disadvantaged (285 generally and 212 specially disadvantaged). Psychological-warning records classified 1,579 students (97.9%) as having no warning, 17 (1.1%) at Level 1, and 17 (1.1%) at Level 2. Political affiliation was distributed as 191 Party members (11.8%), 1,351 Youth League members (83.8%), and 71 unaffiliated students (4.4%). The small sizes of the warning-level and unaffiliated groups are relevant to the interpretation of their comparisons.

3.2 Gender differences by cohort

Table 2 reports GPA by gender for each of the three cohorts. Female students recorded higher mean GPA than male students in every cohort, with $p < .001$ throughout. The gender gap was 0.292, 0.284, and 0.242 GPA points respectively. Cohen's d was 0.715, 0.701, and 0.518, indicating moderate-to-large effects in the first two cohorts and a moderate effect in the third under conventional benchmarks [34]. Male students also showed consistently larger standard deviations, indicating greater within-gender dispersion of attainment among men than among women.

3.3 Geographic origin

Province of origin. One-way ANOVA indicated significant GPA differences across the 29 recorded provinces, $F = 3.104$, $p < .001$, partial $\eta^2 = .050$, Cohen's $f = 0.23$ (Table 3 and Additional file 1: Table S1). The highest means were observed for Shandong ($M = 3.243$), Jiangxi and Fujian ($M = 3.144$), Anhui ($M = 3.142$), Jiangsu ($M = 3.124$), and Zhejiang ($M = 3.115$); the lowest were observed for Guangxi ($M =$

Table 2 Gender Differences in GPA by Cohort (Independent-Samples t Tests)

Statistic	Cohort 2020	Cohort 2021	Cohort 2022
Male *M*	2.873	2.965	2.990
Female *M*	3.165	3.249	3.232
Male *SD*	0.420	0.420	0.478
Female *SD*	0.355	0.340	0.429
t	−6.124	−6.786	−5.118
p	< .001	< .001	< .001
Cohen's *d*	0.715	0.701	0.518

Note. GPA = grade point average.

2.591), Ningxia ($M = 2.621$), Xinjiang ($M = 2.676$), Hainan ($M = 2.709$), Guizhou ($M = 2.729$), and Gansu ($M = 2.739$). Students from the university's home province — by far the largest group ($n = 1{,}141$) — averaged 3.022. One province was represented by a single student ($M = 2.520$) and is not interpretable. Partial η^2 indicates that about 5.0% of GPA variance was attributable to province-level group differences, a small effect.

Table 3 GPA by Province of Origin (Selected Groups and Omnibus Test)

Province	*n*	*M*	*SD*
Shandong	22	3.243	0.423
Jiangxi	16	3.144	0.416
Fujian	19	3.144	0.417
Anhui	16	3.142	0.376
Jiangsu	18	3.124	0.390
Zhejiang	37	3.115	0.456
Hubei (home province)	1,141	3.022	0.436
Gansu	20	2.739	0.563
Guizhou	23	2.729	0.344
Hainan	13	2.709	0.338
Xinjiang	16	2.676	0.313
Ningxia	8	2.621	0.248
Guangxi	18	2.591	0.402
Total	1,613	3.001	0.446

Note. $F = 3.104$, $p < .001$; partial $\eta^2 = .050$; Cohen's $f = 0.23$. The complete 29-province table is provided in Additional file 1: Table S1. GPA = grade point average.

Prefecture of origin within the home province. Because most students came from one province, a separate analysis compared 17 prefecture-level origins plus an out-of-province category. Differences were significant, $F = 2.351$, $p = .002$, partial $\eta^2 = .023$, Cohen's $f = 0.154$ (Additional file 1: Table S2). The highest means were recorded for Ezhou (3.196), Qianjiang (3.146), Xiaogan (3.097), and Xiantao (3.075); the lowest for Enshi Prefecture (2.801), Huanggang (2.910), out-of-province (2.950), Yichang (2.954), Shiyan (2.966), and Xianning (2.973). The provincial capital, Wuhan ($n = 282$), averaged 3.049. Huanggang is notable because it was the second-largest source of students within the province yet recorded the second-lowest mean. Only 2.3% of GPA variance was attributable to prefecture-level group differences.

Urban versus rural origin. No difference was observed (Table 4). Rural ($n = 849$, $M = 3.001$, $SD = 0.450$) and urban ($n = 764$, $M = 3.001$, $SD = 0.441$) students had identical means, $t = 0.022$, $p = .982$, Welch's $t = 0.022$, $p = .982$, mean difference $= 0.000$, $d = 0.001$. This null result is substantively informative given the extensive literature on rural–urban adaptation in Chinese higher education.

Table 4 GPA by Urban Versus Rural Origin

Origin	*n*	*M*	*SD*	*t*	Welch's *t*	Mean difference	Cohen's *d*
Rural	849	3.001	0.450	0.022 ($p = .982$)	0.022 ($p = .982$)	0.000	0.001
Urban	764	3.001	0.441				
Total	1,613	3.001	0.446				

Note. Homogeneity of variance was satisfied; the conventional independent-samples t test is reported alongside Welch's correction. GPA = grade point average.

3.4 Ethnicity, family economic status, psychological-warning level, and political affiliation

Table 5 consolidates four group comparisons. Han students ($M = 3.012$) outperformed ethnic minority students ($M = 2.790$), $t = 4.360$, $p < .001$, Welch's $t = 4.224$, $p < .001$,

$d = 0.500$ — a moderate effect under conventional benchmarks [34]. Family economic status was significantly related to GPA, $F = 8.971$, $p < .001$, Welch's $F = 10.563$, $p < .001$, partial $\eta^2 = .011$, $f = 0.106$; notably, students classified as generally disadvantaged recorded the highest mean (3.098), above specially disadvantaged (3.010) and non-disadvantaged students (2.974). Psychological-warning level was significantly related to GPA, $F = 10.313$, $p < .001$, Welch's $F = 4.494$, $p = .023$; students with no warning averaged 3.008 versus 2.616 (Level 1) and 2.709 (Level 2). Political affiliation showed the largest omnibus difference among these four factors, $F = 99.821$, $p < .001$, Welch's $F = 124.931$, $p < .001$, partial $\eta^2 = .110$, $f = 0.352$, with Party members averaging 3.343, Youth League members 2.974, and unaffiliated students 2.591.

Table 5 GPA Differences Across Four Recorded Categorical Factors

Factor	Group	*n*	*M*	*SD*	Test	Effect size
Ethnicity	Han	1,533	3.012	0.443	$t = 4.360$, $p < .001$; Welch $t = 4.224$, $p < .001$	$d = 0.500$
	Ethnic minority	80	2.790	0.458		
Family economic status	Not disadvantaged	1,116	2.974	0.442	$F = 8.971$, $p < .001$; Welch $F = 10.563$, $p < .001$	partial $\eta^2 = .011$; $f = 0.106$
	Generally disadvantaged	285	3.098	0.398		
	Specially disadvantaged	212	3.010	0.504		
Psychological-warning level	No warning	1,579	3.008	0.437	$F = 10.313$, $p < .001$; Welch $F = 4.494$, $p = .023$	—
	Level 1	17	2.616	0.643		
	Level 2	17	2.709	0.709		
Political affiliation	Party member	191	3.343	0.312	$F = 99.821$, $p < .001$; Welch $F = 124.931$, $p < .001$	partial $\eta^2 = .110$; $f = 0.352$
	Youth League member	1,351	2.974	0.421		
	Unaffiliated	71	2.591	0.626		
Total		1,613	3.001	0.446		

Note. Where homogeneity of variance was violated, Welch's corrected statistic is reported alongside the conventional statistic. No effect size was available for the psychological-warning comparison. GPA = grade point average.

The distribution of psychological-warning levels across recorded subgroups is provided in Additional file 1: Table S3. Descriptive patterns included somewhat higher

warning prevalence among female than male students, among ethnic minority than Han students, among specially disadvantaged students, among students from certain prefectures, and among urban compared with rural students. Because only 34 students in total carried a warning flag, these percentages should be read as descriptive rather than inferential.

3.5 Second-classroom engagement: clustering and group differences

K-means clustering of second-classroom credits produced four groups with a silhouette coefficient of 0.649, indicating acceptable separation (Table 6). The distribution was strongly skewed: two-thirds of students fell into the lowest-engagement cluster, whereas only 19 students (1.178%) formed the highest-engagement cluster.

Table 6 K-Means Clusters of Second-Classroom Credits

Cluster label	*n*	%	Cluster centre
Excellent	19	1.178	54.82
Good	92	5.704	23.97
Average	427	26.472	10.68
Low	1,075	66.646	4.20
Total	1,613	100.0	—

Note. Silhouette coefficient = 0.649. Cluster centres are expressed in second-classroom credits.

GPA rose monotonically across the four clusters (Table 7): 2.848 (Low), 3.269 (Average), 3.436 (Good), and 3.513 (Excellent). The omnibus difference was significant and large, $F = 173.774$, $p < .001$, Welch's $F = 218.480$, $p < .001$, partial $\eta^2 = .245$, Cohen's $f = 0.569$. Approximately 24.5% of GPA variance was attributable to cluster membership — the largest effect observed in any single group comparison in this study.

Table 7 GPA Differences Across Second-Classroom Clusters

Cluster	*n*	*M*	*SD*
Average	427	3.269	0.307
Low	1,075	2.848	0.423
Good	92	3.436	0.296
Excellent	19	3.513	0.274
Total	1,613	3.001	0.446

Note. $F = 173.774$, $p < .001$; Welch's $F = 218.480$, $p < .001$; partial $\eta^2 = .245$; Cohen's $f = 0.569$. GPA = grade point average.

3.6 Stepwise multiple regression

The seven predictors retained by the stepwise procedure are reported in Table 8. The model was significant, $F(7, 1605) = 96.804$, $p < .001$, with $R^2 = .297$ and adjusted $R^2 = .294$, and yielded the following equation:

$$\begin{aligned}\text{GPA} = {} & 2.218 + 0.182(\text{gender}) + 0.120(\text{ethnicity}) + 0.006(\text{origin}) \\ & + 0.029(\text{family economic status}) - 0.127(\text{psychological warning level}) \\ & + 0.232(\text{political affiliation}) + 0.022(\text{second classroom credits}).\end{aligned} \tag{1}$$

Second-classroom credits had the largest standardized coefficient ($\beta = 0.377$, $t = 17.445$, $p < .001$), followed by political affiliation ($\beta = 0.206$) and gender ($\beta = 0.166$). Psychological-warning level was the only predictor with a negative coefficient ($\beta = -0.065$, $p = .002$). All variance inflation factors were below 1.10 and the Durbin–Watson statistic was 1.761, indicating no material multicollinearity or autocorrelation.

4 Discussion

This study asked which routinely recorded student characteristics are associated with cumulative GPA in a single school of computer science, and how much of the variation

Table 8 Stepwise Multiple Linear Regression Predicting GPA

Predictor	*B*	*SE*	β	*t*	*p*	VIF	Tolerance
Constant	2.218	0.054	—	41.075	< .001	—	—
Gender	0.182	0.024	0.166	7.749	< .001	1.048	0.954
Ethnicity	0.120	0.044	0.059	2.759	.006	1.028	0.973
Province of origin	0.006	0.002	0.060	2.869	.004	1.004	0.996
Family economic status	0.029	0.013	0.047	2.230	.026	1.022	0.979
Psychological-warning level	−0.127	0.041	−0.065	−3.092	.002	1.008	0.992
Political affiliation	0.232	0.025	0.206	9.431	< .001	1.094	0.914
Second-classroom credits	0.022	0.001	0.377	17.445	< .001	1.064	0.939

Note. $R^2 = .297$; adjusted $R^2 = .294$; $F(7, 1605) = 96.804$, $p < .001$; Durbin–Watson = 1.761. VIF = variance inflation factor. GPA = grade point average.

they jointly account for. Three findings organise the discussion: co-curricular engagement showed the strongest association with attainment; several socio-demographic and institutional-status markers showed smaller but systematic differences; and students flagged for psychological warning recorded substantially lower GPA. Each is interpreted below as an association within one institution, not as a causal effect.

4.1 Co-curricular engagement

The second-classroom gradient was the clearest result. Students in the highest engagement cluster averaged 0.665 GPA points more than those in the lowest, partial $\eta^2 = .245$, and second-classroom credits carried the largest standardized regression coefficient ($\beta = 0.377$). This pattern is consistent with student involvement theory, which holds that what students do with the institutional environment matters more for outcomes than the environment's formal characteristics [17, 18]. Contemporary evidence likewise links academic engagement, self-efficacy, and co-curricular participation to achievement [19–22], including among engineering students, where co-curricular and extracurricular supports predict belonging and outcomes [23, 26].

Three interpretations are plausible and cannot be distinguished here. Engagement may support learning through practice, peer interaction, and the consolidation of professional skills; academically successful students may be more likely to seek

extracurricular opportunities; or both may reflect a third variable such as motivation, self-regulation, or prior preparation [25]. The cross-sectional design precludes adjudication. What the administrative measure adds is a behavioural trace that is independent of self-report, and a highly skewed distribution: 66.6% of students clustered at the lowest engagement level. That concentration suggests substantial untapped capacity rather than a ceiling effect, and it makes co-curricular participation a practical target for institution-level intervention — provided participation is broadened rather than used as a screening label for already-successful students.

4.2 Socio-demographic and institutional-status markers

Female students outperformed male students in all three cohorts with moderate-to-large effects, consistent with documented gender differences in attainment in STEM fields [38]. Male students also showed greater within-group dispersion, a pattern that is more relevant to the design of academic support than the mean difference itself. The finding should be read in light of the field-specific context: computer science programmes in China enrol substantially more men than women, so the female subgroup is comparatively small and may be selectively composed.

Socio-demographic differences were statistically detectable but small in magnitude. Province of origin explained 5.0% of GPA variance and prefecture of origin 2.3%; family economic status explained 1.1%; ethnicity showed a moderate standardized difference. These magnitudes are broadly compatible with a literature in which socioeconomic and cultural gradients are robust at system level but attenuated within a single institution [11, 12], and with Chinese research showing that rural background and cultural capital shape academic and social adaptation [13–16].

Two results resist a simple deficit reading. First, urban and rural students had virtually identical means ($d = 0.001$). Within this school, the urban–rural distinction carried no attainment penalty, which suggests that the adaptation difficulties

documented in qualitative work [14, 15] do not necessarily translate into GPA differences once students are enrolled. Second, generally disadvantaged students recorded the *highest* mean GPA (3.098), above non-disadvantaged students (2.974). Financial disadvantage is associated with academic risk in other settings [27], but institutional need-based recognition in China is coupled with financial aid, work-study, and targeted support; selection into the category, institutional support, and student effort may operate in opposing directions. The very small effect size (partial $\eta^2 = .011$) indicates that this difference should not be over-interpreted.

Ethnic minority students averaged 0.222 GPA points below Han students ($d = 0.500$), a moderate difference. Research on ethnic minority students in China points to linguistic, cultural, and institutional factors that shape academic engagement and achievement [28, 29]. With only 80 minority students in the sample and no information on language background or pre-university preparation, the present data can document the disparity but cannot explain it.

Political affiliation showed the second-largest standardized coefficient ($\beta = 0.206$) and the largest omnibus difference (partial $\eta^2 = .110$). This variable has no direct international analogue. Party and Youth League membership are formal statuses conferred through processes that themselves consider academic standing and conduct, so the association plausibly reflects institutional selection as much as any effect of participation. It is best interpreted as a marker of formal institutional integration, consistent with the broader involvement framework [18, 22], and is reported with that caveat rather than as an intervention lever.

4.3 Psychological-warning status

Students with a Level 1 or Level 2 psychological-warning flag averaged 2.616 and 2.709 respectively, compared with 3.008 for students without a warning. The negative regression coefficient ($\beta = -0.065$) was the only one in the model with a negative sign.

This aligns with a substantial international literature linking psychological distress, depression, burnout, and sleep difficulties to lower academic performance [31–33, 39], including evidence that mental health mediates the relationship between behavioural factors and attainment [40, 41] and that sleep duration prospectively predicts first-year GPA [42]. Chinese national survey data also document substantial geographic variation in student mental health [30].

Two cautions are essential. Only 34 students carried a warning flag, so the estimates are imprecise and the Welch-corrected test ($p = .023$) is more appropriate than the conventional F. More importantly, the direction of the relationship is indeterminate: psychological difficulty may impair study, academic difficulty may precipitate distress, or both may follow from common antecedents. Psychological and academic difficulty are therefore treated as co-occurring rather than as a unilateral pathway. Network-analytic work on anxiety and depression symptoms across performance levels likewise suggests heterogeneous symptom profiles rather than a uniform pathway [32]. Support should therefore be integrated — combining counselling with academic assistance — rather than assigning students to a single category.

4.4 Integration and boundaries

Taken together, the results are consistent with the theoretical proposition that, at higher educational levels, social and behavioural factors carry explanatory weight alongside cognitive ones [24], and that involvement is a central correlate of college outcomes [17, 18]. They also illustrate what administrative data can and cannot deliver. The model accounted for 29.7% of GPA variance — comparable to other institution-based prediction efforts [1, 3, 4] — leaving most variation unexplained, as should be expected when prior attainment, motivation, teaching, and course-taking patterns are unavailable. Interpreted with that boundary, the value of the analysis is descriptive and diagnostic: it identifies where differences accumulate and which recorded

indicators travel together with attainment, rather than estimating the effect of any intervention.

4.5 Practical implications

Three implications follow, each bounded by what the design can support.

First, co-curricular participation deserves attention as a modifiable feature of the learning environment. Because two-thirds of students fell into the lowest engagement cluster, institutions could lower barriers to participation — through early information, accessible scheduling, and recognition of a wider range of activities — and monitor whether participation broadens beyond already high-achieving students. Any evaluation of such an initiative should use longitudinal or quasi-experimental designs, because the present cross-sectional association cannot establish that increasing participation raises GPA.

Second, academic and psychological support should be coordinated. The co-occurrence of warning flags and lower GPA, together with evidence that distress, sleep, and attainment are interlinked [33, 42], suggests that referral pathways between counselling services and academic advising are more appropriate than treating either difficulty in isolation. Support should be individualised and must avoid stigmatising students on the basis of an administrative flag.

Third, group-difference monitoring should be used to allocate support, not to label groups. Several differences were statistically significant yet small in effect (partial η^2 = .011–.050), and categories such as political affiliation partly reflect institutional selection. Reporting effect sizes alongside significance, as done here, and combining administrative indicators with qualitative inquiry into students' experiences [16, 28] would reduce the risk of deficit interpretations. Future research would benefit from multi-institution samples, longitudinal linkage of engagement and attainment, and

the inclusion of prior attainment and motivational measures that were unavailable in the present records.

4.6 Limitations

Several limitations qualify the findings. First, the sample was drawn from one school within one university, and roughly 70% of students came from a single province; generalisation to other institutions, disciplines, and national contexts is not warranted. Second, the data are cross-sectional and retrospective. All reported relationships are associations, and no causal direction — particularly between second-classroom participation and GPA, or between psychological-warning status and GPA — can be inferred.

Third, measurement was constrained by what institutional systems retained. Personality, achievement motivation, self-efficacy, entrance-examination scores, library use, student–faculty interaction, and technology use were unavailable for these graduated cohorts, and the psychological-warning and political-affiliation variables are administrative categories rather than validated scales. The psychological-warning groups contained only 17 students each, and one category of political affiliation contained 71; estimates for these groups are correspondingly imprecise.

Fourth, the stepwise selection procedure is known to capitalise on sample-specific variation, bias coefficients, and inflate apparent model fit [36, 37]. The regression results should be regarded as exploratory; theory-driven entry or cross-validation would be preferable in future work. Fifth, the large number of group comparisons inflates the family-wise error rate; corrections for multiple testing were not applied, and the smallest effects (partial $\eta^2 = .011$–$.023$) should be interpreted with particular caution even where $p < .05$. Sixth, effect-size benchmarks follow conventional thresholds [34], which are heuristics rather than domain-specific criteria for GPA differences.

Seventh, administrative records were created for management purposes and may contain classification changes over time, missing values, or inconsistencies in how financial-difficulty and psychological-warning categories were assigned; the extract does not document how missing values were handled. The analysis involves sensitive personal attributes; only de-identified aggregate results are reported, and no individual-level data are released.

5 Conclusions

Drawing on de-identified administrative records for 1,613 computer science undergraduates across three cohorts at a Chinese public university, this study found that cumulative GPA was associated with gender, province and prefecture of origin, ethnicity, family economic status, psychological-warning level, political affiliation, and second-classroom participation, but not with urban versus rural origin. Co-curricular engagement showed the strongest association, and students flagged for psychological warning recorded the lowest attainment. The seven retained predictors accounted for approximately 30% of GPA variance. The findings support the practical value of institutionally held data for describing attainment differentials and for locating groups that may benefit from integrated academic and wellbeing support, while underscoring that such records cannot establish causal mechanisms. Meaningful use of administrative data therefore requires both transparent reporting of what the records contain and explicit acknowledgement of what they omit.

List of abbreviations

ANOVA: analysis of variance; GPA: grade point average; I-E-O: input–environment–outcome; SD: standard deviation; VIF: variance inflation factor.

Declarations

Ethics approval and consent to participate. This study was approved by the School of Computer Science and Technology, Wuhan University of Science and Technology. All procedures were carried out in accordance with the relevant institutional guidelines and regulations. Permission to use the institutional administrative records for research purposes was granted by the same body. The analysis used pre-existing de-identified records; no direct contact with students took place, no intervention was administered, and no identifiable individual information was extracted or reported. The approving body determined that individual informed consent was not required for this retrospective analysis of de-identified administrative records.

Consent for publication. Not applicable.

Availability of data and materials. The datasets generated and/or analysed during the current study are not publicly available because they contain sensitive individual-level student records governed by institutional data-protection rules, but de-identified aggregate tables sufficient to reproduce all reported group comparisons are available from the corresponding author on reasonable request, subject to institutional approval.

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