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Procrastination's price: LMS-driven digital phenotyping reveals widespread impact of academic procrastination on sleep and grades

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ABSTRACT

Academic procrastination is prevalent among university students and often associated with poor grades and wellbeing outcomes. While traditionally assessed with self-report instruments, here we leverage on over 1.4 million interactions with the university's learning management system (LMS) from 563 freshmen (277 males; 286 females) across their first semester at university to passively identify profiles of those at-risk of procrastination. Profiles were derived from LMS behaviours in the 72 h period prior to 7,261 assignments, and area under the curve (AUC) values of these profiles were used to classify students into Low, Moderate and High Procrastination phenotypes based on a tertile split. These LMS-driven phenotypes were found to align with survey-based procrastination reports indicating higher levels of self-reported procrastination ($F(2,443) = 4.86$, $p = 0.008$), as well as with lower conscientiousness levels ($F(2,433) = 3.63$, $p = 0.02$) in High compared to Low Procrastinators consistent with prior literature. High Procrastinators also submitted more assignments in the last 24 h (78% compared to 50% and 20% in Moderate and Low Procrastinators), and achieved lower end-of-semester academic grades ($F(2,532) = 19.33$, $p < 0.001$). Furthermore, integration of these profiles with longitudinal, objective sleep tracking and time use diaries revealed that High Procrastinators consistently slept shorter, later and more irregularly than Low Procrastinators (all $p < 0.005$), and were more likely to engage in social activities close to bedtime (all $p < 0.05$) despite reporting similar aspirational sleep schedules (all $p > 0.37$). Our findings support LMS as a passive and scalable early detection tool that could inform interventions to improve student sleep and academic performance through enhanced time-management and self-regulation strategies.

1. Introduction

Academic procrastination - the delay in action toward academic tasks (Solomon & Rothblum, 1984; Svartdal & Lokke, 2022; Tice & Baumeister, 1997) ahead of an impending assignment deadline or exam, is prevalent in university settings (Richardson et al., 2012). Between 46% and 95% of college students report having engaged in procrastination (Solomon & Rothblum, 1984; Steel, 2007), with 50% procrastinating frequently and problematically (Day et al., 2000), a trend that may reflect the increase in autonomy students face over schedules and time-use particularly as they transition into university life. This newfound independence (Arnett et al., 2014) places significant demands on self-regulation skills (Steel, 2007), and is possibly why procrastination, often described as a failure to self-regulate (Fernie et al., 2017; Limone et al., 2020; Ragusa et al., 2023; Steel, 2007), increases during this period (Clariana et al., 2012; Janssen, 2015; Svartdal et al., 2020).

Procrastination is commonly associated with specific personality traits such as high impulsivity (Gustavson et al., 2014) and low conscientiousness (Eerde, 2004; Johnson & Bloom, 1995; Nieto et al., 2024), and has been linked to a range of negative outcomes including poorer grades (Goroshit, 2018; Lakshminarayan et al., 2013; Richardson et al., 2012), increased anxiety (Haycock et al., 1998) and stress (Sirois, 2023; Sirois et al., 2023; Steel, 2007; Tice & Baumeister, 1997), maladaptive coping strategies (Sirois & Kitner, 2015), poorer quality sleep (Li et al., 2020; Sirois et al., 2015), unhealthy behaviours (Sirois et al., 2003, 2023), and worser health outcomes (Johansson et al., 2023; Sirois et al., 2003). Reasons for procrastination vary, ranging from task aversion (Steel, 2007), to a fear of failure (Schouwenburg, 1992), or poor time management (Lay & Schouwenburg, 1993). For some, procrastination is situationally tied to specific academic tasks, while for others it reflects a broader trait disposition that affects not only

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academic performance, but also relationships and health behaviours (Rozental et al., 2022; Sirois et al., 2003, 2023). As the frequency of procrastination behaviour increases across years in university (McCown & Roberts, 1994)) and is detrimental to both workplace productivity (D'Abate & Eddy, 2007) and employee outcomes (Nguyen et al., 2013), identification of students at-risk for procrastination behaviour could allow for early intervention before these habits become further entrenched later on in life.

Procrastination has been traditionally measured with self-report questionnaires (Choi & Moran, 2009; Johansson et al., 2023; Lay, 1986; Nieto et al., 2024; Steel, 2010) or submission timestamps (Tice & Baumeister, 1997). However, these single indicators provide limited insight into how procrastination unfolds over time in real-world settings. They often do not distinguish between when students begin working on tasks and how they engage with those tasks prior to submission, making it difficult to characterise heterogeneity in procrastination-related behaviours. Finally, although procrastination has been linked to health behaviours and academic performance, these domains are typically examined in isolation, at a single time-point.

Recent advances using passive tracking from online learning portals has allowed for new models to be developed that do not rely on self-report measures which are burdensome and prone to recall bias. These models can additionally incorporate time spent studying/working on an assignment, distinguishing between academically weaker students who start early but submit late because they need to spend more time on an assignment vs. students who start and submit late for different reasons (Leinonen et al., 2021). In this manner, we can relate procrastination as a psychological construct, to LMS engagement patterns which are observable digital traces of students' interactions with course materials (e.g., timing and frequency of platform access), and use these patterns as a proxy of procrastination-related behavioural delay. Furthermore, by integrating LMS engagement patterns with daily lifestyle habits from a sleep or activity tracker, and contextual information from time-use diaries or ecological momentary assessments, we can holistically characterize profiles of student behaviour across academic and non-academic domains.

In the present study, we leveraged usage of the university's learning management system (LMS) to passively identify profiles of freshmen at-risk of procrastination in their first semester at university. We corroborated these profiles with self-report procrastination and personality surveys traditionally reported in the literature, and explored how these profiles relate to end-of-term grade point average (GPA) scores, habitual sleep patterns (using a well-validated sleep tracker (Ong et al., 2024; Willoughby et al., 2024) and time-use diaries which could help identify intervention targets in high procrastinators.

2. Methodology

2.1. Data collection and setting

638 participants were recruited for a study looking at the impact of the academic calendar on freshmen sleep as they transition into their first semester (20 weeks) of university (14 Aug-31 Dec 2023). Protocols were approved by the university's Institutional Review Board. Of these 638 participants, 569 completed the entire 20-week protocol. In the present analyses, we utilize data from 563 of these participants (mean (SD) age: 20.4 (1.3) y, 277 males; Table 1) who interacted with the university's learning management system (Canvas LMS) for assignment-related activities. Here, we distinguish between assignment *completion* (i.e., time spent working on assignments), and *submission* (i.e., the final upload of the assignment). Assignment completion was operationalized using LMS requests as a proxy for time spent working on assignments, up until the point of submission. These requests comprised all logged interactions with the LMS portal, including accessing lecture materials, viewing e-learning content, downloading assignment files, and participating in discussion forums.

2.2. Computation of LMS-driven procrastination profiles

Individual procrastination profiles were constructed following the rationale that proactive students would start working on assignments and show more interactions with the LMS (LMS requests) at an earlier stage, while procrastinators would interact with the LMS only closer to the assignment deadline.

16,852 (92%) of assignments were submitted within a 10-day period prior to the assignment deadline and were considered in subsequent analyses. Following filtering of assignments with overlapping deadlines (within 3 days before and 1 day after; retaining only, the earliest assignment), 1,483,791 LMS requests prior to 7,261 assignments [M $(SD)_{participant} = 12.9$ (4.5) assignments] were averaged in 73 hourly bins (i.e., 72 h before each set deadline T [T-72] to 1 h after [T+1]) to generate individual LMS-based procrastination profiles for each participant. Time 0 represents the assignment deadline, and the number of requests prior to each assignment are cumulatively summed from time T-72 to T+1 to create a cumulative distribution function (cdf). T+1 submissions were allowed to account for technical issues that could have prevented timely submissions, but these only accounted for 1% of submissions. These cdf curves were then normalized and averaged per subject to create LMS-procrastination profiles (Fig. 1A–C) for each participant, which indicate the probability of assignment completion with time to the deadline. Area under the curve (AUC) was computed, and a tertile split was used to characterize participants into Low [LoPro],

Table 1
Demographic characteristics of the 563 participants, split by procrastination phenotype: High Procrastination [HiPro], Moderate Procrastination [ModPro] and Low Procrastination [LoPro]. No differences across groups were observed on variables surveyed here (p's > 0.05).

Variable	Overall (N = 563)	HiPro (N = 187)	ModPro (N = 187)	LoPro (N = 189)	F-value/χ^2-test	*p*-value
Age, mean (SD), y	20.2 (1.29)	20.3 (1.33)	20.3 (1.31)	20.2 (1.23)	1.85	0.158
Sex, N (%)					0.51	0.773
Female	286 (50.8)	99 (52.9)	94 (49.7)	93 (49.7)		
Male	277 (49.2)	88 (47.1)	95 (50.3)	94 (50.3)		
Ethnicity, N (%)					8.75	0.188
Chinese	486 (86.3)	156 (83.4)	162 (85.7)	168 (89.8)		
Indian	37 (6.6)	17 (9.1)	13 (6.9)	7 (3.7)		
Malay	18 (3.2)	9 (4.8)	6 (3.2)	3 (1.6)		
Other	22 (3.9)	5 (2.7)	8 (4.2)	9 (4.8)		
Residence, N (%)					2.51	0.285
On-campus	308 (54.7)	109 (58.3)	105 (55.6)	94 (50.3)		
Off-campus	255 (45.3)	78 (41.7)	84 (44.4)	93 (49.7)		
PSQI, mean (SD)	5.90 (2.50)	5.88 (2.61)	6.17 (2.64)	5.64 (2.21)	1.924	0.147
MEQ, mean (SD)	44.8 (8.54)	43.6 (8.47)	44.5 (8.30)	46.0 (8.73)	2.357	0.096
BAI, mean (SD)	10.6 (9.24)	10.7 (8.77)	10.5 (9.78)	10.7 (9.17)	0.027	0.973
BDI, mean (SD)	12.9 (11.0)	12.2 (9.98)	13.8 (12.1)	12.6 (10.9)	0.967	0.381

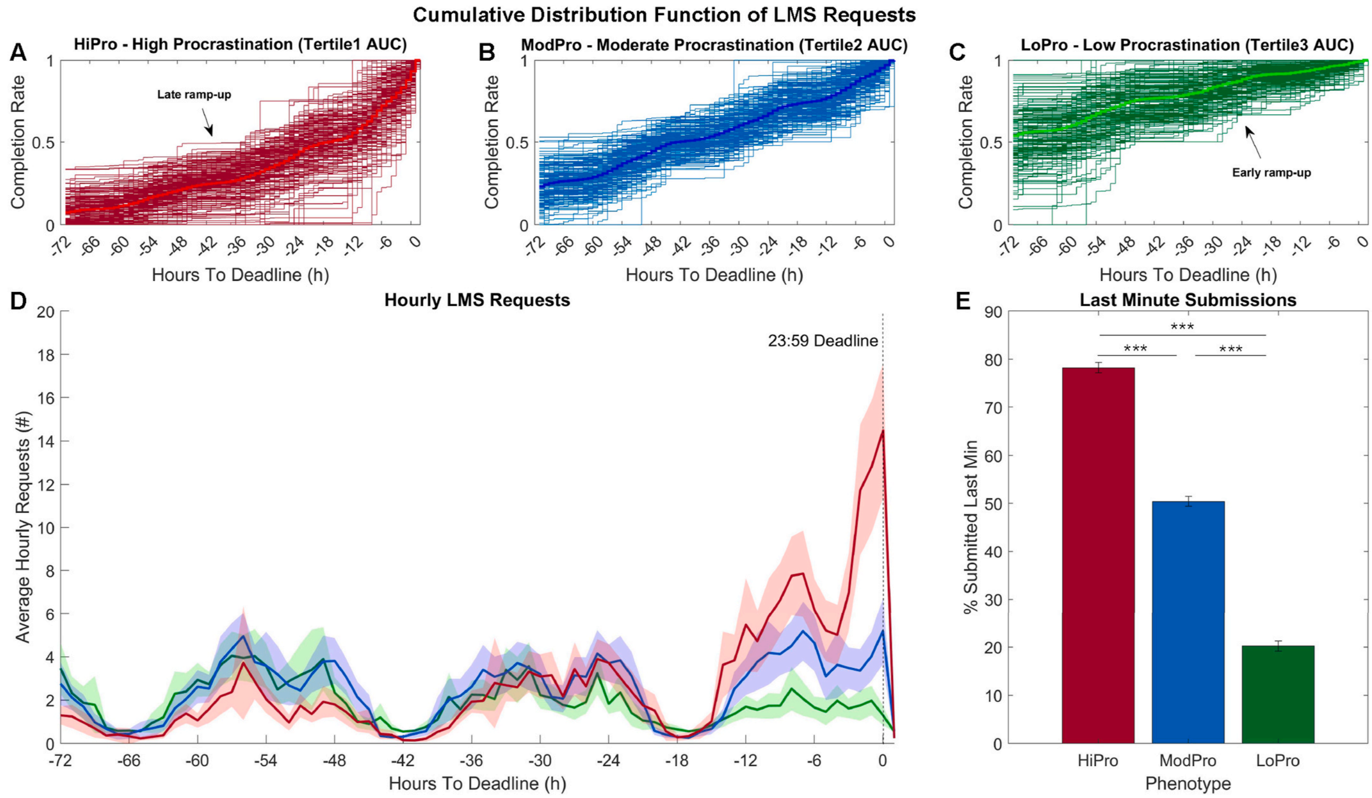

Fig. 1. LMS-driven passive profiling of procrastination phenotypes.
Procrastination profiles per participant were created based on averaged cumulative distribution plots of 1,483,791 LMS requests leading up to 7,261 individual assignment deadlines. Area under the curve (AUC) values were used to delineate **(A)** High Procrastination [HiPro] **(B)** Moderate Procrastination [ModPro] and **(C)** Low Procrastination [LoPro] phenotypes based on a tertile split. Bold curves denote the group mean, which show a late ramp-up to the assignment deadline in HiPro compared to LoPro. **(D)** Averaged hourly requests leading up to 23:59 deadlines (the predominant deadline) by phenotype. Most LMS requests in HiPro were logged in the last 3 h, while requests in LoPro were logged much earlier before the deadline (even prior to the 72 h period shown here). **(E)** Percentage of last-minute assignments submitted within a 24 h period prior to its deadline by phenotype. Multiple comparisons were performed using Tukey's test and asterisks show pairwise comparisons that reached statistical significance (*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$).

Moderate [ModPro] and High Procrastination [HiPro] phenotypes. Assignments that were completed prior to the 72 h period had an AUC of 1, while those completed within the 72 h period had an AUC of <1, decreasing with a later assignment start/completion time. Late assignments submitted after T+1 were a minority (1.8%) and not included in this analysis, as these could represent more extenuating and unusual circumstances (e.g. illness, significant personal events).

Sensitivity analyses were conducted to (1) compare AUC profiles across different time windows (24h, 48h, and 72h), which showed similar but slightly stronger associations with GPA for the 72h profile; Supplementary Methods; Figs. S8-S9), and (2) compare the tertile-split approach with a data-driven clustering approach based on principal components (Supplementary Methods; Figs. S10-S11), which indicated that the tertile-split approach explained more variance in this sample.

2.3. Daily/weekly EMA assessments

Participants completed a series of 5-min ecological momentary assessments (EMA) pushed out on a smartphone app (Z4IP) daily between 2000 and 2359 h throughout the 20-week semester. Pertinent to the current set of analyses, weekly questions probing procrastination ('In the past 7 days, how much did you procrastinate') in 5 domains (Studying or doing assignments, Health/medical, Leisure, Everyday tasks and obligations, Family/Friend relationships) over a 0-100 scale were assessed to evaluate validity of these LMS-driven procrastination profiles.

Although these brief assessments were delivered daily across the 20-week period, only the first 17 weeks of data were analysed as subsequent vacation periods did not contain assignment deadlines. Only participants with a minimum of 5 daily/weekly ratings across the 17 weeks were included in the final analyses (EMA: N = 551/563 (97.9%); Procrastination: N = 446/563 (79.2%)).

2.4. Periodic surveys and time-use diaries

For more trait-like measures that are expected to be relatively stable across the semester, periodic surveys and time-use diaries were pushed out over three fortnights (Week 1-2, Week 7-8 and Week 15-16).

Phenotype clusters were compared across key demographic characteristics (age, sex, ethnicity, place of residence), commonly used sleep and mental health scales: global sleep quality (Pittsburgh Sleep Quality Index (Buysse et al., 1989) [PSQI]), chronotype (Morningness-Eveningness Questionnaire (Horne & Ostberg, 1976) [MEQ]), anxiety (Beck's Anxiety Inventory (Beck & Steer, Robert A., 1993) [BAI]) and depression (Beck's Depression Inventory (Beck & Steer, Robert A., 1996) [BDI]) (Table 1) as well as onpreferred bed and wake timings (Table S1).

Personality traits used in this report (N = 436/563 (77.4%)) were assessed by the Big5 personality inventory (John et al., 1991) in Survey Set 2 and scored on dimensions of conscientiousness [9–45], extraversion [8–40], openness to experience [9–50], neuroticism [8–40] and agreeableness [9–45]. Internal consistency of the Big Five personality traits measured by Cronbach's α was acceptable to good in the present sample (Extraversion $\alpha = 0.86$, Agreeableness $\alpha = 0.73$, Conscientiousness $\alpha = 0.80$, Neuroticism $\alpha = 0.84$, Openness $\alpha = 0.75$).

Daily activities were reported in 15-min bins from an original list of 20 categories, but for brevity only 11 major time-use categories were analysed (Self-study, Leisure-Digital, Leisure-Non-Digital, Social, Cocurricular Activities, Commuting, Classes, Meals, Self-care, Exercise, Sleep), while the remaining 9 categories were collapsed into an 'Others' category as they represented a minority of cases. Daily diaries were editable for up to three days. Only days with at least 75% completion and 3 or more activity types were included for analyses. Activities were summarized in 3 h bins for ease of interpretation in the final analyses. As weekday and weekend differences between procrastination phenotypes did not materially differ, we combined all days reported for each individual.

2.5. Academic performance

Grade point averages (GPA) were obtained from the university's official educational records system (EduRec) representing the weighted average grade point of all courses taken by an individual. GPA scores ranged from 0 (F) to 5.0 (A+/A) for each course taken. As first year medical students do not have grade points that contribute towards calculation of a GPA, 28 individuals were excluded from this analysis (final N = 535/563 (95%)).

2.6. Sleep tracking

Participants were loaned an Oura Ring 3 (Oura Health OY, Oulu, Finland) and required to charge, wear and sync this daily across the 20-week semester. For the present analyses, only main sleep periods, i.e., those with the longest sleep duration between 1800h the previous day to 1800h the present day were considered. Days with sleep duration ≥15 h were excluded as these likely represented inaccurate, or unrepresentative sleep episodes (e.g., due to illness). If a day's longest recorded sleep duration was <3 h, or if no sleep was recorded, only days with minimum wear time of at least 20 h were included to ensure that main sleep periods were not missed due to non-wear or other technical reasons. Weighted average sleep outcomes were computed for each participant with at least 10 days of valid sleep logs using (5/7 × weekday + 2/7 × weekend sleep), while sleep variability was computed using standard deviation of sleep duration outcomes (final N = 563/563 (100%)).

2.7. Statistical analysis

Trait differences between procrastination phenotypes in survey measures, academic grades, sleep and time-use patterns were assessed using one-way ANOVAs. Significant results were followed up using Tukey's HSD method for multiple comparisons between phenotype pairs.

3. Results

3.1. Characterization of LMS-driven procrastination phenotypes

Time stamps of student LMS interactions were used to create individual procrastination profiles (Fig. 1A–C). Participants were categorized into High (HiPro; N = 187), Moderate (ModPro; N = 189) and Low (LoPro; N = 187) Procrastination phenotypes, based on a tertile split of Area Under the Curve (AUC) values of their procrastination profile curves. Fig. 1D shows averaged hourly requests leading up to 23:59 deadlines (the predominant deadline) by phenotype, indicating that most HiPro requests were logged in the last 3 h. Fig. 1E further confirms that a significantly higher percentage of assignments were submitted in the last 24 h in HiPro compared to ModPro and LoPro (mean [SD] LoPro: 20.2 [14.1]%, ModPro: 50.4 [13.7]%, HiPro: 78.2 [15.1]%; $F(2,560) = 767.48$, $p < 0.001$; $\eta^2 = 0.73$, 95% CI [0.70, 0.76]). Table 1 describes key demographic characteristics, baseline sleep quality, chronotype and depression and anxiety levels in the cohort, which did not significantly differ by procrastination phenotype (p's > 0.096).

3.2. LMS profiles show convergent validity with self-report procrastination measures and personality traits

Weekly self-reported procrastination [0-100] in the academic domain confirmed validity of LMS-driven procrastination phenotypes, with LoPro participants reporting significantly lower average procrastination levels compared to HiPro (mean [SD] LoPro: 37.0 [19.6], ModPro: 42.2 [20.1], HiPro: 43.8 [19.1]; $F(2,443) = 4.86$, $p = 0.008$, $\eta^2 = 0.02$, 95% CI [0.002, 0.052]; Tukey's post-hoc: LoPro vs. HiPro, $p = 0.009$; Fig. 2A). Similar trends were observed for procrastination in other domains of student life surveyed (Fig. 2B–E) with significant differences between procrastination phenotypes for everyday tasks and leisure activities (Everyday Tasks: mean [SD] LoPro: 26.3 [19.5], ModPro: 30.4 [21.0], HiPro: 32.5 [19.3]; $F(2,443) = 3.69$, $p = 0.03$, $\eta^2 = 0.02$, 95% CI [0.000, 0.044]; Tukey's post-hoc: LoPro vs. HiPro, $p = 0.022$; Leisure Activities: mean [SD] LoPro: 17.3 [19.0], ModPro: 17.6 [15.9], HiPro: 22.5 [18.9]; $F(2,443) = 3.81$, $p = 0.03$, $\eta^2 = 0.02$, 95% CI [0.000, 0.045]; Tukey's post-hoc: LoPro vs. HiPro, $p = 0.036$, ModPro vs. HiPro, $p = 0.048$) but not for health or relationships (F's < 2.54, p's > 0.08).

In addition, conscientiousness, as assessed by the Big5 personality inventory (John et al., 1991) administered in Week 7-8 of the study was higher in LoPro compared to HiPro (mean [SD] LoPro: 29.8 [5.10], ModPro: 29.0 [5.00], HiPro: 28.3 [4.77]; $F(2,433) = 3.63$, $p = 0.03$, $\eta^2 = 0.02$, 95% CI [0.000, 0.045]; Fig. 2F), in accordance with prior findings (Eerde, 2004; Johnson & Bloom, 1995). Interestingly, in this cohort, HiPro also exhibited higher levels of extraversion and openness compared to LoPro (Extraversion: mean [SD] LoPro: 22.1 [5.97], ModPro: 23.1 [5.46], HiPro: 24.1 [5.85]; $F(2,433) = 4.63$, $p = 0.01$, $\eta^2 = 0.02$, 95% CI [0.001, 0.052]; Openness: mean [SD] LoPro: 31.5 [5.49], ModPro: 32.8 [5.49], HiPro: 34.4 [4.89]; $F(2,433) = 11.0$, $p < 0.001$, $\eta^2 = 0.05$, 95% CI [0.015, 0.090]; Tukey post-hoc p's < 0.01; Fig. 2F), while other personality traits (i.e., neuroticism, agreeableness) did not differentiate across phenotypes (F's < 2.80, p's > 0.06). Post-hoc tests also revealed a significant difference between HiPro and ModPro for openness ($p = 0.03$), but not for the other traits.

3.3. High Procrastinators obtained poorer grades compared to Moderate and Low Procrastinators

GPA scores (of non-medical students in the cohort) ranged from 2.2 to 5.0. LoPro performed significantly better than both ModPro and HiPro (mean [SD] LoPro: 4.24 [0.38], ModPro: 4.10 [0.45], HiPro: 3.93 [0.53]), both on a continuous scale (by AUC-values of procrastination profiles per participant; $r = 0.26$, $p < 0.001$; Fig. 3A) as well as on a categorical scale (by tertile split of these AUC-values; $F(2,532) = 19.33$, $p < 0.001$, $\eta^2 = 0.07$, 95% CI [0.031, 0.110]; Fig. 3B).

3.4. High Procrastinators have poorer sleep habits, and socialize close to bedtime

Although self-reported aspirational bedtimes did not differ by phenotype (p's > 0.37; Table S1), objective sleep patterns obtained from the Oura ring showed that HiPro tended to have later bedtimes (mean [SD] LoPro: 01:32 [01:10], ModPro: 02:04 [01:09], HiPro: 02:04 [01:12]; $F(2,560) = 13.02$, $p < 0.001$, $\eta^2 = 0.04$, 95% CI [0.016, 0.080]), later wake times (mean [SD] LoPro:08:59 [01:03], ModPro: 09:22 [01:10], HiPro: 09:18 [01:13]; $F(2,560) = 6.13$, $p = 0.002$, $\eta^2 = 0.02$, 95% CI [0.003, 0.049]), shorter sleep duration (mean [SD] LoPro: 399 [34], ModPro: 392 [32],HiPro: 387 [36] min; $F(2,560) = 6.28$, $p = 0.002$, $\eta^2 = 0.02$, 95% CI [0.003, 0.049]) and more irregular or variable sleep durations (mean [SD] LoPro: 76 [22], ModPro: 83 [24], HiPro: 89 [27] min; $F(2,560) = 13.65$, $p < 0.001$, $\eta^2 = 0.05$, 95% CI [0.017, 0.083]) than LoPro (LoPro) averaged across the semester (Fig. 4A–D). These differences in sleep patterns between LoPro and HiPro were evident on both weekdays and weekends and

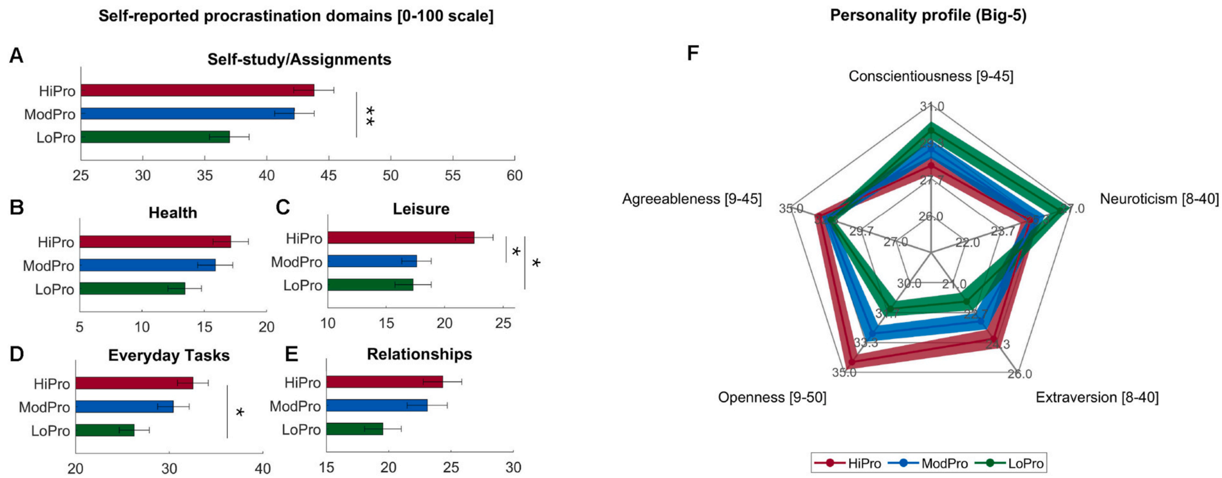

Fig. 2. LMS-driven passive profiling of procrastination phenotypes relate to self-report procrastination measures and personality traits.
Comparisons between LMS-driven procrastination phenotypes (High Procrastinators [HiPro], Moderate Procrastinators [ModPro] and Low Procrastinators [LoPro]) and self-report procrastination measures across 5 domains **(A)** Studying/Assignments, **(B)** Health, **(C)** Leisure, **(D)** Everyday tasks, and **(E)** Relationships. The possible range of each subscale is denoted in square brackets. Multiple comparisons were performed using Tukey's test and asterisks show pairwise comparisons that reached statistical significance (*p < 0.05, **p < 0.01, ***p < 0.001). **(F)** Radar plot showing differences in Big5 personality traits. LoPro exhibited significantly higher conscientiousness and lower extraversion and openness levels compared to HiPro, while neuroticism and agreeableness did not differ across phenotypes.

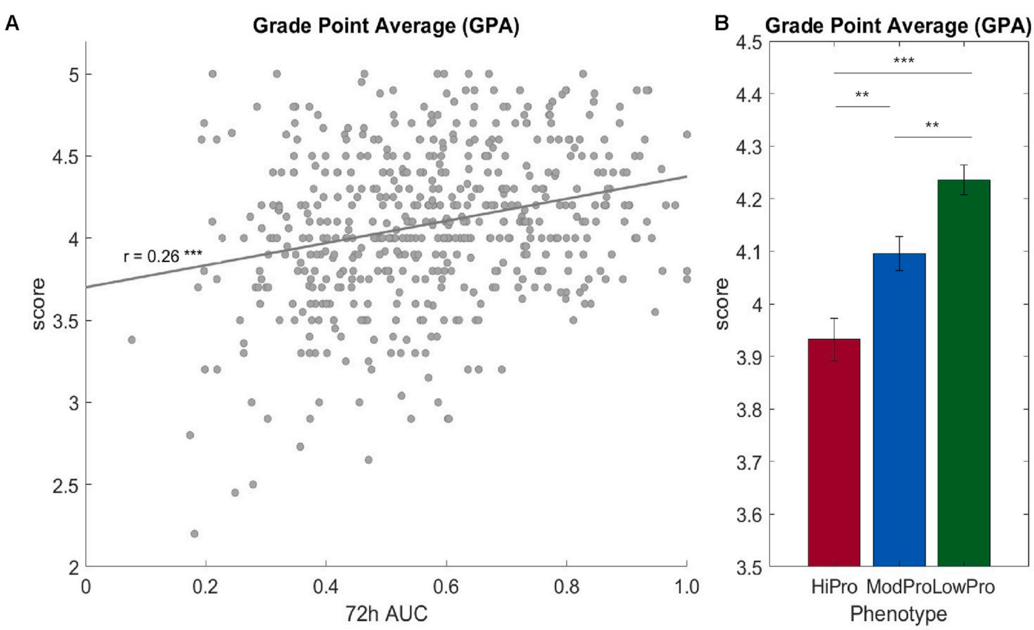

Fig. 3. Procrastination phenotypes on continuous and categorical scales relate to GPA outcomes.
Relationship between GPA and procrastination profiles defined on a **(A)** Continuous scale (AUC-values of procrastination profiles per participant) and **(B)** Categorical scale (AUC-values of procrastination profiles per participant split into tertiles). Multiple comparisons were performed using Tukey's test and asterisks show pairwise comparisons that reached statistical significance (*p < 0.05, **p < 0.01, ***p < 0.001).

stable across the semester, even during Reading Week periods when students are not required to attend classes (Fig. S1). Comparisons between ModPro and LoPro were largely not significant, except for sleep variability (Tukey post-hoc tests between ModPro and LoPro; $p = 0.02$; Fig. 4D).

Time-use diaries further showed that LoPro reported greater self-study time compared to HiPro and ModPro, particularly earlier in the day (9 A M-6PM). Following corrections for multiple comparisons, only the 3 P M-6PM bin remained significant between LoPro and ModPro (ANOVA for 3 P M-6PM bin: $F(2,399) = 3.39$, $p = 0.03$, $\eta^2 = 0.02$, 95% CI [0.000, 0.046]; Tukey HSD between ModPro and LoPro: −8.18 min, $p = 0.03$; Fig. 4E). This finding also concurred with >11 million objective LMS requests across the semester, where LoPro logged more total, average and median requests per day, particularly compared to HiPro (Fig. S2).

However, in the hours leading up to midnight (i.e. the preferred bedtimes in this cohort; Table S1), HiPro reported socializing more from 6 P M to 12 A M compared to LoPro (6 P M-9PM bin: $F(2,333) = 3.30$, $p = 0.038$, $\eta^2 = 0.02$, 95% CI [0.000, 0.054]; Tukey HSD between LoPro and HiPro: −5.12 min, $p = 0.03$; 9 P M-12 A M bin: $F(2,267) = 3.10$, $p = 0.047$, $\eta^2 = 0.023$, 95% CI [0.000, 0.064]; Tukey HSD between LoPro and HiPro: −7.13 min, $p = 0.037$; Fig. 4F) while ModPro reported more non-digital leisure activities from 9 P M to 12 A M compared to LoPro ($F(2,267) = 3.68$, $p = 0.03$, $\eta^2 = 0.027$, 95% CI [0.000, 0.071]; Tukey HSD between ModPro and LoPro: 2.82 min, $p = 0.02$; Fig. 4G). These results also align with the lower levels of conscientiousness, and

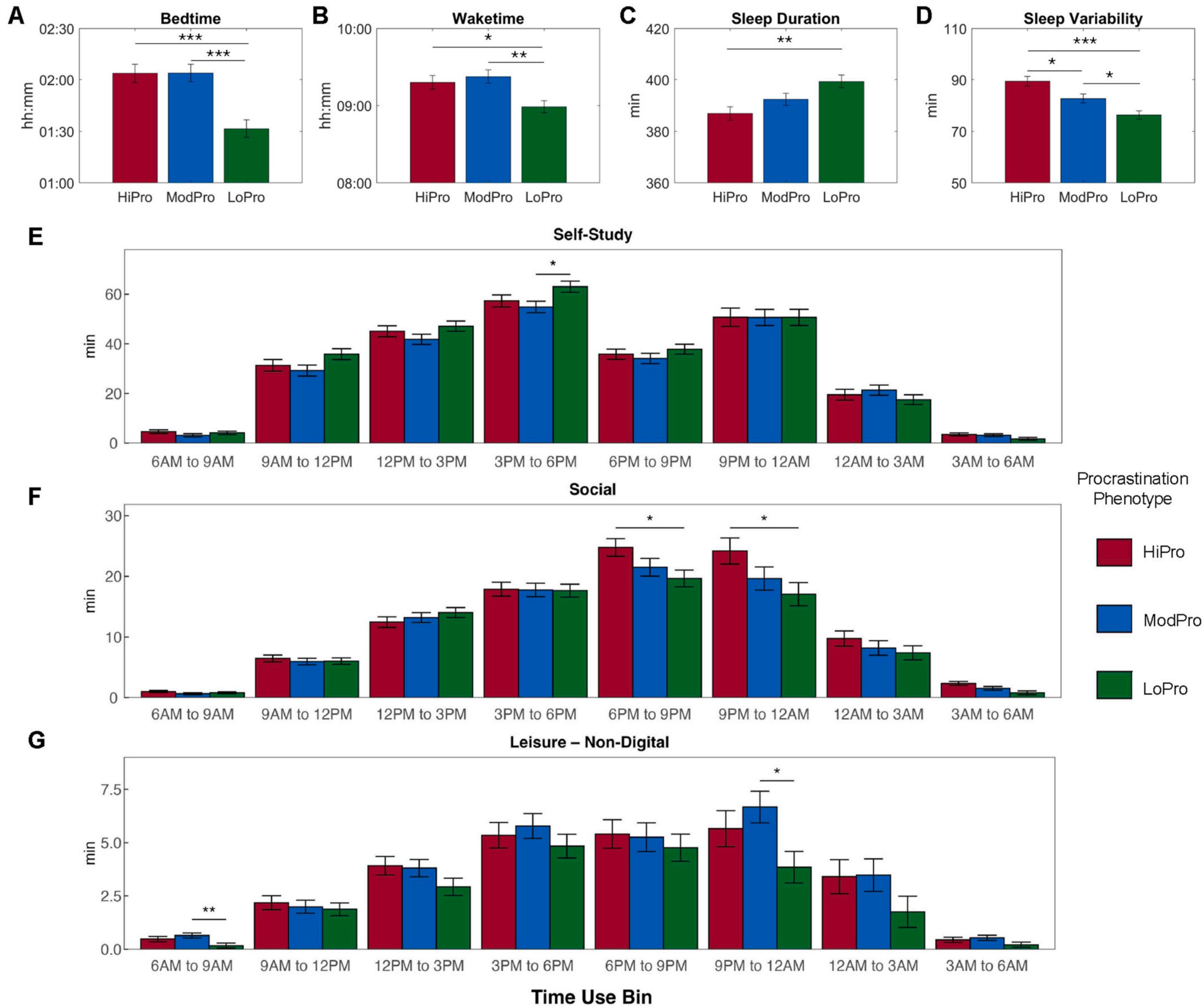

Fig. 4. Sleep and time-use patterns by procrastination phenotype.
Comparisons between LMS-driven procrastination phenotypes (High Procrastinators [HiPro], Moderate Procrastinators [ModPro] and Low Procrastinators [LoPro]) and sleep patterns on the Oura ring for **(A)** Bedtimes, **(B)** Wake times, **(C)** Sleep duration, and **(D)** Sleep variability, as well as 24 h self-report time-use patterns for **(E)** Self-study **(F)** Social **(G)** Non-digital leisure activities. Multiple comparisons were performed using Tukey's test and asterisks show pairwise comparisons that reached statistical significance (*p < 0.05, **p < 0.01, ***p < 0.001). Only time-use categories that differentiate between phenotypes are shown here; the remaining 9 time-use categories are presented in Fig. S3.

higher levels of extraversion and openness observed in HiPro compared to LoPro as earlier discussed (Fig. 2F). Other categories of time use apart from sleep however, did not differentiate across phenotypes (Fig. S3).

4. Discussion

Digital phenotyping, first defined in 2016 (Onnela & Rauch, 2016; Torous et al., 2016), was explored as a tool for early identification and intervention in populations at risk of disease to improve patient outcomes and reduce long-term healthcare costs in a scalable manner. While originally reliant on personal devices such as smartphones and wearable trackers, digital phenotyping can now also leverage on a growing array of rich data sources that capture individuals' daily activities in their natural environments, often with high temporal resolution. In the present work, we demonstrate the utility of combining digital traces generated passively on the university's learning management system with sleep data from a digital tracker, and time-use surveys pushed out on a smartphone app to characterise behavioural profiles associated with procrastination, academic performance and sleep patterns among freshmen in their first semester.

Recent advances in LMS systems have allowed for more passive tracking of procrastination behaviour to uncover its relationship with academic performance. For example, Tan and Samavedham identified four distinct clusters of student learning behaviour based on video viewing patterns on an online course. The 'procrastinate learner' group, who typically engaged with the LMS only just before assignment deadlines tended to score the lowest marks, while the group that started early and distributed their learning throughout the course scored the highest (Tan & Samavedham, 2022). In a separate study, Leinonen and colleagues found that students who start working on course assignments early performed slightly better on average (Leinonen et al., 2021), while a follow-up study by the same group a year later found a decreasing trend in the correctness of assignments the closer to the deadline it was submitted (Castro et al., 2022). In the present study, we incorporated time spent working on assignments using LMS requests leading up to each assignment deadline to identify procrastination profiles, and then showed that higher procrastination levels in our study were indeed associated with lower grades.

Beyond academic grades, higher levels of procrastination have also been found to be associated with poorer lifestyle habits, mental and physical health (Li et al., 2020; Sirois et al., 2003, 2023). We suggest that these outcomes associate with a phenotype characterized by lower levels of conscientiousness, poorer self-regulation habits and less organized behaviours (Bogg & Roberts, 2004), alongside a greater tendency toward poorer sleep (later bed/waketimes, shorter and more variable sleep) (Hill et al., 2022; Kroese et al., 2014, 2016; Phillips et al., 2017), and more last-minute assignment submissions. One study found that key personality predictors of conscientiousness and extraversion appeared to have equal and sometimes even larger associations with sleep than demographic variables (Mead et al., 2021). Similarly, we found that high procrastinators in the present study also tended to be less conscientious and more extroverted. Time-use diaries further confirmed that high procrastinators tended to socialize more at night close to preferred bedtime hours, while moderate procrastinators reported greater non-digital leisure activities, which could contribute to later bedtimes observed in both these groups. In addition, self-report measures of procrastination in the present study also suggest that procrastination may not just be circumscribed to a single area of life, but can manifest across various domains including everyday tasks and leisure activities.

5. Conclusion

The present findings demonstrate how LMS data streams can be used to passively identify individuals with higher levels of procrastination at scale, and examine how these behavioural profiles are associated with academic outcomes and sleep patterns derived from complementary digital sources. We observed that high procrastinators exhibited later bed and wake times, shorter sleep duration, and poorer grades. They were also more likely to be extroverted and engage in evening social activities. Future work should examine whether interventions informed by these behavioural profiles—such as time-management or self-regulation strategies will be effective in improving sleep and academic outcomes.

6. Limitations

The courses taken by participants in our study varied in their use of the LMS portal. Paper-based submissions or those completed outside the LMS portal could also not be tracked in the present study without additional reporting burden on participants. Despite this, we were still able to observe well-known behaviours associated with academic procrastination. Further inspection of the 72h AUC and GPA scores in 5 faculties with at least 50 participants - which are more likely to have similarly structured courses and grading criteria, showed that although association strengths differed across faculties ($r = 0.15$-0.42), the direction of effects was consistent (Fig. S4). The utility of these procrastination profiles is expected to be greatest within the same course, as well as in fully online courses – a trend predicted to grow with the rise of asynchronous and distance learning models.

In addition, as participation in our study required one to log daily assessments on our Z4IP smartphone app and sync/charge their Oura ring tracker, we observed that completion rates of Z4IP and Oura were indeed lower in the high procrastinators (Fig. S5), which could be an indirect consequence of academic procrastination (and not having sufficient time to complete study-related tasks), or broader procrastination of everyday tasks itself. It is also possible that more severe procrastinators or students struggling to keep up with academic/study demands would not have participated in the study, or dropped out early, and are thus not represented here. This is also suggested by the overall higher than average GPA in this cohort. However, sensitivity analyses restricted to participants with ≥70% data completion produced similar effect sizes, with modest attenuation of statistical significance, likely attributable to reduced sample sizes within each group (LoPro, ModPro, HiPro: $N = 187, 189, 187$ reduced to $N = 142, 128, 124$; Fig. S6-S7). Nonetheless, our results indicate that if we are able to detect meaningful signals of procrastination even among these better-performing students, then passive tracking of LMS data university-wide would likely be able to pick out the even more, extreme cases of procrastination with no additional burden to the student.

Finally, while LMS-derived behavioural profiles offer a scalable approach for identifying students at risk of procrastination, implementation could be more feasible and effective at the course level. Course-specific assignment structures and deadlines provide a natural framework for deriving and applying these profiles, enabling timely and targeted feedback (e.g., nudges prior to deadlines) by course instructors. For example, behavioural patterns observed in the first term could be used to calibrate personalised feedback and support strategies in subsequent terms.

CRediT authorship contribution statement

Ju Lynn Ong: Writing – original draft, Visualization, Investigation, Formal analysis, Data curation, Conceptualization. **Yashmit Lepcha:** Writing – review & editing, Visualization, Project administration, Investigation, Formal analysis, Data curation. **Xin Yu Chua:** Project administration, Methodology, Investigation, Data curation. **Chun Siong Soon:** Writing – review & editing, Methodology, Investigation, Data curation. **Shuo Qin:** Writing – review & editing, Supervision, Resources, Conceptualization. **Stijn A.A. Massar:** Writing – review & editing, Supervision, Resources, Conceptualization. **Michael W.L. Chee:** Writing – review & editing, Supervision, Resources, Funding acquisition.

Ethics declaration

Written informed consent to take part in the study and to publish the article has been obtained from all participants or their legal representatives. The privacy rights of participants have been observed.

This study was performed in compliance with relevant laws, regulatory frameworks and guidelines where the research took place. This study was approved by the Institutional Review Board of the National University of Singapore. (Approval No. NUS-IRB-2023-110)

Declaration of the use of AI

During the preparation of this work the authors used ChatGPT to improve sentence clarity and flow of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declarations

M.W.L.C. is a member of the medical advisory board of Ouraring Inc. He also partially supported the development of the Z4IP Ecological Momentary Assessment App used in this study. As of August 2026, J.L.O, X.Y.C, S.Q. and S.A.A.M. are members of the Oura–National University of Singapore (NUS) Joint Lab. This work was however conducted independently of the Joint Lab and was designed, funded, and executed solely by NUS. No other disclosures were reported.

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Declaration of competing interest

☒ Michael W. L. Chee reports a relationship with Ouraring Inc. That includes: board membership and consulting or advisory. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Abbreviations:

PSQI	Pittsburgh Sleep Quality Index
MEQ	Morningness-Eveningness Questionnaire
BAI	Beck's Anxiety Inventory
BDI	Beck's Depression Inventory

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2026.101281.

Data availability

Anonymized sleep and survey data can be made available by writing to the corresponding author. Educational and learning management records cannot be shared due to legal and university restrictions.

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