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An Application Study of Data Science in Enhancing Time Management and Learning Efficiency Among High School Students

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Abstract:
This study explores the application of data science methods in optimizing time management and enhancing learning efficiency among high school students. Against the backdrop of the "Double Reduction" policy and concurrent academic anxiety, high school students urgently need to transition from a "time-based" to an "efficiency-based" learning paradigm. Inspired by "Quantified Self" and "Precision Learning" theories, this research attempts to construct a data-driven time management diagnostic and optimization model tailored for individual high school students. The author conducted a four-week data tracking study on themselves, collecting multidimensional data including study duration, subject distribution, sleep time, screen usage time, and subjective efficiency ratings. Utilizing Excel tools for data cleaning, descriptive statistics, and visualization analysis, patterns and potential issues within personal learning habits were identified, such as peak efficiency during specific time periods and the positive correlation between sleep and efficiency. Ultimately, personalized time management optimization strategies were developed based on these data insights. This study demonstrates the feasibility and effectiveness of the "quantified self" concept for high school students in self-awareness and self-optimization, proving the immense potential of data science as a "personal learning advisor" in enhancing students' self-awareness and self-regulation capabilities.

Keywords: Data Science, Self-Quantification, Time Management, Learning Efficiency

1. Introduction

Currently, Chinese high school students universally face challenges of heavy coursework, fragmented time, and immense pressure. We often feel time is insufficient, or despite investing substantial hours in study, outcomes remain unsatisfactory. Traditional learning advice, such as "ensure adequate sleep" or "balance work and rest," is largely based on general experience and lacks precise guidance tailored to individual characteristics. How to manage time more scientifically and efficiently has become an urgent practical issue.

With the advancement of the big data era, the concept of "Quantified Self" has gained traction [1]. This approach involves using technology to collect and analyze personal data for self-awareness and self-optimization. Its application in education has demonstrated significant potential. For instance, in university management, collecting objective behavioral data and subjective assessment information enables the creation of precise individual development profiles, providing a foundation for personalized guidance [2]. Furthermore, researchers have indicated that quantifying and analyzing learning behavior data represents an effective pathway for students to achieve self-awareness and ultimately progress toward self-directed learning management [3]. This data-driven approach is not only applicable to macro-level educational management but also provides theoretical support for individuals to engage in precise self-reflection and optimization. This study aims to investigate whether data science methods can be used to record and analyze a high school student's learning and daily life data, thereby uncovering the intrinsic connection between time utilization patterns and learning efficiency, and providing data-driven decision-making support for enhancing personal efficiency [4].

The author served as the research subject, conducting a four-week data tracking period to collect multidimensional data, including study duration, subject distribution, sleep time, screen usage time, and subjective efficiency ratings. Excel tools were utilized for data cleaning, descriptive statistics, and visualization analysis.

This study transforms data science from an abstract concept into a practical tool accessible to high school students [5]. It offers a scientific self-reflection method for individuals, shifting from the subjective feeling of "I worked hard" to the objective evidence of "data proving how hard I worked." The paper explores a low-cost, easy-to-operate data analysis paradigm that peers can reference. Simultaneously, this research cultivates data thinking and scientific inquiry literacy, aligning with the competency requirements for talent in the new era.

2. Research Methods and Data Collection

2.1 Research Period and Subject

This study employs a self-tracking methodology with a research period spanning four weeks from September 1 to October 1, 2025. The research subject is the author, a senior high school student enrolled in a science-track class in a top-tier city in China.

2.2 Data Metrics and Collection Tools

To comprehensively reflect learning and daily life, this study tracked five categories of data:

Learning Data: Utilized the "Pomodoro ToDo" app to record daily net study duration (in minutes) and content for each subject.

Efficiency Data: After each study session, a subjective efficiency rating (1–5 points, with 5 indicating highest efficiency) was assigned.

Sleep Schedule Data: Daily bedtime and wake-up times were recorded to calculate sleep duration.

Screen Usage Data: Daily recreational screen time (e.g., social media, games, videos) was tracked using the built-in "Screen Time" feature on mobile devices.

Grade Data: Record scores from two weekly math tests conducted during the period. All data is consolidated daily into a single Excel spreadsheet.

2.3 Data Analysis Methods

This study primarily employs descriptive statistics and data visualization methods, with all analyses conducted using Microsoft Excel. Data cleaning was performed to exclude invalid records. For instance, if the efficiency score was forgotten for a particular day, all learning data from that day were excluded from efficiency-related analyses. Concurrently, this paper comprehensively utilizes line charts for trend analysis, pie charts for proportional analysis, and scatter plots for relationship analysis, exploring the connections between various external factors and learning efficiency.

3. Data Analysis and Findings

3.1 Overall Time Distribution Description

Over four weeks, the author accumulated 11,200 minutes (approximately 200 hours) of study time. Figure 1 illustrates the distribution of time allocated to each subject.

Finding 1: Mathematics and Physics accounted for 57% of my total study time, aligning with my academic priori-

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ties and areas needing improvement. English and Chinese received relatively less time, indicating room for optimization.

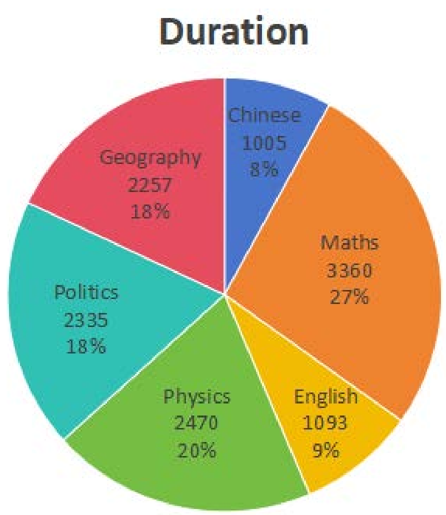

Figure 1: Pie Chart of Study Time Allocation by Subject

3.2 Daily Study Patterns and Efficiency Analysis

To precisely identify high- and low-efficiency periods throughout the day, this study categorized all collected study session data from the past four weeks by hour, using their start times as the reference point. The average subjective efficiency score for all study records within each hour was then calculated and plotted as the time-series line chart below. The horizontal axis represents the 24 hours of a day, while the vertical axis shows the average efficiency score (Figure 2).

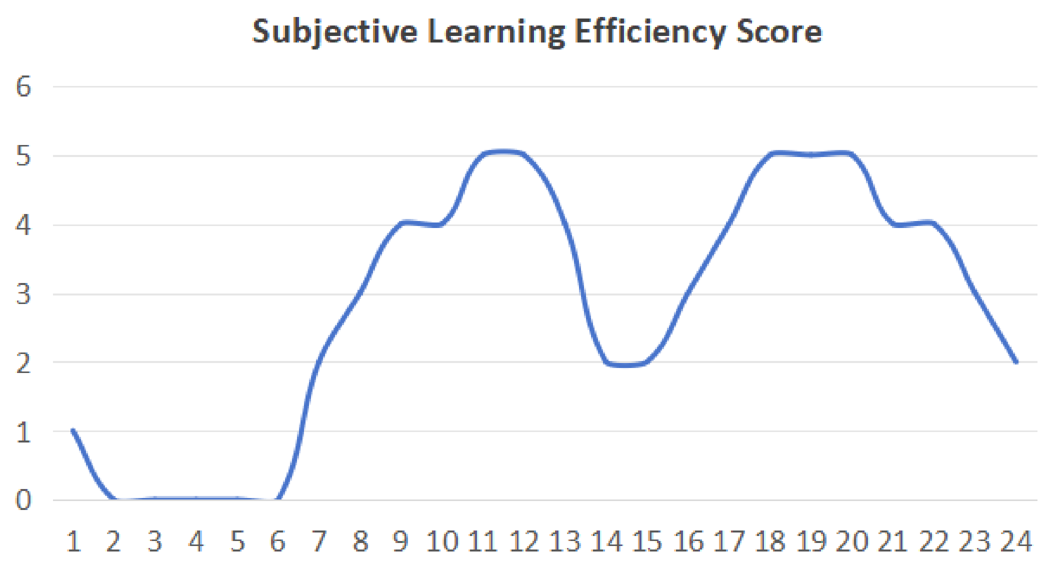

Figure 2: Average Learning Efficiency Line Chart by Time Slot

The study revealed a distinct "periodic" pattern in the author's learning efficiency, clearly divisible into three primary phases: the afternoon recovery period, the evening peak period, the sustainable high-efficiency evening period, and the late-night fatigue period.

Through in-depth analysis of Figure 2, the author categorized their learning efficiency into the following four phases:

The first is the Afternoon Recovery Period (13:00 - 15:00), representing a gradual climb following an efficiency trough. Between 1:00 PM and 3:00 PM, the author's average efficiency score reached its lowest point of the day (approximately 2.8 points). This aligns perfectly with the common phenomenon of "afternoon fatigue."

The second phase is the Dusk Peak Period (16:00-18:00), the first cognitive high point of the day. Efficiency scores surge sharply starting at 4 PM, reaching the first daily peak between 4 PM and 6 PM (average 4.5 points).

The third phase is the Sustained Evening Efficiency Period (20:00-22:00), representing the second peak for focus and memory. Data shows efficiency scores remain elevated between 8:00 PM and 10:00 PM (average 4.2 points).

The fourth stage is the late-night fatigue period (after 10:00 PM), which represents an "effort trap" where productivity declines sharply. Data analysis reveals that after 10:00 PM, the author's learning efficiency exhibits a "cliff-like drop." By 11:00 PM, average efficiency scores fall below 3 points, and the number of learning entries recorded also decreases significantly.

Data research reveals that the marginal benefit of late-night studying is extremely low, even negative. Physiologically, late night is when the brain begins secreting melatonin, preparing for sleep mode. Studying at this time not only impairs comprehension and memory retention but also causes cognitive overload and sleep deprivation, severely affecting the next day's learning efficiency. This creates a vicious cycle: "staying up late → low efficiency the next day → being forced to stay up late again."

3.3 Correlation Between Sleep, Screen Time, and Efficiency

To explore the intrinsic connection between lifestyle habits and learning efficiency, this paper presents scatter plots of "sleep duration" (Figure 3) and "average efficiency score the following day" (Figure 4).

3.3.1 Relationship Between Sleep Duration and Learning Efficiency

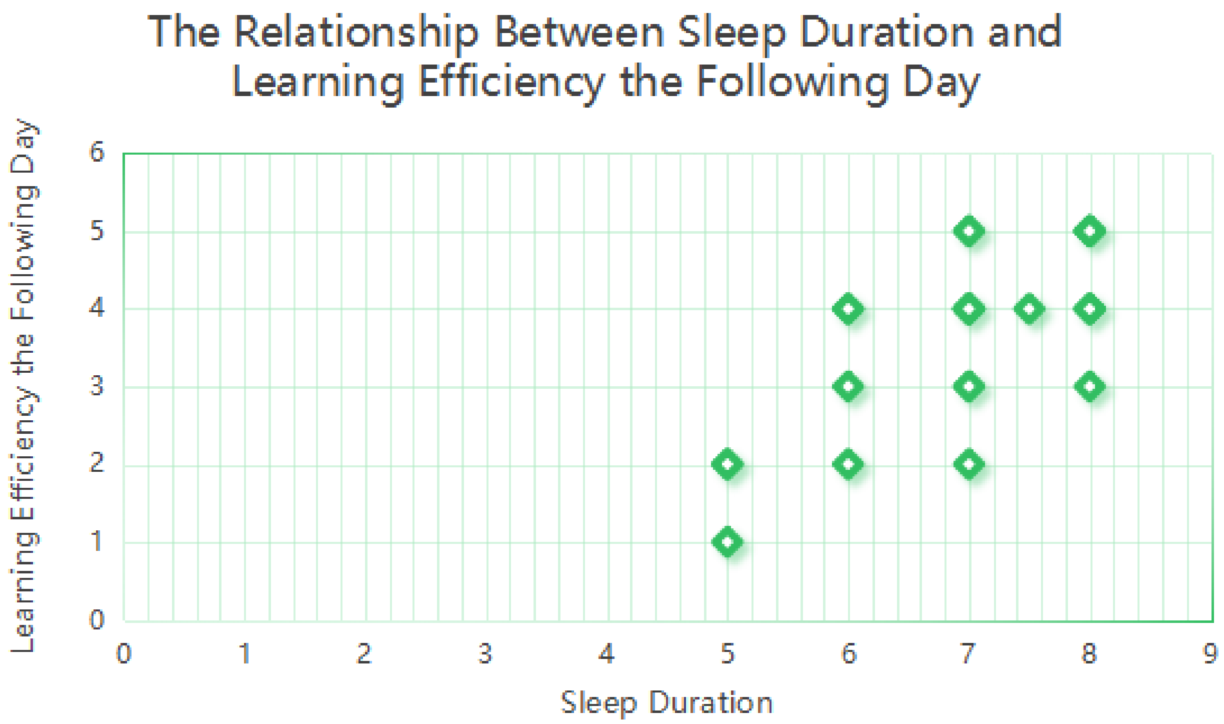

Figure 3: Scatter Plot of Sleep Duration and Next-Day Efficiency

Figure 3 clearly shows that when sleep duration falls below 7 hours, data points are widely distributed in the low-efficiency zone (with efficiency scores generally below 3 points). However, once sleep duration reaches and exceeds 7.5 hours, nearly all data points cluster in the high-efficiency zone (efficiency scores ≥ 4). This "7.5-hour threshold" acts like a magic switch, distinctly separating low-efficiency and high-efficiency states.

If sleep falls below 7 hours for two consecutive days, the efficiency decline on the second day becomes particularly severe. For example, sleeping only 6 hours one day results in an efficiency score around 3 the next day; if the following day still only gets 6.5 hours of sleep, the efficiency score further drops to 2 or below.

Sleep debt accumulates. An occasional night of insufficient sleep might be repaid through subsequent catch-up sleep. However, consecutive deficits cause "sleep pressure" to surge dramatically, severely impairing the prefrontal cortex—the "command center" responsible for our focus, decision-making, and self-control. This makes students more prone to distraction during study, harder to resist phone temptations, and trapped in a vicious cycle:

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"poor sleep → low efficiency → staying up late to catch up → even worse sleep."

3.3.2 Relationship Between Screen Time and Learning Efficiency

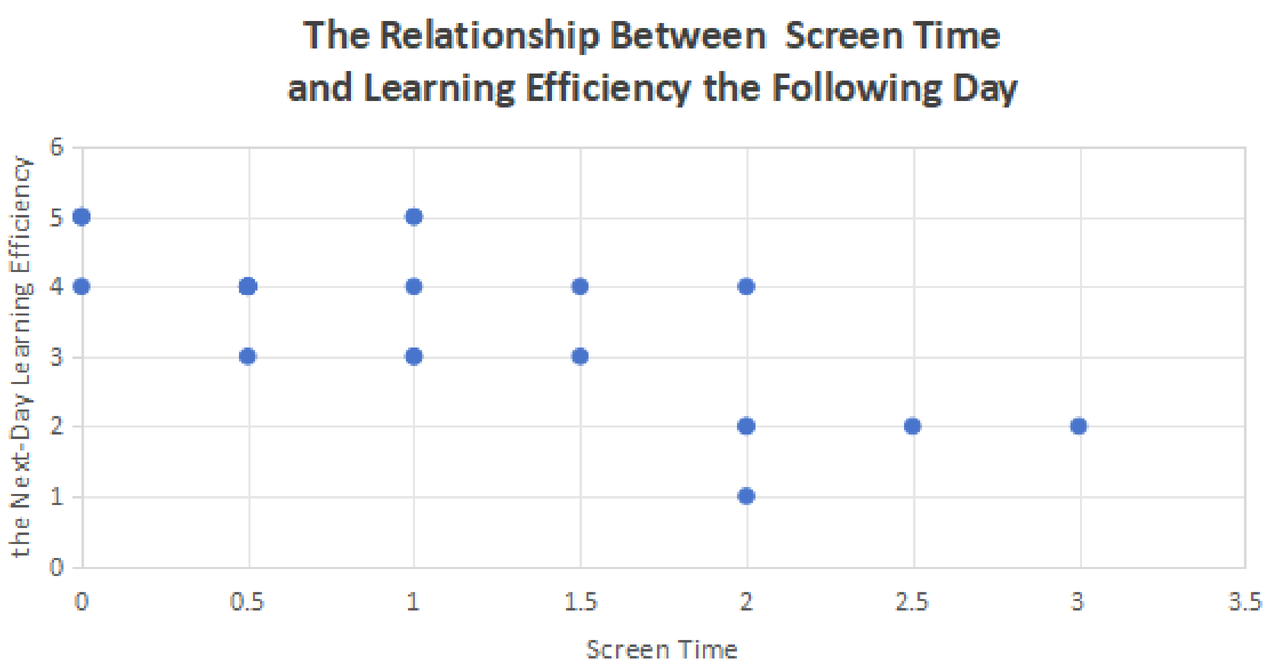

Figure 4: Scatter Plot of Screen Time vs. Daily Efficiency

Figure 4 shows that when daily recreational screen time is kept under 1.5 hours, learning efficiency remains high (above 3 points). However, once it exceeds the 2-hour threshold, daily learning efficiency scores almost invariably drop to 2 points or below. This serves as a clear warning line.

This high-intensity, fragmented stimulation reshapes our brains, making it difficult to adapt to deep learning tasks requiring sustained, steady focus. When we put down our phones and pick up textbooks, our brains experience "boredom" and "withdrawal symptoms," leading to scattered attention. Even when you're not actively using your phone, unread message notifications and engaging video content linger as "mental residue" or "attention residue." This persistent mental load continuously drains your precious cognitive resources, preventing you from fully immersing yourself in learning.

Cross-analysis revealed a more insidious hazard: when combining sleep data with screen time data, the author found that even if total sleep duration met standards, using a phone for over 30 minutes within the hour before bed systematically lowered the next day's average efficiency score by 1-2 points.

3.3.3 Summary

Analysis of Figures 3 and 4 reveals that sleep acts as a "power bank" for cognitive performance, while screen entertainment functions as an "energy vampire." The data clearly shows a significant positive correlation between sleep duration and next-day efficiency, and a pronounced negative correlation between entertainment screen time and same-day efficiency—both exhibiting critical "threshold effects."

3.4 Phased Output Analysis

The scores for two weekly math tests were 82 and 88 points, respectively. Comparing the math study data from the week preceding each exam reveals that before the second test, the average daily math study time decreased by 15 minutes, yet the efficiency score increased from 3 to 4. This indicates that the quality (efficiency) of learning is more important than the quantity (duration).

4. Discussion and Optimization Plan

4.1 Summary of Key Findings

Through four weeks of self-observation and analysis, this study revealed several key learning behavior patterns and efficiency-influencing factors. First, time allocation exhibited significant imbalance, characterized by excessive investment in science subjects while relatively neglecting humanities studies. Second, learning efficiency was not uniformly distributed. The study identified specific afternoon and evening periods as the individual's "golden learning times," when energy and focus peaked. Further exploration of internal and external factors influencing efficiency confirmed that adequate sleep duration is a critical external condition for maintaining high learning efficiency the following day. Simultaneously, excessive screen time and leisure activities severely erode effective learning, exhibiting a clear negative correlation with efficiency. These findings collectively point to a core principle: the "quality" of learning far outweighs its "quantity" [5]. One hour of highly focused, efficient study yields significantly greater outcomes than two hours of distracted, inefficient procrastination.

4.2 Personalized Optimization Plan

To systematically enhance learning effectiveness, this study implemented a comprehensive self-management intervention program. Its core involves first making precise adjustments to time allocation, adding 3 to 4 dedicated "Pomodoro timer" sessions weekly for cumulative learning in Chinese and English. Building on this foundation, it strictly followed individual cognitive patterns: high-intensity thinking tasks like math and physics were scheduled during the afternoon's peak energy window (4-6 PM), while consolidation activities like knowledge review and organization were placed in the evening (8-10 PM). To ensure cognitive resource recovery, a strict sleep schedule mandated bedtime before 11:30 PM and guaranteed 7.5 hours of adequate sleep. Simultaneously, digital environments are strictly managed through applications, limiting daily recreational screen time to under 1.5 hours and mandating focus mode during study sessions to block distractions. Ultimately, all these strategies serve a fundamental shift: cultivating a goal-oriented "efficiency mindset" that emphasizes tangible output per unit of time, thereby transcending inefficient learning patterns reliant solely on prolonged duration.

5. Conclusion

This study employed data science methods to empirically analyze the relationship between time allocation and learning efficiency among high school students through a four-week self-tracking process. Findings reveal distinct temporal patterns in learning efficiency, with clear high-efficiency windows in the afternoon and evening. Sleep duration positively correlates with next-day learning efficiency, exhibiting a critical threshold at 7.5 hours. Recreational screen time negatively impacts same-day learning efficiency, with a threshold effect observed around 1.5 hours daily. These discoveries validate the applicability of a quantified self-based time management diagnostic model at the individual level.

This study has three limitations: First, while subjective efficiency ratings are convenient to implement, their reliability and validity require further validation due to individual perceptual fluctuations. Second, the four-week research period did not cover special learning phases like exam weeks, limiting the comprehensive reflection of dynamic learning behavior changes. Finally, as a single case study, the generalizability of its conclusions is constrained.

Future research should deepen this topic in three directions: First, incorporate objective performance metrics (e.g., task completion speed and accuracy) to enhance data reliability; second, extend the observation period to encompass an entire semester to establish a more comprehensive learning behavior cycle model; Third, the current research paradigm will be extended to the group level. Through questionnaire surveys and multi-case tracking, the relationship patterns between time management factors and learning efficiency across different student groups will be explored. This will enhance the external validity of the research conclusions and provide empirical evidence for constructing a scientific student development guidance system.

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