Student Receptiveness to Circadian-Aware AI-Driven Scheduling

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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***Abstract*—Circadian rhythm alignment plays a crucial role in our health and performance, yet most scheduling tools do not take it into account. College students, in particular, are affected by circadian misalignment due to their social and academic commitments. This paper investigates the desirability of an AI-driven scheduling application optimized for circadian rhythm alignment for students. Our initial interviews and observation of using GenAI tools with 16 undergraduate student participants indicated that while 81.2% of them use AI daily, only 12.5% utilize it for scheduling purposes. We further designed prototypes of an LLM-based scheduling application with varying levels of circadian awareness and evaluated their usefulness and desirability with 102 participants. Overwhelmed participants found the prototypes less helpful than those struggling with time management and exhaustion. However, our results indicate that students would prefer a personalized circadian-aware AI scheduler. This preference offers valuable insights for designing future circadian-aligned AI applications.**

I. Introduction

Balancing academic and social life can be challenging for college students. While planning is a common time management strategy, it is often unrealistic or overwhelming as it ignores contextual factors, e.g., the current or future internal state of the planner [1], [2]. Although digital scheduling tools help organize time, they often create a sense of busyness, leading people to take on more tasks because they seem manageable [2]. While Generative AI scheduling systems Monday.com and ClickUp have aimed to automate scheduling processes [3], they fail to consider important physiological and behavioral factors that influence daily routines [4].

This project investigates the potential interest in an AI-driven scheduling app that incorporates personal biobehavioral data among undergraduate students. We began by conducting interviews with 16 students to understand how they currently utilize large language models (LLMs) in their academic routines. Based on insights gathered from these interviews, we designed an online study in which 102 students interacted with three prototypes of a hypothetical LLM-based scheduling app. Each prototype differed in how it integrated biobehavioral information, such as sleep patterns and activity levels, into daily scheduling. Participants assessed the perceived effectiveness and desirability of each prototype. We analyzed our data with a focus on the following research questions::

RQ1: How are students currently using LLMs to schedule their tasks? We found that 87.5% of our participants use LLMs for school work, but only 12.5% utilize these tools for scheduling.

RQ2: How is circadian-aware AI-based scheduling perceived among students? 67.1% of our survey participants preferred the LLM-driven prototype that utilized biobehavioral data, clearly indicating such a system would be desirable to students.

II. Background and Related Work

Circadian rhythms regulate sleep-wake cycles and other physiological processes, playing a crucial role in cognitive function, emotional stability, and overall health [5]. Recent research highlights the significant impact that misaligned circadian rhythms can have on students, worsening issues such as sleep deprivation, stress, and mental health disorders [6], [7]. The disconnect between an individual's biological circadian rhythm and the socially mandated timing, like school schedules, is known as Social Jetlag (SJL) [8]–[11]. Scheduled activities, such as classes, can significantly delay sleep onset and reduce sleep duration, impacting students' mental and physical health [12]. Research shows effective scheduling and time management significantly impact students' performance and well-being [13]–[15]. Students who plan when to complete tasks tend to perform better on quizzes than those who do not [14]. One study found that aligning study times with an individual's circadian rhythm is positively correlated with improved grades and more effective learning [16]. Another study highlighted the potential of using circadian rhythm-based scheduling to help students follow healthier daily routines, which in turn enhances their overall well-being [17]. Despite the known benefits of circadian rhythm alignment, few technologies exist to assist with it.

Current scheduling and task-tracking tools do not utilize biobehavioral information, such as circadian rhythms, in their scheduling processes. Even when these tools incorporate AI, the added functionality primarily focuses on assisting users in creating schedules more quickly [18]. While AI has been utilized in the workplace to reduce stress and fatigue [19], [20], its potential for improving wellness through better schedule design remains unstudied. Large Language Models (LLMs) have been used to create context-aware text messaging interventions that help manage stress by timing motivational messages based on users' digital calendar data [21]. However, this approach focuses solely on personalizing messages based on existing commitments and does not suggest changes to the user's calendar. Aligning student schedules with their biological rhythms could reduce issues like sleep deprivation and stress [22]. However, research on using circadian rhythms in AI scheduling is limited, pointing to an important area for future development.

III. Study Design

Our methodology consisted of two studies, a formative interview to understand how students currently engage with generative AI and an online study to collect their perceived usefulness of circadian-aware AI-scheduling. These studies were approved by the Institutional Review Board at our university.

A. Formative Interviews

We first interviewed 16 university undergraduate student participants who were recruited via word of mouth to better understand their current scheduling practices and experiences with AI tools. During these sessions, participants described their methods for organizing school days, shared their experiences and preferred types of AI technologies, and discussed how they might instruct an AI tool, specifically Microsoft Copilot, to assist in scheduling their day. Subsequently, participants were asked to prompt Microsoft Copilot and evaluate the effectiveness of the results. They also provided feedback on potential improvements they would make to their prompt if they were to do this again. Each interview lasted about 15 minutes.

B. Prototype Design

A total of 102 undergraduate students participated in the prototype survey, consisting of 7 first-year students, 33 second-years, 23 third-years, and 37 fourth-years. We designed three prototype versions of a scheduling application, including 1) manual scheduling, 2) AI-based without circadian information, and 3) AI-based with circadian information (Figure 1). We also designed the following student personas with challenges related to time management, burnout, and overwhelm:

Avery is excited to start their journey as a first-year engineering student; however, the transition from high school to college has been challenging. With a heavy course load, new responsibilities, and a strong desire to excel, Avery often feels overwhelmed by the number of tasks they need to manage.

Ethan is a third-year electrical engineering student who is committed to his academic success. However, his demanding schedule leaves him feeling physically and mentally drained.

Sarah is a second-year mechanical engineering student who frequently struggles with time management. She juggles many responsibilities and has trouble sticking to a routine, prioritizing tasks, and meeting deadlines.

Manual Scheduling: Based on the chosen persona, the participant was shown a manual prototype that replicated the associated scenario. This prototype required participants to manually create a task, providing a title, start time and date, and duration (Figure 1A). After creating the event, it appeared on the students' to-do list (Figure 1B).

AI-Based Scheduling: Within the mockup, the participant was taken to a welcome screen where they were able to select a response to "What do you struggle with the most?" as shown in Figure 1C. Participants were guided to select the answer that matched their persona. Unlike the manual persona, where participants must provide all information for the task, they could provide the estimated duration, priority level (high/low), and start time. All tasks were compiled in a list (Figure 1D), and then scheduled without requiring exact placements by the user. Participants could see the created schedule and had the opportunity to manually adjust the timing or duration of a task. All schedules shown by this prototype were created by Microsoft Copilot. For the remainder of this paper, we refer to this prototype as the 'AI-based' prototype.

Circadian-Aware AI Scheduling: This prototype followed a similar process to the AI-based without circadian awareness. However, in this mockup, participants were provided with an extra page (Figure 1E), which showed artificial circadian status data for the persona. This page was shown after the user defined the tasks they wanted to add and viewed the created schedule. The mockup told participants that this information was being used to create the schedule. For the remainder of this paper, we refer to this prototype as the 'circadian-aware' prototype for clarity.

C. Online Prototype Interaction Study

We incorporated these prototypes into an online survey and conducted a user study to gain insight into which version students would prefer. One hundred and two participants were recruited through word of mouth, physical flyers, and email listservs. The participants were students at an American University, including 7 first-year students, 33 second-years, 23 third-years, and 37 fourth-years. 58 participants self-identified as female, 39 as male, and 3 as non-binary or other. 74 of our participants routinely use a digital calendar (i.e. Google Calendar) to help manage their schedules, 16 used physical planners, 3 used AI-based tools, 3 relied on their memory, and 4 used other methods (i.e. note-taking apps).

Prior to the study, each participant answered background questions related to their demographics. Participants were asked to select the productivity issue they struggled with most: feeling overwhelmed, exhausted, or time management. Participants were then assigned a persona reflecting the challenges of their selected issue. This ensured they could relate to the prepared schedules, making the experience more accurate and personal. Each prototype varied slightly according to the participant's persona. For example, the overwhelmed schedule was filled with classes and clubs, while the exhausted person had both early morning and late night events. Participants then engaged with the three prototypes in random order and navigated through scheduling an event using an interactive mockup created in Figma. Participants rated the prototypes on a series of 5-point Likert scale questions, assessing factors such as helpfulness with time, workload, and energy management. Additionally, they evaluated how well the schedule

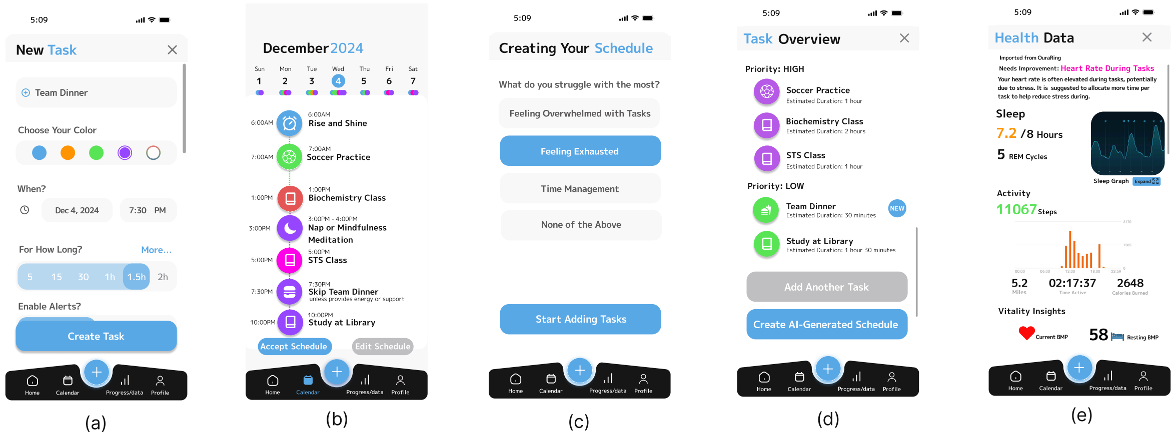

Fig. 1: Figma screens from multiple prototypes used in the survey: (a) users input task details including timing preferences; (b) AI generates a personalized schedule based on passively-sensed data and behavioral trends, with options to accept or edit; (c) users select main productivity struggle such as exhaustion or time-management; (d) an interactive dashboard displays upcoming tasks, priorities, and durations; (e) users view insights from their sleep, activity, and focus data to understand scheduling decisions.

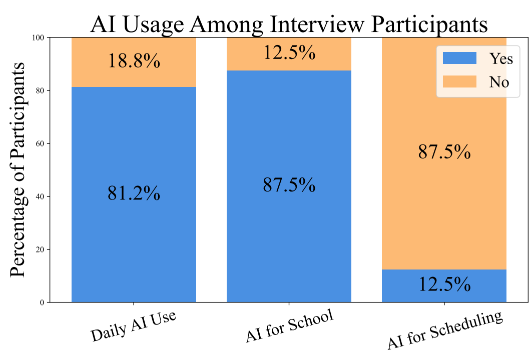

Fig. 2: AI Usage Among Interview Participants (%): While 13 out of 16 students use AI daily, only 2 use it specifically for scheduling purposes.

aligned with the persona's needs, its flexibility, the time saved, and the likelihood of adhering to the schedule.

IV. Results

A. How are students currently using LLMs to help schedule their tasks?

a) Participants use AI daily, but rarely for scheduling: Out of 16 participants, 13 said they use AI in their daily lives, but only 2 have tried to use it to help schedule their day. 14 students reported using LLMs to assist with schoolwork (Figure 2). However, despite this, 2 of these students were not using AI for task scheduling, indicating a gap between AI familiarity and its application in optimizing daily routines.

b) Participants expressed concerns about AI-generated schedules: Among those who experimented with AI-generated scheduling, only 6 The remaining 10 indicated they would not adhere to the schedule created by the AI, citing reasons such as unrealistic time allocations, omitted events, personal preferences, and the AI's inability to fully capture their unique scheduling needs. This suggests that current AI scheduling tools may not align well with students' real-world needs and constraints. A significant barrier to using Copilot for schedule generation was the perception that entering all the required details would take too much time. These details include time constraints and task durations. For example, P27 shared, "I would expect the output to not be helpful or feasible because of how long it would take to input the schedule." P22 echoed this notion, stating that AI is "fairly reliable if you provide a good prompt." This highlights a concern among some participants: the effectiveness of AI-generated schedules heavily depends on the input quality and specificity, which may be time-consuming or tedious.

c) Participants had specific expectations from AI-generated schedules: 11 of the 16 interviewed students expected the AI-generated schedule to be presented in a format structured around specific time constraints or time blocks. For instance, a bulleted list with events organized in hourly blocks such as "10:00-11:00 AM: Biology Class." P21 anticipated "a tailored schedule with timestamps of when to complete each thing I need to do." P22 shared that "Based on my prompt, I would expect a schedule that cements the time-constrained tasks in each day and fills in the time around it with everything else." These responses provided valuable insights into how students envisioned AI's role in their scheduling process, setting a benchmark for evaluating the LLM-generated outputs. A majority of participants (12 out of 16) indicated that they found AI to be at least moderately reliable, reflecting a general sense of trust in its capabilities. However, more nuanced perceptions emerged in the open-ended responses. P18 noted, "AI is reliable in certain areas, but still lacks trust in my opinion. It's not always right and not always the best," demonstrating a more cautious approach to AI's perceived accuracy and dependability. P19 remarked, "Depending how much you pay for it, you can pay for it to always get your answers correct," pointing to concerns around access, performance, and the role of premium prototypes in shaping LLM expectations.

B. How do students perceive manual, AI-driven, and circadian-aware scheduling systems?

a) Main productivity struggles identified by participants differed across class years: At the start of our survey, participants were asked to identify their biggest productivity struggle: feeling overwhelmed, burned out (exhausted), or managing their time. The responses were fairly evenly distributed, with 34 participants reporting feeling overwhelmed, 34 feeling exhausted, and 32 struggling with time management.

As shown in Table I, the struggles reported varied slightly by class year. While the first-year group was small, most (5 out of 7) reported feeling overwhelmed, with two citing time-management difficulties. No first-year students mentioned exhaustion. Second- and fourth-year students showed a more balanced mix of struggles, with all three being frequently selected. Interestingly, a majority of third-year students (13 out of 23) reported feeling exhausted. Despite the small sample sizes, these trends suggest that productivity struggles may change as students progress through college.

TABLE I: Participants' chosen productivity struggle sorted by class year.

Class Year	Overwhelmed	Exhausted	Time Management
First	5	0	2
Second	10	10	13
Third	4	13	6
Fourth	15	11	11
Total	34	34	32

b) Participants preferred the circadian-aware prototype: 67.1% of all participants found the AI-based prototype that incorporated personalized biobehavioral data to be the most helpful and applicable prototype compared to the others. This prototype was also most frequently ranked first regardless of whether they struggled with feeling overwhelmed, exhausted, or managing their time. This prototype was ranked first by 52% of students struggling with time management, 41% of those dealing with exhaustion, and 54% of those feeling overwhelmed, indicating a strong preference for its higher level of personalization (Table II). In contrast, the manual prototype was consistently poorly ranked. The majority of participants ranked it last: 70% for time management, 77% for exhaustion, and 57% for overwhelmed.

Participants were also asked, on a 5-point Likert scale, how likely they would be to use their top-selected prototype over their current scheduling method. Responses to this question did not follow a normal distribution (Shapiro-Wilk: $p = 3.962 * 10^{-5}$), so our analysis of this question uses Kruskal-Wallis tests. Participants who preferred the manual prototype ($\mu = 2.6, \sigma = 0.952$) were significantly ($p = 0.011$) less likely to prefer the prototype to their current approach than participants who preferred the circadian-aware prototype ($\mu = 3.428, \sigma = 1.030$). Responses from the nine participants who preferred the AI based prototype ($\mu = 3.556, \sigma = 1.066$) were not significantly different than those for the manual ($p = 0.055$) or circadian-aware prototype ($p = 0.753$).

TABLE II: Distribution of Rankings for Each Prototype by Struggle Type (1st = Most Helpful, 3rd = Least Helpful)

Prototype Ranking	Time Management			Exhaustion and Burnout			Overwhelmed		
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
Manual	22%	9%	70%	18%	5%	77%	21%	21%	57%
AI-Based	26%	57%	17%	41%	36%	23%	25%	39%	36%
Circadian-Aware	52%	35%	13%	41%	59%	0%	54%	39%	7%

c) Participants found the circadian-aware prototype to be the most helpful in managing sleep and energy, but responses varied between personas: For responses to every remaining Likert scale question, we first verified that the participants' responses followed a normal distribution using Shapiro-Wilk tests. Unless otherwise noted, all results were calculated using an ANOVA test.

d) Comparison Across Prototypes: Participants' ratings of each prototype's ability to improve sleep and energy management significantly varied between the prototypes. Across all three personas' the circadian-aware prototype was consistently rated as the most helpful ($\mu = 3.57, \sigma = 0.986$). The AI-based prototype ($\mu = 2.870, \sigma = 1.073$) was rated as marginally more helpful than the manual prototype ($\mu = 2.846, \sigma = 1.039$). A series of tests confirmed the circadian-aware prototype was rated as significantly more helpful than the AI-based prototype ($p = 4.62 * 10^{-5}$), and the manual prototype ($p = 1.797 * 10^{-5}$). There were no significant differences between the manual and AI-based prototypes ($p = 0.889$). As shown in Figure 3, these trends are mostly consistent within each persona. Only responses for the time management category varied slightly, identifying no difference between the circadian-aware and AI-based prototypes ($p = 0.113$). While not present across all three personas, we also identified minor differences in the prototypes' helpfulness in addressing workload management for the exhausted persona. The circadian-aware prototype ($\mu = 3.464, \sigma = 1.052$) was significantly ($p = 0.019$) more helpful than the manual prototype ($\mu = 2.786, \sigma = 1.013$).

e) Comparison Across Personas: Overwhelmed participants consistently rated the prototypes as less helpful than those struggling with time management and exhaustion. Across all prototypes and questions, the overwhelmed participants' ratings ($\mu = 3.12, \sigma = 1.095$) were significantly lower than the ratings from the time management ($\mu = 3.375, \sigma = 0.992, p = 6.498 * 10^{-5}$) and exhaustion ($\mu = 3.430, \sigma = 0.892, p = 3.980 * 10^{-7}$) participants. There was no significant difference between the ratings from the time management and exhaustion participants ($p = 0.349$). As shown in Figure 3, Overwhelmed participants' lower ratings are also observable for specific questions and prototypes. These overwhelmed participants rated the AI-based prototype ($\mu = 2.5, \sigma = 1.150$) as significantly less effective ($p = 0.048$) in energy management than participants struggling with time management ($\mu = 3.130, \sigma = 0.992$). Overwhelmed participants also rated the manual prototype's ($\mu = 2.786, \sigma = 1.013$) ability to

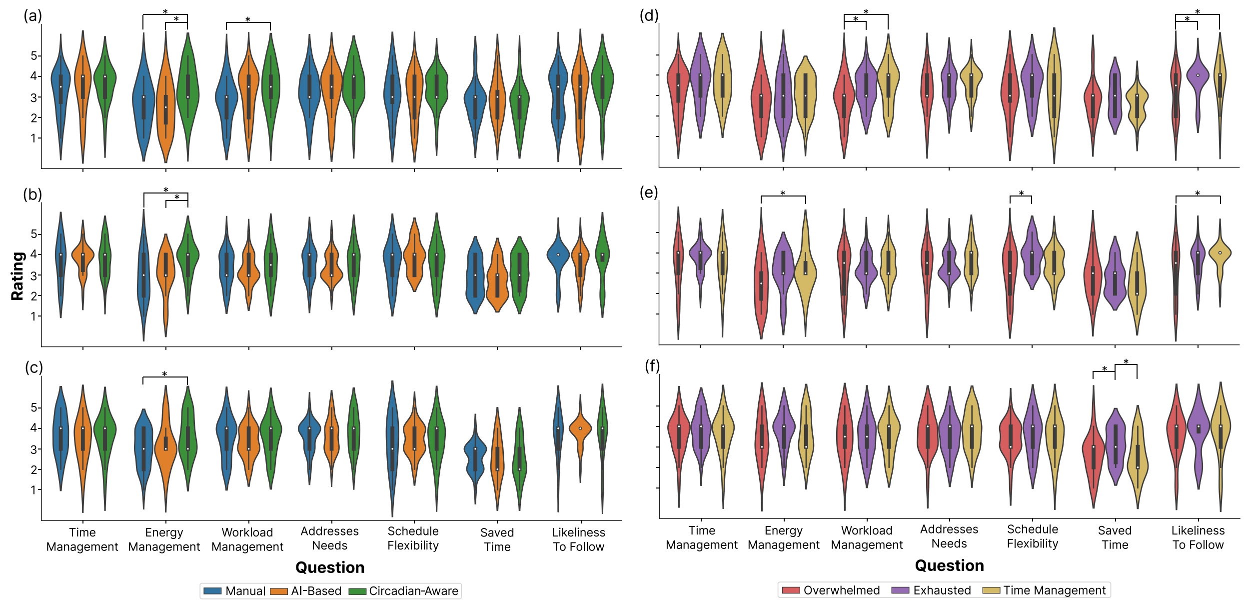

Fig. 3: Participants' ratings of the prototypes' perceived helpfulness for different metrics. Questions were scored on a 5-point Likert scale, with higher values indicating stronger agreement. (a) Overwhelmed focus. (b) Exhausted focus. (c) The time management focus. (d) Manual prototype. (e) AI-based prototype. (f) Circadian-aware prototype. * indicates significant difference at 95% confidence.

manage workload significantly lower than both the exhausted ($\mu = 3.333, \sigma = 0.799, p = 0.041$) and time management ($\mu = 3.52, \sigma = 0.943, p = 0.010$) participants.

Keeping with the overall trend across personas, overwhelmed participants were again more critical than others in how likely they would follow the schedule provided for the manual and AI-based prototypes. They rated the likeliness to follow for the manual prototype ($\mu = 3.071, \sigma = 1.100$) significantly lower than the exhaustion ($\mu = 3.708, \sigma = 0.735, p = 0.022$) and time management participants ($\mu = 3.72, \sigma = 1.001, p = 0.033$). A similar trend was observed for the AI-based prototype, with overwhelmed participants ($\mu = 3.071, \sigma = 1.252$) rating their persona as significantly less likely ($p = 0.018$) to follow the schedule than participants struggling with time management ($\mu = 3.783, \mu = 0.587$). We also found that exhausted participants rated the AI-based prototype's schedule ($\mu = 3.857, \sigma = 0.0709$) as significantly ($p = 0.006$) more flexible than overwhelmed participants ($\mu = 3.036, \sigma = 1.117$). Lastly, for the saved time category, the exhausted participants ratings for the circadian-aware prototype ($\mu = 3.091, \sigma = 0.793$) were significantly higher than both the overwhelmed participants ($\mu = 2.571, \sigma = 0.942, p = 0.048$) and the time management participants ($\mu = 2.52, \mu = 0.943, p = 0.034$).

Interestingly, our results also indicated that the variance of ratings significantly differed between the three personas (Levene's Test: $p = 0.017$). In particular, ratings from the overwhelmed participants were significantly more variable than the ratings from the exhaustion participants ($p = 0.037$). There were no significant differences in variance for the ratings from the time management participants and the exhausted ($p = 0.057$) or overwhelmed ($p = 0.627$) participants.

V. Discussion

We explored how participants use AI tools for scheduling and their receptiveness towards an AI tool that considers their biobehavioral data when scheduling events. Our results highlighted several design considerations.

1) AI-Based Schedulers Must Ensure Schedules are Practical: Our formative interview revealed that almost 70% of participants would not follow the AI-Based schedule. They frequently expressed concerns about unrealistic time allocation or missed events. These systems should incorporate existing knowledge to ensure time allocations are reasonable. Similarly, validation should be included to ensure all requested events are present in the final schedule.

2) Incorporating Passive Sensing may Reduce User Burden: A cited barrier to the adoption of AI-generated schedules is the perceived effort required to input detailed constraints, which often outweighs the perceived benefits. This suggests a behavioral tendency towards cognitive efficiency. Students, who frequently juggle tight schedules and fatigue, may prefer low-friction tools over highly personalized ones that demand a larger upfront investment. Entering biobehavioral data, class times, and task durations can feel more cumbersome than simply creating a schedule manually. These insights have important implications for design. To encourage broader adoption of AI-based scheduling tools, it is essential to reduce the effort required during setup. Features such as passive data integration—like automatic syncing with fitness trackers—and intuitive input methods could potentially make the scheduling experience easier than manual methods.

3) Presenting schedules in clear, timestamped formats will match user expectations: Around 69% of students expected AI-generated schedules to follow a simple, time-blocked format. This may stem from the fact that most students are already accustomed to manual scheduling in this structure. Aligning AI-generated schedules with familiar formats may help ease the transition for those who prefer manual scheduling, making it easier for them to adopt and trust AI-based tools.

A. Limitations and Future Work

Some participants may not have fully understood how their assigned persona would respond to the prototypes or whether those responses would be applicable and useful to them. To address this in a future study, we could implement a brief persona immersion step to help participants better understand their assigned perspective. Alternatively, we could eliminate personas altogether and gather feedback directly based on participants' personal preferences and challenges. This approach would reduce potential confusion and allow for more authentic, individualized responses. However, the results of our study remain largely valid, as the personas were assigned based on the participants' most significant struggles, which corresponded to the core challenges associated with their respective personas.

VI. Conclusion

We investigated the potential of integrating circadian rhythm-based data with AI-driven scheduling tools to enhance the academic and overall well-being of undergraduate students. We assessed participants receptiveness to manual and AI-based scheduling models. Our evaluation involved 102 undergraduates who provided feedback based on their experiences with these models. The data revealed a strong preference for the AI model that included biobehavioral data, indicating that this model was most effective in aligning students' schedules with their natural biological rhythms, thereby optimizing their academic performance and health. These results suggest scheduling personalization grounded in biobehavioral data can enhance both usability and impact. As AI-driven productivity tools continue to evolve, developers may be able to integrate biobehavioral data to bridge the gap between reliability and real-world adoption. These systems have the potential to not only support academic performance but also promote long-term student well-being.

Acknowledgments

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