Chapter 8
Orderliness of Campus Lifestyle Predicts Academic Performance: A Case Study in Chinese University

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Abstract Different from the western education system, Chinese teachers and parents strongly encourage students to have a regular lifestyle. However, due to the lack of large-scale behavioral data, the relation between living patterns and academic performance remains poorly understood. In this chapter, we analyze large-scale behavioral records of 18,960 students within a Chinese university campus. In particular, we introduce orderliness, a novel entropy-based metric, to measure the regularity of campus lifestyle. Empirical analyses demonstrate that orderliness is significantly and positively correlated with academic performance, and it can improve the prediction accuracy on academic performance at the presence of diligence, another behavioral metric that estimates students' studying hardness. This work supports the eastern pedagogy that emphasizes the value of regular lifestyle.

Keywords Computational social science · Orderliness · Academic performance · Human behavior

8.1 Introduction

Asian traditional culture considers regularity as an important and valuable personal trait. Therefore, in addition to being diligent, parents and teachers in most Asian countries ask students to live disciplined and regular lives. Accordingly, a hard-working and self-disciplined student is usually recognized as a positive model. To maintain large-size classes, teachers in Far East Asia create the highly disciplined

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classes (Ning et al. 2015; Baumann and Krskova 2016), while western teachers rarely emphasize discipline in class or regularity in life. In 2015, BBC broadcasted a documentary about an attempt of Chinese-style education in the UK (BBC 2015), where Chinese teachers and UK students were maladjusted to each other at the beginning but English pupils taught by Chinese teachers eventually got better scores than their peers in a series of exams.

Although eastern and western have different pedagogies, they face the same challenge in education management, that is, to uncover underlying ingredients affecting students' academic performance. Previous studies have demonstrated that educational achievement is related to health conditions (Santana et al. 2017; Hoffmann 2018), IQ (Duckworth and Seligman 2005) and even to molecular genetic markers (Okbay 2016; Selzam et al. 2017). For example, scientists identified 74 genome-wide significant loci associated with the years of schooling (Okbay 2016). Since students' mentality and behavior are more interventional, the majority of studies concentrate on psychological and behavioral issues (Conard 2006). Experiments have demonstrated correlations between academic performance and personality (Chamorro-Premuzic and Furnham 2003; Poropat 2014). In particular, conscientiousness is the best predictor of GPA, while agreeableness and openness are of weaker effects (Vedel 2014). Behaviors of students are also associated with their academic performance, for example, students with more class attendance (Credé et al. 2010; Kassarnig et al. 2018), longer time on study (Grave 2011; Cattaneo et al. 2017), good sleep habits (Taylor et al. 2013; Urrila et al. 2017) and more physical activity (Erwin et al. 2017) perform better on average.

This said, it is still debated in the scientific community if a regular lifestyle in general represents an important prerequisite for academic study or not. One of the reasons for this ongoing debate is that, statistical validation of these observations based on large-scale behavioral data remains lacking. Traditional framework relies on data coming from questionnaires and self-reports, which usually contains a small number of participants (Vedel 2014) and suffers from being biased by the tendency to answer in a social desirable fashion (Fisher 1993). Second, previous studies rarely isolate regularity in living patterns from diligence in studies. As a more regular studying pattern may be correlated with a longer studying time, it is hard to distinguish their independent effects on academic performance. So far, to our knowledge, a quantitative relationship between regularity in everyday life and academic achievement has not been demonstrated. Fortunately, rapid development of information technologies has made it possible to study students' activities in an unobtrusive way by collecting their digital records through smartphones (Wang et al. 2014), online course platforms (Brinton et al. 2016), campus WiFi (Zhou et al. 2016), and so on (Gao et al. 2019). These large-scale extracurricular behavioral data offer chances to quantify the regularity of campus lifestyle and explore its relation to academic performance.

In this chapter, we present a case study on the relation between students' campus lifestyles and their academic performance. Through campus smart cards, we have collected the digital records of 18,960 undergraduate students' daily activities including taking showers, having meals, entering/exiting library and fetching water. Accordingly, we proposed two high-level behavioral characters, orderliness

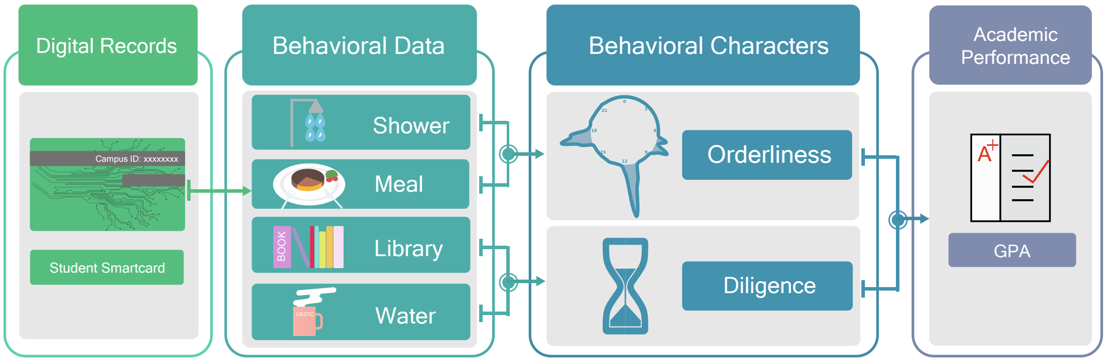

Fig. 8.1 Illustration of the methodology to reveal the relation between campus lifestyle and academic performance. Four types of behavioral records are collected by campus smart cards. Taking showers and having meals are used to measure orderliness, which represents the regularity level of campus life. And entering/exiting library and fetching water are used to measure diligence for which the reason is that cumulative occurrences of these behaviors in study places is naturally recognized as the total efforts taken on studying hardness. Correlations between behavioral features and academic performance are analyzed, and the predictive powers of orderliness and diligence are compared

and diligence (see Fig. 8.1 for the methodology). The orderliness factor is a novel entropy-based metric that measures the regularity of campus life, which is calculated based on temporal records of taking showers and having meals. The diligence factor is roughly estimated based on the cumulative occurrences of entering/exiting library and fetching water. Empirical analyses demonstrated that academic performance (GPA) is significantly correlated with orderliness and diligence. Moreover, orderliness can improve the prediction accuracy on academic performance at the presence of diligence. Some primary results have been published in a recent article (Cao et al. 2018), and the present chapter is an extension with more detailed analyses.

8.2 Data and Metrics

8.2.1 Data Description

In most Chinese universities, every student owns a campus smart card which is used for student identification and serves as the unique payment medium for many on-campus consumptions. For example, there are toll gates in shower rooms, where students have to keep the smart card inserted during the shower. Here, we introduce a specific case study in a Chinese university, the *University of Electronic Science and Technology of China* (UESTC), which provides on-campus dormitories to all undergraduate students and in principle does not allow students to live off-campus. Therefore, smart cards record large volume of behavioral data in terms of students' living and studying activities. Accordingly, we have collected digital records of $N = 18,960$ undergraduate students' daily activities from September 2009 to July 2015, covering the period from the beginning of their first year to the end of their third year. The data includes the purchase records for showers ($n = 3, 151, 783$) and meals ($n = 19, 015, 773$), the entry-exit records in library ($n = 3, 412, 587$) and fetching water records in teaching buildings ($n = 2, 279, 592$). GPAs of students in each semester are also collected.

8.2.2 Orderliness

We calculate orderliness based on two behaviors: taking showers in dormitories and having meals in cafeterias. Indeed, the meaning of orderliness is twofold, say timing and order. The happening times of the same kind of events should be close to each other, for example, having breakfast at about 8:00 is more regular than between 7:00 and 9:00. The temporal order of different events should also be regular, for instance, having meals following the order breakfast → lunch → supper → breakfast → lunch → supper is more regular than breakfast → supper → lunch → supper → breakfast → lunch. With these insights, we turn to the mathematical formula of orderliness. Considering a student's specific behavior within total n recorded actions happening at time stamps $\{t_1, t_2, \dots, t_n\}$, where $t_i \in [00:01, 24:00]$ denotes the precise time with resolution in minutes. We first arrange all actions in the order of occurrence, namely, the i-th action happens before the j-th action if $i < j$, while we ignore the date information. Then, we divide one day into 48 time bins with a 30 minutes step (specifically, 0:01-0:30 is the 1st bin, 0:31-1:00 is the 2nd bin, ...), and map the time series $\{t_1, t_2, \dots, t_n\}$ into a discrete sequence $\{t'_1, t'_2, \dots, t'_n\}$, where $t'_i \in \{1, 2, \dots, 48\}$. 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 $\mathcal{E} = \{43, 44, 43, 44, 44\}$. Next, we apply the actual entropy (Kontoyiannis et al. 1998; Xu et al. 2019) to measure the orderliness of any sequence $\mathcal{E}$. Formally, the actual entropy is defined as

$$S_{\mathcal{E}} = \left(\frac{1}{n} \sum_{i=1}^{n} \Lambda_i \right)^{-1} \ln n, \tag{8.1}$$

where Λ_i represents the length of the shortest subsequence which starts from t'_i of $\mathcal{E}$ and has never appeared previously. Note that we set $\Lambda_i = n - i + 2$ if such subsequence cannot be found (Xu et al. 2019). Finally, we define orderliness as $O_{\mathcal{E}} = -S_{\mathcal{E}}$ and calculate regularized orderliness by normalizing $S_{\mathcal{E}}$ via *Z-score* (Kreyszig 2010):

$$O'_{\mathcal{E}} = \frac{O_{\mathcal{E}} - \mu_O}{\sigma_O} = \frac{\mu_S - S_{\mathcal{E}}}{\sigma_S}, \tag{8.2}$$

where μ_O and σ_O are the mean and standard deviation of orderliness O, μ_S and σ_S are the mean and standard deviation of actual entropy S, and $O'_{\mathcal{E}}$ is the regularized orderliness for the student with binned sequence $\mathcal{E}$. The larger orderliness corresponds to higher regularity of a student's campus lifestyle.

8.2.3 Diligence

Diligence measures to what extent people take efforts to strive for achievements. As an important behavioral character, diligence is intuitively related to students' academic performance. Due to the lack of ground truth, however, it is difficult to quantify students' diligence. Here, we roughly estimate diligence based on two behaviors: entering/exiting the library, and fetching water in teaching buildings. Specifically, we use a student's cumulative occurrences of library entering/exiting and water fetching as a rough estimate of his/her diligence. Basically, self-studying and borrowing books are the most common purposes of going to the library, while attending courses usually take place in the teaching buildings. As teaching buildings have no check-in devices or entry terminals like the library, we use records of water fetching as the proxy.

8.3 Result

8.3.1 Validation of Behavioral Characters

Figure 8.2a and b present the distributions of actual entropies on taking showers and having meals, respectively. The broad distributions guarantee the discriminations of students with different orderliness. For student H with very high orderliness (at the 5th percentile) and student L with very low orderliness (at the 95th percentile), we notice that student H takes most showers around 21:00 while student L may take showers at any time in a day (Fig. 8.2c). We observe the similar discrepancy on having meals (Fig. 8.2d). Figure 8.2e and f present the distributions of cumulative occurrences for entering/exiting the library and fetching water. The two distributions are both broad, showing that the two diligence metrics can distinguish students with different levels of studying hardness.

We next explore the consistency and dependence of the two behavioral characters. As either orderliness or diligence is measured by two types of behavioral records, their intra correlations should be high if they are properly measured. That is, orderliness-meal should be correlated with orderliness-shower, and diligence-water should be correlated with diligence-library. Moreover, the effect of orderliness should be isolated from diligence, i.e., their inter correlations should be low. Figure 8.3 presents the Spearman's correlation matrix between each pair of behavioral features. The intra correlations are all positive and significant, with the correlation $r = 0.226$ between two orderliness metrics and $r = 0.262$ between two diligence metrics. Moreover, if orderliness provides additional information to diligence, the correlation between any pair of orderliness metric and diligence metric should be insignificant. As shown in Fig. 8.3, all inter correlations are close to 0, suggesting the absence of significant correlation between orderliness and diligence. These results validate the robustness of the two behavioral characters and demonstrate their independence.

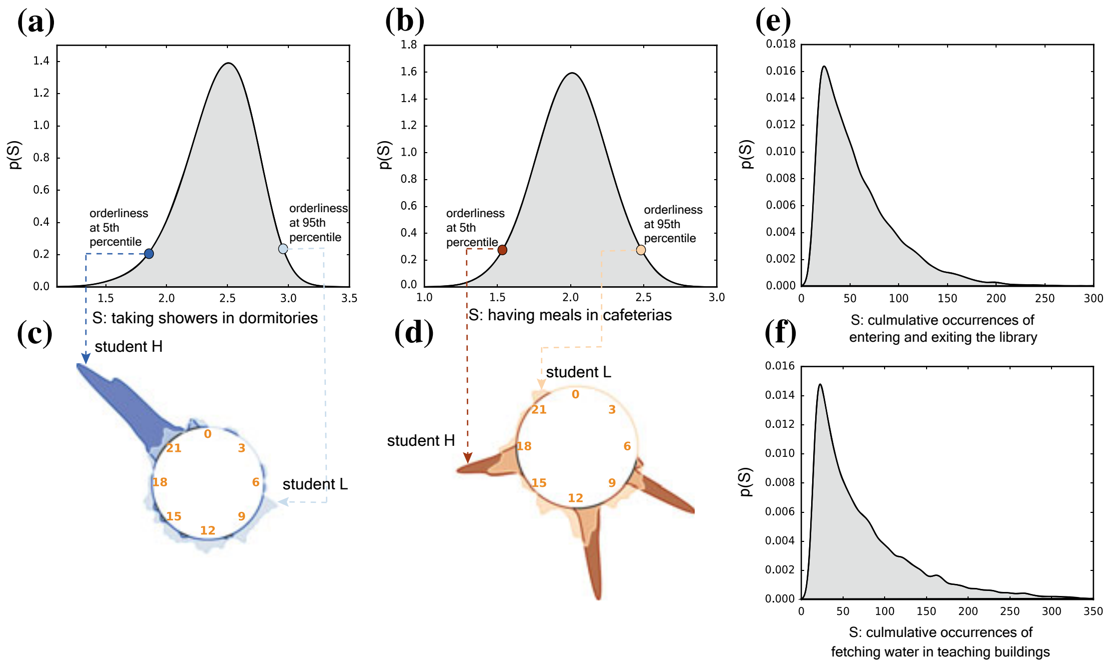

Fig. 8.2 Distributions of actual entropies and cumulative occurrences. Distributions $p(S)$ of students in taking showers (**a**) and having meals (**b**). The x-axis represents the actual entropies S, calculated in each semester. The broad distributions guarantee the discriminations of students with different orderliness. The behavioral clocks of two students at the 5th percentile and the 95th percentile are shown for taking showers (**c**) and having meals (**d**), where student H has high orderliness and student L has low orderliness. Distributions $p(C)$ of students in entering/exiting library (**e**) and fetching water (**f**), calculated in each semester. The broad distributions distinguish students with different diligence levels

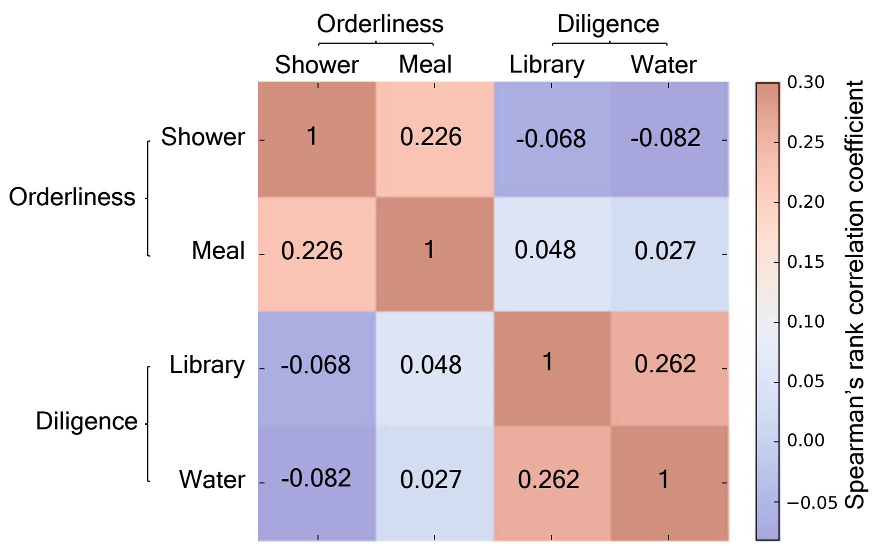

Fig. 8.3 Correlations among behavioral features. Shower and Meal are the two orderliness features, while Library and Water are the two diligence features. The color denotes the corresponding Spearman's rank correlation coefficient. Significance level: all p-values are less than 10^{-15}

8.3.2 Correlation Analysis

Students of higher orderliness and diligence are expected to have better grades. Here, we empirically assessed how students' orderliness and diligence are related to their academic performance (GPA). The regularized GPA for student i is defined as $G'_i = (G_i - \mu_G)/\sigma_G$, where G_i is his/her GPA, and μ_G and σ_G are the mean and standard deviation of G for all considered students.

Figure 8.4a and b present how regularized GPA is positively correlated to regularized orderliness-shower and regularized orderliness-meal, respectively. As the relationships between orderliness and GPA are not simply linear, we apply the well-known Spearman's rank correlation coefficient (Spearman 1904) to quantify the strength of correlation. Results show that the correlation between orderliness-meal and GPA is $r = 0.182$, and the correlation between orderliness-shower and GPA is $r = 0.157$, both with statistical significance $p < 0.0001$. Analogously, Fig. 8.4c and d present how regularized GPA is positively correlated to regularized diligence-library and regularized diligence-water, respectively. The correla-

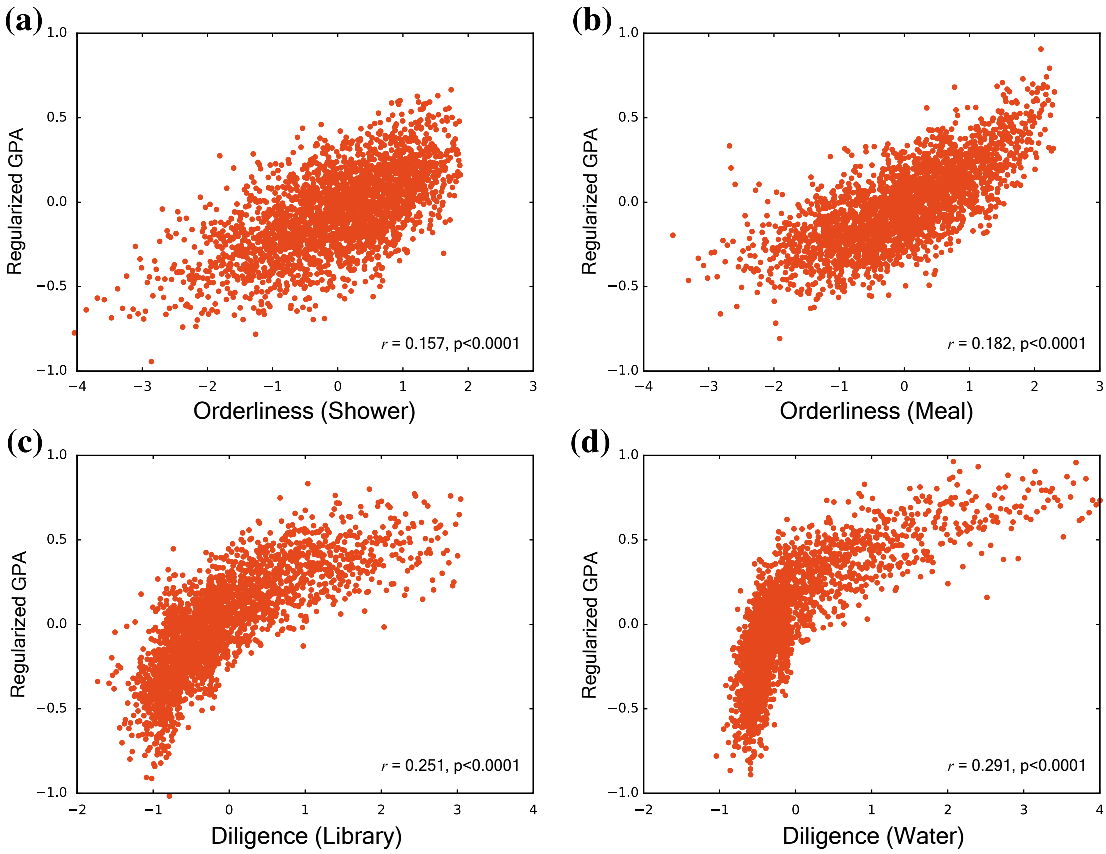

Fig. 8.4 Relations between behavioral features and academic performance. How regularized GPA is positively correlated with **a** regularized orderliness-shower, **b** regularized orderliness-meal, **c** regularized diligence-library, and **d** regularized diligence-water. The corresponding Spearman's rank correlation coefficients and the level of statistical significance are shown in each plot

tion between diligence-library and GPA is $r = 0.291$, and the correlation between diligence-water and GPA is $r = 0.251$.

As a summary, the two behavioral characters are significantly correlated to academic performance with correlations being about 0.2. The Spearman's rank correlations for diligence (library and water) are stronger than for orderliness (shower and meal), while eyeballing the data suggests the opposite (Fig. 8.4). As a robustness check, we additionally calculated the Pearson correlation coefficients. Results showed that correlations for diligence remain stronger than for orderliness. The visual discrepancy may be because the data points are dispersive. As orderliness is largely independent to diligence, the results suggest their independently potential effects on students' academic performance.

8.3.3 Predictive Analysis

The significant correlations between behavioral features and GPA imply that orderliness and diligence can be used as different feature classes to predict students' academic performance. Here, we predict the ranks of students' semester grades by applying a well-known supervised learning-to-rank algorithm named RankNet (Burges et al. 2005). Given a feature vector $\mathbf{x} \in \mathbb{R}^p$ of each student, 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. The consistence is measured by the 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 $i \rhd j$) is defined as $P(i \rhd j) = \sigma(f(\mathbf{x}_i) - f(\mathbf{x}_j))$, where $\sigma(z) = 1/(1 + e^{-z})$ is a sigmoid function.

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 given by

$$\mathcal{L} = -\sum_{(i,j):i \rhd j} \log \sigma(f(\mathbf{x}_i) - f(\mathbf{x}_j)) + \lambda \Omega(f), \tag{8.3}$$

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

$$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \sum_{(i,j):i \rhd j} (\sigma(f(\mathbf{x}_i) - f(\mathbf{x}_j)) - 1) \left(\frac{\partial f(\mathbf{x}_i)}{\partial \mathbf{w}} - \frac{\partial f(\mathbf{x}_j)}{\partial \mathbf{w}} \right) + \lambda \frac{\partial \Omega(f)}{\partial \mathbf{w}}. \tag{8.4}$$

The prediction accuracy is evaluated by AUC value (Hanley and McNeil 1982), which is equal to the percentage of student pairs whose relative ranks are correctly predicted. 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.

Table 8.1 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

Features	Semester 2	Semester 3	Semester 4	Semester 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

We train RankNet based on the extracted orderliness and diligence features in one of the first four semesters and predict students' ranks of grades in the next semester. We use the abbreviations O, D and O+D to stand for utilizing features on orderliness only, on diligence only and on the combination of orderliness and diligence, respectively. Table 8.1 presents the results of AUC values under different feature combinations, where the column semester j represents the case in which we train the data of semester $j-1$ and predict the ranks of grades in semester j. Obviously, both orderliness and diligence are predictive to academic performance, and orderliness can improve the prediction accuracy at the presence of diligence, showing its independent role in facilitating academic studying.

8.4 Discussion

Large parts of the Eastern world value regularity in campus lifestyle, while large parts of the Western world tend to provide a more unconstrained lifestyle to students. The disparity in educational philosophy between these different parts of the world may originate from their culture differences. Yet, the core question is whether regularized campus lifestyle is helpful to achieve higher academic performance. To answer this question, we presented the data-driven case study based on large-scale behavioral records of students' living and studying activities in a Chinese university campus (Cao et al. 2018). Specifically, we calculated orderliness based on temporal records of taking showers and having meals, which is not directly related to studying activities. Empirical analyses show that academic performance is significantly and positively correlated with orderliness. Moreover, orderliness can remarkably improve the accuracy of academic performance prediction even at the presence of diligence, suggesting the independent predictive power of orderliness.

Our work not only provides a quantitatively understanding of the relationships between students' behavioral patterns and academic performances, but probably also takes a significant step towards better educational management. On the one hand, education administrators could design personalized teaching and caring programs for individuals with different behaviors. For example, recent works have discussed the prediction of course failures and dropping out for K12 education (Kindergarten and the 1–12 grades) (Jayaprakash et al. 2014; Lakkaraju et al. 2015), and thus teachers could pay more attentions in advanced to those students who may develop difficulties in studying.

On the other hand, education managers can detect students' undesirable abnormal behaviors from traced data (e.g., Internet use disorder (IUD) Montag and Reuter 2017; Brand et al. 2016; Peterka-Bonetta et al. 2019) and implement interventions in time. IUD is negatively correlated with academic performance (Akhter 2013; Khan et al. 2016), and IUD is among the most important reasons resulting in the failure of college study in China. Two issues need to be discussed in the context of IUD, formerly also known as Internet addiction. Firstly, the sharp fall of exam performance or even failure of many courses appears about one or two semesters after developing IUD. Secondly, it requires a long time (usually a few months) for a student to rebuild learning ability after proper treatment of IUD.

Therefore, a student's academic performance would not drop immediately, while IUD immediately will impact on the student's behaviors (e.g., absence from classes). Students suffering from IUD demonstrated largely different behavioral patterns compared to those not suffering from IUD, for example, students with IUD have irregular bedtimes and dietary behavior (Kim et al. 2010), and their diligence and orderliness usually dramatically decline. Accordingly, it might be possible to establish models being able to predict whether students are more prone to develop IUD, and thus those problem students can be helped as soon as possible.

Even though traditional questionnaire surveys are limited by sample sizes and suffering from response biases such as tendencies to answer in a social desirable way (Paulhus and Vazire 2007), these two methodologies can complement and benefit each other. The use of unobtrusive digital records is helpful in improving the quality of questionnaires (Montag et al. 2016), meanwhile the assessment of psychological characteristics related to a target behavior can be also complemented by self-report questionnaires, e.g., assessing conscientiousness, which would have been of interest also in the present work. Indeed, it has been shown that is possible to infer self-reported personality and other private attributes from available online information such as Facebook-Likes (Kosinski et al. 2013; Youyou et al. 2015). Moreover, it is promising to establish a causal link between behavioral features and academic performance through designing controlled experiments. We are expecting psychologists and computer scientists to work together on such a promising research endeavor in the near future (Gao et al. 2019).

As we know from our culture, Chinese universities value disciplinary behaviors (Baumann and Krskova 2016). However, whether orderliness will be of same positive quality for academic study performance in other countries remains an open question. On the one hand, orderliness relies in our work on campus activities while students in other countries may live off-campus or spend a considerable portion of time doing part-time jobs, resulting perhaps in lower orderliness (but such differences between "West" and "East" need to be systematically evaluated on an empirical level and we explicitly state this to be a working hypothesis). On the other hand, it is difficult to isolate orderliness from the capacity to follow the teacher's advice (whatever that is) in and out of classes. Although previous studies have shown that better classroom discipline leads to better academic performance (Ning et al. 2015), whether a student's capacity to follow advice is related to her/his achievements is not clear or may be also attributable to other person characteristics including intelligence.

We hope that recent works leveraging large-scale behavioral data analysis and machine learning techniques also find its way into pedagogical sciences (Kassarnig et al. 2018; Wang et al. 2014; Gao and Zhou 2016). Indeed, uncovering factors that affect educational outcome play a significant role in future quantitative and personalized education management and could help to improve the schooling process.

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