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Orderliness predicts academic performance: behavioural analysis on campus lifestyle

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Quantitative understanding of relationships between students' behavioural patterns and academic performances is a significant step towards personalized education. In contrast to previous studies that were mainly based on questionnaire surveys, recent literature suggests that unobtrusive digital data bring us unprecedented opportunities to study students' lifestyles in the campus. In this paper, we collect behavioural records from undergraduate students' ($N = 18\,960$) smart cards and propose two high-level behavioural characters, orderliness and diligence. The former is a novel entropy-based metric that measures the regularity of campus daily life, which is estimated here based on temporal records of taking showers and having meals. Empirical analyses on such large-scale unobtrusive behavioural data demonstrate that academic performance (GPA) is significantly correlated with orderliness. Furthermore, we show that orderliness is an important feature to predict academic performance, which improves the prediction accuracy even in the presence of students' diligence. Based on these analyses, education administrators could quantitatively understand the major factors leading to excellent or poor performance, detect undesirable abnormal behaviours in time and thus implement effective interventions to better guide students' campus lives at an early stage when necessary.

1. Introduction

A major challenge in education management is to uncover underlying ingredients that affect students' academic performance, which is significant in working out teaching programmes, facilitating personalized education, detecting harmful abnormal behaviours and intervening students' mentation, sentiments and behaviours when it is very necessary. For example, it has been demonstrated that physical status (e.g. height and weight) [1–5], intelligence quotient (IQ) [6,7] and even DNA [8–10] are correlated with educational achievement. Accordingly, we can design personalized teaching and caring programmes for different individuals. Since we cannot change a student's height or DNA via education, more studies concentrate on the aspects of psychology and behaviour, with a belief that learning problems resulting from psychological and behavioural issues can be at least partially intervened. For example, early interventions according to the predictions on course scores or course failures have been discussed recently for K12 education [11–14].

Extensive experiments about relationships between personality and academic performance have been reported in the literature, suggesting that agreeableness, openness and conscientiousness, among the big five personality traits, are significantly correlated with tertiary academic performance, say GPA and course performance [15–17]. In particular, the correlation between

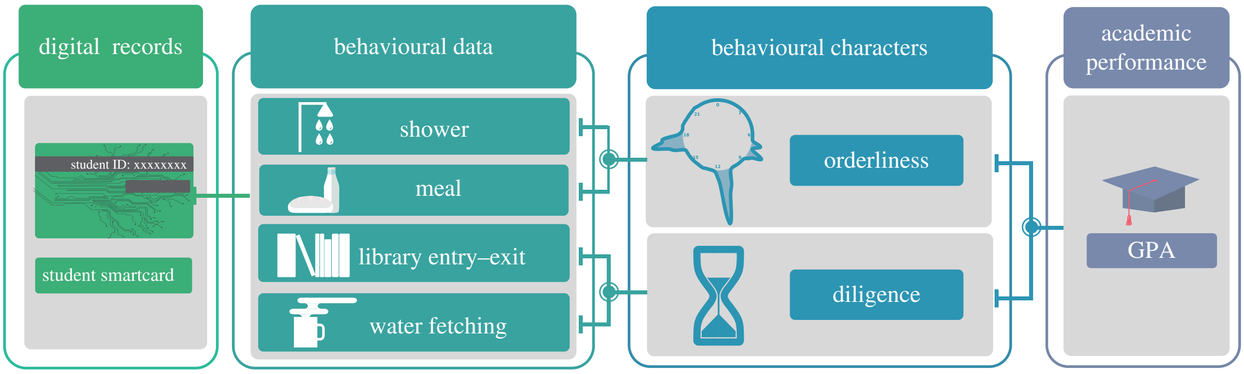

Figure 1. Methodology used to analyse correlations between campus daily routine and academic performance, and then to predict future academic performance. First of all, a large volume of digital entry–exit and consumption records are collected by the real-name campus smart cards with ID encryption. Then, four kinds of behaviours are used to measure two high-level behavioural characters: orderliness and diligence. Specifically, taking showers in dormitories and having meals in cafeterias contribute to the orderliness measure, while entering/exiting the library and fetching water in teaching buildings contribute to the diligence measure. After that, empirical analysis is performed to show the correlation between academic performance and behavioural characters (i.e. orderliness and diligence). Last but not least, the predictive powers of orderliness and diligence are also presented and compared. (Online version in colour.)

conscientiousness and GPA is the strongest (at about 0.2) [15–17]. Behaviours are also associated with academic performance. Class attendance has long been known as an important determinant of academic performance [18–22], and additional studying hours are positively correlated with GPA [23–25]. In addition to studying behaviours, some experimental evidences indicate that students with healthy lifestyles and good sleep habits have higher GPAs on average [26–29].

Under the traditional research framework, a large portion of datasets come from questionnaires and self-reports, which are usually of very small sizes (most sample sizes scale from dozens to hundreds, see meta-analysis reviews [15,16,18,23,26]) and suffer from social desirability bias [30,31], resulting in the difficulties to draw valid and solid conclusions. Thanks to the fast development of modern information technology, we have unprecedented opportunities to collect real-time records of students' living and studying activities in an unobtrusive way, through smartphones [32], online courses [33], campus WiFi [34] and so on. Analyses on these data revealed many unreported correlations between behavioural features and academic performance. For example, watching more of the video and pausing more than once are two strong indicators for better course performance in MOOCs [33], and students who spend more time partying at fraternities or sororities have lower GPAs on average [35].

To quantitatively understand the relationships between university students' behavioural patterns and academic performance as well as the predictive power of the patterns of students' further academic performance, through campus smart cards, we have collected digital records of undergraduate students' ($N = 18\,960$, all of them are pseudonymous) daily activities in the University of Electronic Science and Technology of China (UESTC) from September 2009 to July 2015 (see Data collection in Material and methods for detailed description). The data resolution was reduced before analysis to protect the individuals' privacy (see Privacy protection in Material and methods). According to the methodology (figure 1) used in this study, we have extracted two high-level behavioural characters from the records, including *orderliness* (evaluated by the purchase records for showers ($n = 3\,151\,783$) and meals ($n = 19\,015\,773$)), which quantifies daily-life regularity and *diligence* (evaluated by the entry–exit records in the library ($n = 3\,412\,587$) and fetching water records in teaching buildings ($n = 2\,279\,592$)), which estimates how long time is spent on studies. Empirical results suggested the significant correlation between academic performance (GPA) and orderliness. Further, we found that orderliness as an important feature improves the prediction accuracy for academic performance even in the presence of students' diligence. Our work helps education administrators quantitatively understand the major behavioural factors that affect academic performance and provides a promising methodology towards quantitative and personalized education management.

2. Results

2.1. Orderliness

Intuitively, a regular lifestyle would stand us in good stead for college study. In particular, teachers and administrators in most Asian countries, (e.g. Japan, Korea, Singapore, China, etc.) ask students to be self-disciplined both in and out of class [36], and a significantly positive relationship between disciplinary climate and school performance has been revealed [37,38]. Moreover, previous studies based on questionnaires showed that to improve the regularity of class attendance [18,39] and to cultivate regular studying habits [23] will enhance academic performance. However, these studies have not distinguished orderliness in living patterns from diligence in study, since more regular studying habits will result in longer studying time. To our knowledge, a clear and quantitative relationship between orderliness in living patterns and academic performance of college students has not yet been unfolded in the literature. Fortunately, with the large-scale behavioural data, especially the extracurricular behavioural records, we are able to quantitatively measure the orderliness of a student's campus lifestyle.

According to the dataset, taking a specific behaviour, say taking showers, as an example, if the starting times of taking showers of student A always fall into the range [21:00, 21:30] while student B may take a shower at any time, we could say student A has a higher orderliness than student B for showers. Next, we turn to the mathematical issue of quantifying the orderliness of a student. Again, considering a specific

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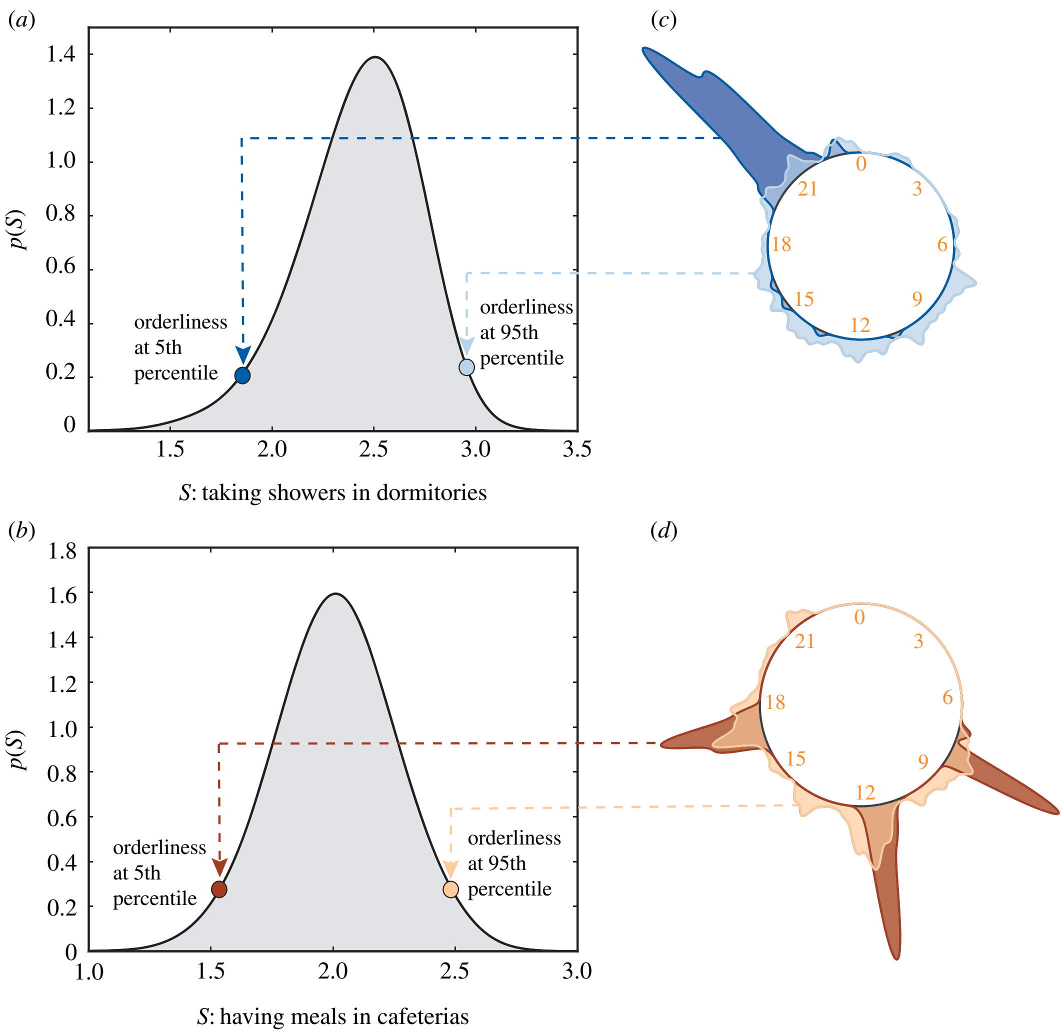

Figure 2. The distributions of actual entropies. (*a*,*b*) Distributions, $p(S)$, of students in taking showers in dormitories (*a*) and having meals in cafeterias (*b*). The broad distributions guarantee the discriminations of students with different orderliness. (*c*,*d*) To better illustrate the differences in behavioural patterns, the behavioural clocks of two students at the 5th percentile and the 95th percentile are shown for taking showers in dormitories (*c*) and having meals in cafeterias (*d*). Intuitively, the students with higher orderliness have more concentrated behaviours over time while the students with lower orderliness have much more dispersed temporal activities. The huge differences between their behavioural patterns demonstrate the relevance of the orderliness measure. (Online version in colour.)

behaviour (e.g. taking showers, having meals, etc.) of an arbitrary student, within total n recorded actions happening at time stamps $\{t_1\text{–}d_1, t_2\text{–}d_2, \ldots, t_n\text{–}d_n\}$, where $t_i \in$ [00:01, 24:00] denotes the precise time with resolution in minutes, and $d_i \in$ [1 September 2009, 20 July 2015] records the date. All actions are arranged in order of occurrence, namely, the i-th action happens before the j-th action if $i < j$. A typical example could be {21:12—20 March 2012, 22:02—22 March 2012, ..., 12:10—09 April 2014}. In the analysis of orderliness, we only concentrate on the precise time within a day, say $\{t_1, t_2, \ldots, t_n\}$. We first divide 1 day into 48 time bins, each of which spans 30 min and is encoded from 1 to 48 (specifically, 0:01—0:30 is the 1st bin, 0:31—1:00 is the 2nd bin, ...). Then, the time series $\{t_1, t_2, \ldots, t_n\}$ can be mapped into a discrete sequence $\{t'_1, t'_2, \ldots, t'_n\}$ where $t'_i \in \{1, 2, \ldots, 48\}$. For example, if a student's starting times of five consecutive showers are {21:05, 21:33, 21:13, 21:48, 21:40}, the corresponding binned sequence is $\mathcal{E} = \{43,44,43,44,44\}$. In this paper, we apply the *actual entropy* [40,41] to measure the orderliness of any sequence $\mathcal{E}$ (see Material and methods for details). The actual entropy is considered as a metric for orderliness: the smaller the entropy, the higher the orderliness. The advantages of using actual entropy instead of some other well-known metrics, such as information entropy [42] and Simpson's diversity index [43], are presented in electronic supplementary material, S1.

Among various daily activities on campus, we calculate orderliness based on two behaviours: taking showers in dormitories and having meals in cafeterias. The reasons to choose these two behaviours are fivefold: (i) they are both high-frequency behaviours so that we have a large number of records; (ii) the data are unobtrusive and thus can objectively reflect students' lifestyles without experimental bias; (iii) they are not directly related to diligence; (iv) they are less affected by the specific course schedules since any schedule will leave time for meals and showers; (v) most university students in China live and study on campus, and thus the used datasets have sufficient coverage to validate the results. We show the distributions $p(S)$ of actual entropies of students on taking showers in dormitories (figure 2*a*) and having meals in cafeterias (figure 2*b*), respectively. The broad distributions guarantee the discriminations of students with different orderliness. We compare two typical students (figure 2*c*), respectively, with very high orderliness (at the 5th percentile of the distribution $p(S)$, named as student H) and very low orderliness (at the 95th percentile of the distribution $p(S)$, named as student L). As clearly shown by the behavioural clock, student H takes most showers around

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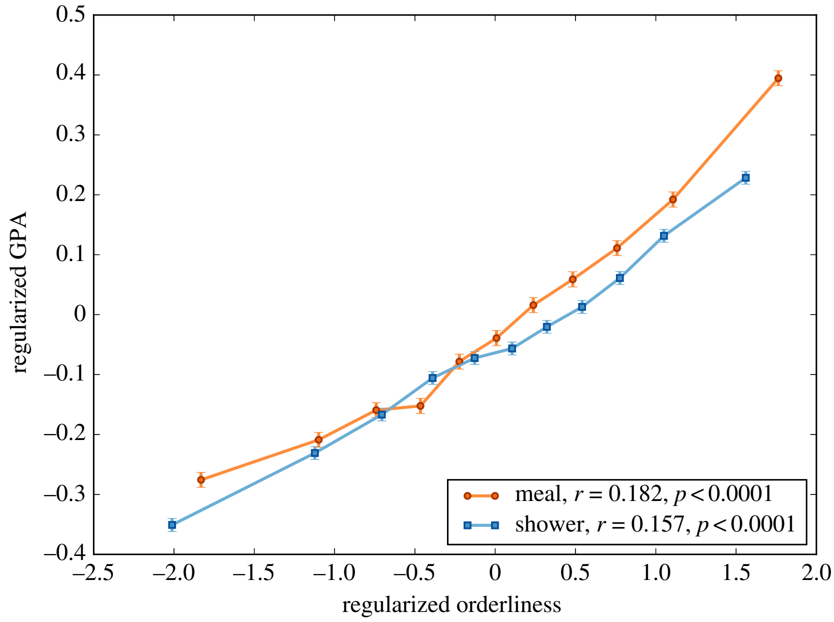

Figure 3. Relationship between orderliness and academic performance for meal (orange circles) and shower (blue squares). Binned statistics are used to aggregate the data points, where regularized orderliness is divided into 11 bins, each of which contains the same number of data points. The mean value of data points in each bin is presented, with error bars denoting the standard error of the regularized GPA. Spearman's rank correlation coefficients for GPA–meal ($r = 0.182$; $p < 0.0001$) and GPA–shower ($r = 0.157$; $p < 0.0001$) suggest the statistical significance. (Online version in colour.)

21:00 while student L may take showers at any time in a day only except for a very short period before dawn, from about 2:30 to about 5:00. We observe a similar discrepancy between two students, respectively, with very high and very low orderliness on having meals (figure 2*d*). In a word, students with higher orderliness have more concentrated behaviours over time while students with lower orderliness have much more dispersed temporal activities.

In addition to orderliness, we have also considered another high-level behavioural character called diligence, which estimates the effort a student makes in his/her academic studies. Considering the difficulties in quantifying diligence due to the lack of ground truth, we roughly estimate diligence based on two behaviours: entering/exiting the library and fetching water in teaching buildings. Specifically, we use a student's cumulative occurrences of entering/exiting the library and fetching water as a rough estimate of his/her diligence (see electronic supplementary material, S2 for details). Empirical analysis also demonstrates that the corresponding distributions are broad enough to distinguish students with different diligence (see electronic supplementary material, figure S1).

2.2. Analysis

Intuitively, students with higher orderliness are probably more self-disciplined since orderliness is an intrinsic personality trait that not only affects meals and showers but also acts on studying behaviours. Hence, we would like to explore whether orderliness is correlated with academic performance, say GPA. The orderliness is simply defined as $O_\mathcal{E} = -S_\mathcal{E}$ and both orderliness and GPA are firstly regularized by *Z-score* [44] (see Material and methods). The relationships between regularized GPA and regularized orderliness (meal and shower) indicate significantly positive correlations (see figure 3). Considering that the relationships between behavioural features and GPA are not simply linear (see electronic supplementary material, figure S3), we apply the well-known Spearman rank correlation coefficient [45] to quantify the correlation strength (see Material and methods). Spearman's rank correlation coefficient r lies in the range $[-1, 1]$, and the larger the absolute value is, the higher the correlation is. Spearman's rank correlation coefficients for meal ($r = 0.182$; $p < 0.0001$) and shower ($r = 0.157$; $p < 0.0001$) both suggest the statistical significance.

The significant correlation implies that orderliness can be considered as a feature class to predict students' academic performance. Diligence is also significantly correlated with academic performance (see electronic supplementary material, figure S2) and thus is considered to be another feature class in the prediction model. We apply a well-known supervised learning to rank algorithm named RankNet [46] (see Material and methods) to predict the ranks of students' semester grades. We train RankNet based on the extracted orderliness and diligence values in one of the first four semesters and predict students' ranks of grades in the next semester. We use the AUC value [47] to evaluate the prediction accuracy, which, in this case, is equal to the percentage of student pairs whose relative ranks can be consistently predicted with the ground truth. The AUC value ranges from 0 to 1 with 0.5 being the random chance, therefore to which extent the AUC value exceeds 0.5 can be considered as the predictive power. We calculate the AUC values under different feature combinations (table 1). It is noticed that both orderliness and diligence are effective for predicting academic performance in all testing semesters, and the introduction of orderliness can remarkably improve the prediction accuracy even at the presence of diligence. At the same time, we have checked that orderliness and diligence are not significantly correlated (see electronic supplementary material, figure S4). That is to say, orderliness has its independent effects on academic performance. In particular, orderliness is for the first time, to our knowledge, proposed as an important behavioural character that is significantly correlated with a student's academic performance.

Table 1. AUC values for the GPA prediction. The abbreviations O, D and O + D stand for utilizing features on orderliness only, on diligence only and on the combination of orderliness and diligence, respectively. SEM is short for semester, for example, SEM 3 represents the case we train the data of semester 2 and predict the ranks of examination performance in semester 3.

	SEMs			
features	SEM 2	SEM 3	SEM 4	SEM 5
O	0.618	0.617	0.611	0.597
D	0.630	0.655	0.663	0.668
O + D	0.668	0.681	0.685	0.683

3. Discussion

In this paper, we proposed novel metrics to measure two high-level behavioural characters, orderliness and diligence, in the university campus. These two types of behavioural features are not correlated themselves (see electronic supplementary material, figure S4), while the correlations between two orderliness features and between two diligence features are both positive and significant (see electronic supplementary material, figure S5 and figure S6), suggesting the robustness of the proposed indices. Extensive empirical analyses on tens of millions of digital records show strong correlations between orderliness and academic performance, as well as between diligence and academic performance. Of particular interests, orderliness is calculated from temporal records of taking showers and having meals, which are not directly related to studying behaviours. We further show the considerable predictive power of orderliness for academic performance. Compared with most previous works in the literature, this work is characterized by large-scale unobtrusive data that allow robust statistical analyses.

The majority of known studies in this domain are mainly based on questionnaires with sample sizes usually scaling from dozens to hundreds [15,16,18,23,26]. In addition, these studies suffer from experimental bias since subjects would like to report socially desirable information instead of disapproved behaviours [30,31]. Therefore, analysing large-scale unobtrusive digital records will become a promising or even mainstream methodology in the near future. However, we do not think such *big-data analyses* should replace questionnaire surveys. Instead, these two methodologies will complement and benefit each other. First of all, with the help of large-scale accessible data on individual daily routines, we can estimate the discrimination of a set of items in a questionnaire on the target behavioural character. Therefore, it is very possible that psychologists and computer scientists will work together not only to make use of unobtrusive digital records, but also to improve the quality of questionnaires [48,49]. Secondly, a few recent works [50–52] show the potential to predict personality and some other private attributes by behavioural data. If these types of reverse predictions are accurate enough to compare with diagnoses, human judgments, self-reports and questionnaire surveys, then we are able to infer questionnaire results of a large population based on the combination of behavioural records and questionnaires of a small fraction of the population.

The present report is relevant to education management. On the one hand, understanding the explicit relationship between behavioural patterns and academic performance could help education administrators to guide students to behave like excellent ones and then they may become excellent later on. On the other hand, we can detect undesirable abnormal behaviours in time and thus implement effective interventions at an early stage. The behavioural pattern of students who are addicted to the Internet may be largely different from those without Internet addiction. For example, previous studies have shown that adolescents with Internet addiction have higher irregular bedtimes and dietary behaviour [53], and there is a significant and negative correlation between Internet addiction and academic performance [54,55]. Therefore, identifying Internet addicts at an early stage is critical for effective interventions.

Yet, the current findings are not beyond their limitations on data and method. First of all, some factors that have large effects on GPA could not be captured by our methods such as psychological factors, talent and luck during the exam. Secondly, we do not have the full scope of data that could be used to estimate orderliness (such as bedtimes) and diligence (such as duration of self-studying). Thirdly, our method may underestimate the diligence of some students with different living habits, for example, some students may mainly drink bottled water instead of fetched water, even though they are also taking classes and studying in the teaching buildings. Some students with low orderliness and diligence may exhibit a high academic performance (see electronic supplementary material, figure S3). Therefore, we will collect more relevant data in future works. In addition, we could not establish the causal link between behavioural features and academic performance based on the current data. We expect to reveal causality relations by designing a controlled experiment.

Another interesting yet challenging issue for future study is the generality of our findings across different cultures and educational atmospheres. For example, East Asia creates a higher level of disciplined atmosphere than other cultures, and student academic performance is significantly positively correlated with the disciplinary climate [37,38]. Although in China orderliness is positively correlated with academic performance, whether orderliness is a quality that is predictive across all cultures still remains an open question. Moreover, most undergraduate students in universities in China live in campus dormitories and most of their activities take place within the campus. However, students in other countries may live off-campus or spend a considerable portion of time doing part-time jobs. Accordingly, the ties between collectable behavioural data and academic performance in other countries may be weaker than those in China.

In summary, we hope the reported approaches in this paper, together with some other works [32,35,50–52] in the same direction, will induce methodological and ideational shifts in pedagogy, eventually resulting in quantitative and personalized education management in the future.

4. Material and methods

4.1. Data collection

In most Chinese universities, every student owns a campus smart card with real-name registration. The smart card can be used for student identification and serves as the unique payment medium for many consumptions in the campus. In addition, almost all Chinese undergraduate students live on campus in dormitories until graduation. In the case of UESTC, the university provides campus dormitories to all undergraduate students and in principle does not allow students to live off-campus. Therefore, smart cards record a large volume of behavioural data in terms of students' living and studying activities. For the 18 960 anonymous students under consideration (they cover almost the whole population of undergraduate students in UESTC, except for very few students who live off-campus for health reasons or have less than 15 actions in one or more types of behaviours under consideration), the data cover the period from the beginning of their first year to the end of their third year. The data used in this paper contain four kinds of daily behaviours within the campus. Specifically, there are 3 151 783 records for taking showers in dormitories, 19 015 773 records for having meals in cafeterias, 3 412 587 records for entering/exiting the library and 2 279 592 records for fetching water in teaching buildings, respectively. In addition, some other consumption and entry–exit behaviours are also recorded, including purchasing daily necessities in campus supermarkets, doing the laundry, having coffees in cafes, taking school buses, entering/exiting the dormitories and so on. GPAs of undergraduate students in each semester are also collected.

4.2. Privacy protection

In the data collection and analyses, we deal with privacy issues very carefully and tried to avoid infringement of student privacy. The students are already pseudonymous in the raw data. Moreover, considering that outside information can be used to link the data back to an individual if the individual's spatio-temporal patterns are unique enough [56,57], we tried to reduce the resolution of the data. For instance, all the information about dates was removed, the precise happening times of behaviours were divided into 48 bins. From the data, we only know a student started to take the shower sometime between 21:00 and 21:30 on some day, while there are about 1000 possible shower rooms, as well as over 15 cafeterias, over 10 teaching buildings and so on. After the raw data were processed, it would be reasonably hard to re-identify individuals by the method reported by Montjoye *et al.* [57].

4.3. Actual entropy

We take the *actual entropy* [40,41] to measure the orderliness of any sequence $\mathcal{E}$. Formally, the actual entropy is defined as

$$S_{\mathcal{E}} = \left(\frac{1}{n} \sum_{i=1}^{n} \Lambda_i \right)^{-1} \ln n, \qquad (4.1)$$

where Λ_i represents the length of the shortest subsequence starting from t'_i of $\mathcal{E}$, which never appeared previously. If such a subsequence does not exist, we set $\Lambda_i = n - i + 2$ [41]. Following this definition, given the binned sequence $\mathcal{E} = \{43,44,43,44,44\}$, we have $\Lambda_1 = 1$, $\Lambda_2 = 1$, $\Lambda_3 = 3$, $\Lambda_4 = 2$, $\Lambda_5 = 2$, and thus $S_{\mathcal{E}} = 0.894$. In this paper, the actual entropy is considered as a measurement for orderliness: the smaller the entropy, the higher the orderliness.

4.4. Data regularization

The distributions of orderliness and GPA are spread around different value scopes. To eliminate the potential effect on correlation analysis, we use the *Z-score* [44] to regularize the data, namely,

$$O'_{\mathcal{E}} = \frac{O_{\mathcal{E}} - \mu_O}{\sigma_O} = \frac{\mu_S - S_{\mathcal{E}}}{\sigma_S}, \qquad (4.2)$$

where $O'_{\mathcal{E}}$ is the regularized orderliness for the student with binned sequence $\mathcal{E}$, μ_O and σ_O are the mean and standard deviation of orderliness O for all considered students, and μ_S and σ_S are the mean and standard deviation of actual entropy S for all considered students. Indeed, orderliness is simply defined as $O_{\mathcal{E}} = -S_{\mathcal{E}}$ under a monotone and one-to-one relationship. Obviously, $\mu_O = -\mu_S$ and $\sigma_O = \sigma_S$. As a result, the predictability of orderliness and entropy is the same. Analogously, the regularized GPA for an arbitrary student i is defined as

$$G'_i = \frac{G_i - \mu_G}{\sigma_G}, \qquad (4.3)$$

where G_i is the GPA of student i, and μ_G and σ_G are the mean and standard deviation of G for all considered students.

4.5. Spearman's rank correlation

In the analysis of relationships between regularized orderliness and regularized GPA, Spearman's rank correlation coefficient [45] is defined as

$$r_S = 1 - \frac{6 \sum_{i=1}^{N} d_i^2}{N(N^2 - 1)}, \qquad (4.4)$$

where N is the number of students under consideration, $d_i = r(O'_i) - r(G'_i)$, with $r(O'_i)$ and $r(G'_i)$ being the ranks for student i's orderliness and GPA, respectively. Spearman's rank correlation coefficient falls into the range $[-1, 1]$, and the larger the absolute value is, the higher the correlation is.

4.6. Prediction approach

Given a characteristic feature vector $\mathbf{x} \in \mathbb{R}^p$ of each student, a pair-wise learning to rank algorithm, RankNet [46], has been exploited to predict students' academic performance. RankNet tries to learn a scoring function $f:\mathbb{R}^p \rightarrow \mathbb{R}$, so that the predicted ranks according to f are as consistent as possible with the ground truth. In RankNet, such consistence is measured by cross entropy between the actual probability and the predicted probability. Based on the scoring function, the predicted probability that a student i has a higher GPA than another student j (denoted as $i \triangleright j$) is defined as $P(i \triangleright j) = \sigma(f(\mathbf{x}_i) - f(\mathbf{x}_j))$, where $\sigma(z) = 1/(1 + e^{-z})$ is a sigmoid function. Here we consider a simple regression function $f = \mathbf{w}^T\mathbf{x}$, where $\mathbf{w}$ is the vector of parameters. The cost function of RankNet is formulated as follows:

$$\mathcal{L} = -\sum_{(i,j):i \triangleright j} \log \sigma(f(\mathbf{x}_i) - f(\mathbf{x}_j)) + \lambda \Omega(f), \qquad (4.5)$$

where $\Omega(f) = \mathbf{w}^T\mathbf{w}$ is a regularized term to prevent over-fitting. Given all students' feature vectors and their ranks, we apply gradient decent to minimize the cost function. The gradient of the lost function with respect to parameter $\mathbf{w}$ in f is

$$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \sum_{(i,j):i \triangleright j} (\sigma(f(\mathbf{x}_i) - f(\mathbf{x}_j)) - 1)\left(\frac{\partial f(\mathbf{x}_i)}{\partial \mathbf{w}} - \frac{\partial f(\mathbf{x}_j)}{\partial \mathbf{w}} \right) + \lambda \frac{\partial \Omega(f)}{\partial \mathbf{w}}. \qquad (4.6)$$

Data accessibility. The dataset needed to evaluate the conclusions in the paper has been uploaded as part of the supplementary material. The original data of precise behavioural records, however, cannot be released in order to preserve the privacy of individuals.

Authors' contributions. Y.C., J.G., Y.W., H.Y. and T.Z. are co-first authors. D.L. and T.Z. designed the research. Y.C., J.S., Q.W., Y.W. and H.Y. performed the research. All authors analysed the data. T.Z. drafted the manuscript. Y.C., J.G. and T.Z. revised the manuscript. All authors gave final approval for publication.

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