Task Planning and Completion Analysis: A Personal Data Science Project

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***Abstract*—This study quantifies the impact of daily planning on task completion rate and backlog task clearance through a single-case, self-tracked productivity analysis conducted over a 96-day period. Using daily planning and backlog datasets recorded in Microsoft Excel, the study examines how written daily task plans relate to planning streak formation, daily task completion, and the clearance of long-term backlog tasks. The objectives were to evaluate the impact of task plans on maintaining a daily planning streak, to determine the minimum planning streak length associated with a 100% daily completion rate, and to assess whether structured daily planning can clear 80–100% of backlog tasks.**

Statistical analyses includes point-biserial correlation, Pearson correlation, linear regression, and a one-tailed binomial test. Results showed a significant positive relationship between having a written daily plan and planning streak length, as well as between planning streak length and daily completion rate. Longer planning streaks were associated with higher and more consistent task completion, with a moderate positive correlation observed. Backlog tasks that were explicitly incorporated into daily plans achieved a 90% completion rate, which was statistically significantly higher than a neutral 50% baseline.

These findings indicate that daily planning supports habit formation, improves task execution, and facilitates the clearance of previously neglected tasks. The study contributes empirical, data-driven evidence to habit formation and time management literature by demonstrating how consistent short-term planning can produce measurable improvements in productivity and backlog reduction at the individual level.

***Index Terms*—daily planning, task completion rate, planning streak, backlog task clearance, habit formation, self-tracked productivity, time management**

I. INTRODUCTION

Background of the Study

Active planning is a key component of effective time management. Research indicates that students with poor time management skills often lack proficient planning abilities [1]. When individuals habitually skip planning, tasks tend to accumulate and get postponed. This absence of planning not only delays task completion but also increases susceptibility to procrastination.

Planning involves documenting tasks that need to be accomplished. By externalizing tasks from memory onto paper or digital platforms, individuals create visible reminders that support follow-through. Studies emphasize that preparation and organization form the foundation of sustained productivity [2].

Past researches show that brief planning sessions alone do not resolve productivity challenges [3]. Meaningful benefits emerge through consistent planning practice, which cultivates self-discipline [4] and progressively improves the capacity to manage complex long-term responsibilities [5]. This combination of regularity and intentionality contributes to improved task completion, reduced procrastination, and steady progress in accumulated work.

Contemporary technological tools further support planning habits. Productivity applications such as ProofHub and nTask offer features for task management, deadline tracking, and real-time collaboration [6]. Simpler tools like Microsoft Excel and Google Keep also facilitate daily planning through user-friendly interfaces and timely reminders, enabling individuals to leverage technology for better time management.

In this project, the researcher applies structured daily planning to address persistent task delays. The accumulation of easily postponed tasks—forming a backlog—serves as motivation to develop a consistent planning routine. By strengthening planning habits, this approach aims to improve time management and reduce procrastination, particularly for individuals juggling multiple responsibilities.

Statement of the Problem

Timeliness is essential not only for students but for anyone tasked with responsibilities. As individuals juggle multiple duties, tasks can easily be overlooked during a busy day. Prolonged delays reinforce a ”mañana” habit—consistently deferring activities to a later time—until obligations fade from awareness altogether. This pattern ultimately undermines performance in both academic and professional settings.

The core issue lies not in forgetting tasks, but in the absence of intentional planning. While discipline is necessary for effective time management, the greater challenge is the failure to translate awareness of pending tasks into concrete daily plans. Although technological tools offer significant potential to mitigate task postponement, their benefits remain unrealized without deliberate planning habits. This study addresses the problem by promoting a consistent daily planning practice.

The approach aims not only to accomplish same-day responsibilities but also to systematically address accumulated backlogs, to work on previously postponed tasks through structured planning.

Research Objectives

This project quantifies the impact of daily planning on completion rate of daily tasks and backlog planning clearance. Specifically, it aims to solve the following:

1) To evaluate the impact of task plans on maintaining a daily planning streak
2) To determine the minimum planning streak length in which daily completion rate equals 100%
3) To clear 80-100% of backlog tasks using routines developed from data

Research Questions and Hypotheses

1) Does creating a daily task plan influence planning streak?
   - $H_{1,0}$: There is no significant relationship between creating daily plans and planning streak.
   - $H_{1,a}$: There is a significant relationship between days with a written plan and its associated planning streak.
2) Does planning streak length affect completion rate?
   - $H_{2,0}$: Planning streak length has no significant effect on the daily task completion rate.
   - $H_{2,a}$: There is a significant relationship between longer planning streaks and daily task completion rate.
3) Does daily planning reduce backlog tasks?
   - $H_{3,0}$: Daily planning has no significant relationship with overall backlog count decrease.
   - $H_{3,a}$: There is a significant relationship between daily planning and backlog clearance.

Significance of the Study

The study is presented to all individuals as a way to change habits that boost daily productivity.

For managers and leaders, this study helps increase focus and improve work output, whether for the short term or long term. It benefits not only the company but also the employees by creating a timely and organized working environment.

For company workers, it reduces burnout and improves work-life balance through task updates and smarter working methods.

For school organizations and institutions, especially regarding long-term approaches, planning plays a role in creating a better system as performance improves over time and small errors are reduced.

For students, an early realization of how planning works improves discipline for accomplishing tasks on time, even enabling them to complete difficult or previously abandoned tasks.

II. LITERATURE REVIEW

A previous study explored the effect of taking a few minutes of planning ahead on older adults in Portugal as they perform complex everyday tasks in a laboratory scenario [3]. One hundred fifty-four participants were assigned where each can have planning or a no-planning condition. They were required to multitask and complete a series of subtasks.

Researchers videotaped everyone and coded their plans for quality. A t-test was used to compare performance between the planning and no-planning groups. It was found that there were no significant differences between the planning and no-planning conditions in accuracy, efficiency, or task duration. However, good planning mattered; initial planning quality was a significant predictor of task execution efficiency [3].

The limitations include participants not being able to look back at their written plans during the task, and the tasks being conducted in a controlled environment rather than reflecting bigger real-world challenges. This study provides insight into planning and concludes that planning supports better performance in the complexity of daily tasks for older adults. It highlights that the quality of planning is relevant.

Another study focuses on habit formation and behavioral change by emphasizing the importance of small, incremental actions in creating sustainable habits. It includes frameworks such as James Clear's Atomic Habits and BJ Fogg's Tiny Habits, which highlight motivation, discipline, environmental design, and strategies for breaking negative habits. The collection of data was from academic databases such as PubMed, Scopus, and Google Scholar. To analyze the data, researchers included search terms like "habit formation," "behavioral change," "incremental improvements," "habit loops," "neuroscience of habits," and "small changes" from studies published over the past two decades. Their analyses were largely theoretical rather than statistical. One of the findings includes motivation and discipline as components of habit formation. This aligns with findings suggesting that specifying concrete goals for pursuit and monitoring behaviors can enhance self-control and facilitate habit formation [4]

Fostering a disciplined approach that prioritizes consistent actions over fluctuating goals can lead to more effective habit formation [5]. This strongly supports why a short daily planning habit can create outsized effects on completing difficult tasks and clearing long-term backlogs. Although the study aligns with the project by emphasizing consistency and disciplined behavior—suggesting that writing or tracking plans strengthens commitment and accountability, which make individuals more likely to complete tasks [5]—it offers no quantifiable proof that habits actually eliminate real-world backlogs.

The Time Management Planning Inventory (TMPI), procrastination questionnaires, and a personal data sheet were used to gather data from 506 students in Grades 7, 8, and 9 in a recent study. It is about time management and its influence on study procrastination, along with the hours spent studying. For the TMPI, planning was divided into two types: short-term planning, involving daily logs and to-do lists, and long-term planning, with questions answered on a five-point Likert scale. The procrastination questionnaire used a similar Likert-scale format. The personal data sheet collected information on gender, age, grade level, and study hours. These instruments were used to examine correlations among the three variables.

The overall analysis was framed within structural equation modeling (SEM) to test the measurement of variables and their relationships. This process began by removing items with uneven distribution, followed by confirmatory factor analysis (CFA) to examine whether survey items correctly measured the intended factors, using acceptable factor loadings greater than or equal to 0.40. Relationships were initially examined using Pearson correlation and then tested further with Structural Regression Analysis (SRA) to evaluate the proposed model and hypotheses. All analyses followed a two-stage approach using SPSS and AMOS version 29: data preparation and cleaning with SPSS, and building complex theoretical models with AMOS.

It was found that students who spent more hours studying tended to organize their time more carefully, particularly in long-term planning, while short-term planning fostered consistent study habits that naturally developed into long-term planning skills [2]. This relates to the project, as one of the objectives seeks to clear most of the long-term backlogs. Daily planning tasks—also known as short-term planning in this study—demonstrate that continuous daily planning forms a consistent habit that builds the ability to create effective long-term plans.

Additionally, the study found a strong connection between time management and procrastination: students who engaged in long-term study planning were less likely to procrastinate. Overall, the findings highlight that effective time management is a key skill that reduces task delays, suggesting that developing strong planning routines—especially long-term ones—helps individuals become more organized [2].

III. METHODOLOGY

A. Overview

This single-case self-experiment project examines daily planning effects on productivity over 96 days. The sole participant self-tracked data daily in Excel using two tables: Daily Plan and Backlog tables.

B. Participants

Personal data collection regarding planning information was gathered daily for 3 months.

C. Data Collection Methods

The study utilized self-tracked personal productivity data collected in two main tables: the Daily Plan Table and the Backlog Table.

Measurement of Variables:

- Automated variables: Date is automatically recorded by the logging application upon entering plans.
- Manual/self-reported variables:
  - Mood before, planning streak, task number, and task description were entered manually in Microsoft Excel in a consistent, methodical manner at the beginning of the day.
  - Expected difficulty and expected motivation were self-rated on a 1–5 Likert scale (1 = lowest/easiest, 5 = highest/most difficult).
  - Completion status, reason for outcome, and mood after were recorded at the end of each day (usually minutes before midnight).

TABLE I
DAILY PLAN TABLE

Data Variable	Type	Unit/Scale	Frequency	Tool/App
date	date	DD-MM-YYYY	daily	Excel
day of week	Categorical	monday – sunday	daily	Excel
planning streak	Quantitative	1, 2, 3, …	daily	Excel
phase (number of planned tasks)	Quantitative	2, 3, 4, …	daily	Excel
task number	Quantitative	1, 2, 3, …	per task	Excel
backlog	Binary	Yes / No	per task	Excel
backlog id	Categorical	B01, B02, B20	per task	Excel
task description	Text	Any text	per task	Excel
expected difficulty	Quantitative	1 – 5	per task	Excel
expected motivation	Quantitative	1 – 5	per task	Excel
complete or not	Binary	Yes / No	per task	Excel
reason if complete or not	Text	Any text	per task	Excel
mood before	Quantitative	1 – 5	daily in morning	Excel
mood after	Quantitative	1 – 5	daily in evening	Excel

* This contains a mixture of planned tasks, unplanned tasks, and backlog tasks, as it serves as the primary daily tracker.

TABLE II
VARIABLES IN THE BACKLOG DATASET

Data Variable	Type	Unit/Scale	Frequency	Tool/App
backlog id	Categorical	B01, B02, B20,	per task	Excel
description	Text	Any text	per task	Excel
date added	date	DD-MM-YYYY	per task	Excel
date completed	date	DD-MM-YYYY	per task	Excel
complete status	Binary	Yes / No	per task	Excel

* This tracks only long-overdue tasks (backlog items) that were resumed and planned during the study period. These are long-term tasks that were neglected prior to the study and were incorporated into daily plans

Study Period

- All entries were self-reported and logged daily in Excel, with Google Notes used as a backup for additional context and task details.

D. Operational Definitions

Daily Plan Table

- Date: The calendar date on which the daily task plan is created and logged (format: DD-MM-YYYY).
- Day of Week:The day of the week corresponding to the Date (Monday, Tuesday, . . . , Sunday)
- Planning Streak: The number of consecutive days on which a daily plan was written (it resets to 0 after any day without a plan).
- Phase: The number of tasks planned for the day, reflecting the intended scope or maturity of the planning habit.
- Task Number:The sequential identifier of each task within the day's plan (1 to Phase value, assigned in the order tasks are written).
- Is Backlog: A binary indicator (Yes/No) classifying whether the task is a carried-over backlog item or a newly created task for that day.
- Backlog ID: A unique alphanumeric identifier linking a backlog task in the Daily Plan Table to its corresponding entry in the Backlog Table.

- Task Description: A brief textual summary describing the specific action or objective of the task.
- Expected Difficulty: Self-rated anticipated difficulty of completing the task before starting it (ordinal scale: 1 = very easy, 5 = very difficult).
- Expected Motivation: Self-rated level of motivation required to complete the task before starting it (ordinal scale: 1 = very low motivation, 5 = very high motivation).
- Status: Binary outcome indicating whether the task was completed (Yes) or not completed (No) by the end of the day.
- Reason Task Outcome: A short free-text explanation provided at the end of the day for why the task was completed or not completed.
- Mood Before: Self-reported mood at the beginning of the day, typically before creating or reviewing the task plan (ordinal scale: 1 = very low/negative, 5 = very high/positive).
- Mood After: Self-reported mood at the end of the day, typically shortly before midnight (ordinal scale: 1 = very low/negative, 5 = very high/positive).

Backlog Table

- Backlog ID: Unique alphanumeric identifier for each backlog task
- Planned: States the backlog task as planned.
- Description: Brief textual summary describing the backlog task.
- Date Added: The calendar date when the backlog task was first incorporated into a daily plan (format: DD-MM-YYYY)
- Complete Status: Binary indicator of whether the backlog task has been finished (Yes) or remains incomplete (No)

E. Data Cleaning

These are the steps the researcher made during Data Preprocessing:

1) Initial loading and inspection Both tables were loaded into Python using pandas. Column data types, summary statistics (describe()), missing values (isna().sum()), and duplicates (duplicated().sum()) were examined.
2) Type conversion
   - Date columns were converted to datetime format (pd.to_datetime)
   - Binary variables (Yes/No) were mapped to 1/0 integers.
   - Text fields (task description, reasons) were retained initially but later excluded from numerical analysis.
3) Handling missing values Missing values were intentionally retained in most cases, as they often represented genuine "no-planning" days. For aggregation purposes, missing planning-related values were treated as 0 (no plan). No rows were dropped due to missingness.
4) Outlier handling: There are data that weren't removed because they were needed for the Statistical Analysis of the project.
5) Aggregation The raw daily task data ("daily_clean", 285 rows) was aggregated by date to produce a daily-level dataset ("daily_agg", 96 rows):
   - Completion rate was computed as the mean of completed tasks per day
   - Task count was taken as the maximum task number per day
   - Backlog tasks were flagged (is_backlog_flag).
   - Other daily variables (streak, planning status) were summarized appropriately.

After preprocessing, no duplicates or remaining missing values were detected in the aggregated dataset.

F. Statistical Analysis

1) Point-Biserial Correlation was used to measure the strength and direction of the relationship between a continuous or ordinal variable and a binary variable. This method is appropriate because it is mathematically equivalent to Pearson correlation when one variable is dichotomous, and it allows assessment of how strongly planning presence predicts higher completion or better mood.
2) Pearson Correlation was used to examine linear relationships between continuous variables such as planning streak, number of tasks, and completion rate. Pearson's r was chosen because these variables are continuous and the method looks for approximate normality.
3) Linear Regression & Visualization: Simple linear regression (with regression plot) was used to model and visualize the relationship between planning streak length and daily completion rate. The regression line and 95
4) One-tailed Binomial Test: Performed on backlog tasks only (n=20, all planned) to test whether the completion rate was significantly greater than a neutral 50
5) Visualizations
   - Bar graphs and histograms were used to show distributions of completion rate task planned and planning streak.
   - Skewness statistics were computed and reported for continuous variables to assess normality.
   - Time-series line plots displayed trends in completion rate and planning streak over the 96-day period.

IV. RESULTS

	has_written_plan	planning_streak	tasks_number	completion_rate	backlog_tasks
count	96.000000	96.0	96.0	96.000000	96.000000
mean	0.812500	12.927083	2.96875	0.695312	0.208333
std	0.392361	11.760097	1.099791	0.402991	0.408248
min	0.000000	0.0	1.0	0.000000	0.000000
25%	1.000000	2.0	2.0	0.500000	0.000000
50%	1.000000	10.5	3.0	1.000000	0.000000
75%	1.000000	22.25	4.0	1.000000	0.000000
max	1.000000	39.0	4.0	1.000000	1.000000

A. Descriptive Analysis

1) Daily Plan (has_written_plan):

- Mean (˜0.81): This indicates the days in the dataset with a written plan.
- Median (1.0): The written plan is present more than half of the the total days.
- Standard Deviation (˜0.39): There is a relatively low spread in daily written plan.
- Range (0 to 1): Variable being a binary with only two possible states: 0 as No Plan and 1 is Plan

2) Planning Streak (planning_streak):

- Mean (nearly 12.93 days): The average planning streak is about 13 days, habits are maintained nearly for two weeks.
- Median (nearly 10.5 days): Half of the planning streaks are 10.5 days or shorter, and half are longer.
- Standard Deviation (nearly 11.76 days): There's a relatively large spread in streak lengths, indicating variability in how consistently planning is maintained. Some streaks are short, while others are significantly longer.
- Range (0 to 39 days): Streaks from 0 days (no planning for a given day, often indicating a break) to a maximum of 39 consecutive days.

3) Tasks Number (tasks_number):

- Mean (˜2.97 tasks): On average, approximately 3 tasks are planned per day when a plan is made.
- Median (3 tasks): The typical number of tasks per day is 3.
- Standard Deviation (˜1.10 tasks): The number of tasks per day doesn't vary drastically, usually staying between 1 and 4 tasks.
- Range (1 to 4 tasks): Days with written plans typically involve 1 to 4 tasks, indicating a focused and manageable daily workload.

4) Completion Rate (completion_rate):

- Mean (nearly 70%): On average, about 70% of planned tasks are completed each day.
- Median (100%): The median completion rate being 1.00 indicates that on more than half of the days, all planned tasks were fully completed.
- Standard Deviation (˜0.40): There's considerable variability in daily completion rates, implying that while many days are 100% successful, there are also days with lower completion rates.
- Range (0.00 to 1.00): Completion rates span the entire spectrum, from no tasks completed (0%) to all tasks completed (100%).

5) Backlog Tasks (backlog_tasks):

- Mean (˜0.21 tasks): On average, a very small fraction of a backlog task is addressed each day. This suggests that backlog tasks are not an everyday occurrence in daily planning.
- Median (0 tasks): Half of the days involve no backlog tasks being included in the daily plan.
- Standard Deviation (˜0.41): There is variability, but it's often 0 or 1, reflecting that backlog tasks are either not present or just one is included.
- Range (0 to 1 task): This indicates that on any given day, at most one task from the backlog is typically incorporated into the daily plans.

B. Correlation Matrix

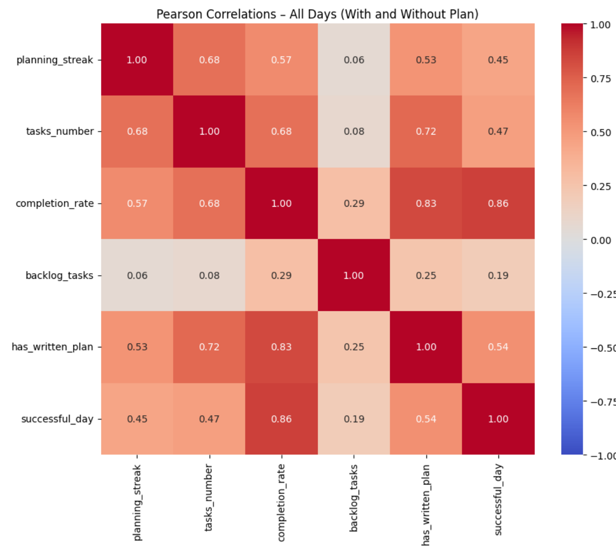

Fig. 1.

Based on the Correlation Matrix, there are positive correlations between successful_day and completion_rate (r = 0.86), completion_rate and has_written_plan (r = 0.83), tasks_number and has_written_plan (r = 0.72), planning_streak and tasks_number (r = 0.68), and completion_rate and tasks_number (r = 0.68). Weak correlations were observed between backlog_tasks and planning_streak (r = 0.06) and between backlog_tasks and tasks_number (r = 0.08).

C. Distribution of Planning Streak Length (planning_streak)

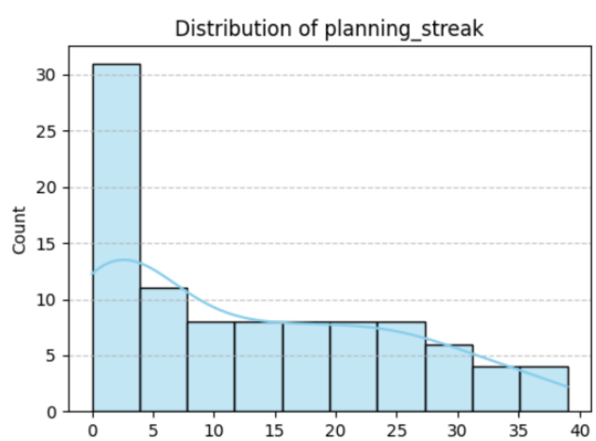

Fig. 2.

The histogram shows a distribution heavily skewed to the right, meaning it is a positive skew. There is a high frequency of short planning streaks around 0–5 days, with the count of days decreasing significantly as the streak length increases. There are also a few days with very long streaks, extending up to 39 days.

D. Distribution of Completion Rate

This is heavily skewed to the left or negative skew, and bimodal-it has two distinct peaks. There is a very large peak at 1.0 (100% completion rate) that indicates that on many days, all planned tasks are successfully completed. There is another, smaller peak near 0.0 (0% completion rate), suggesting days where no tasks were completed. The values in between these extremes are less frequent.

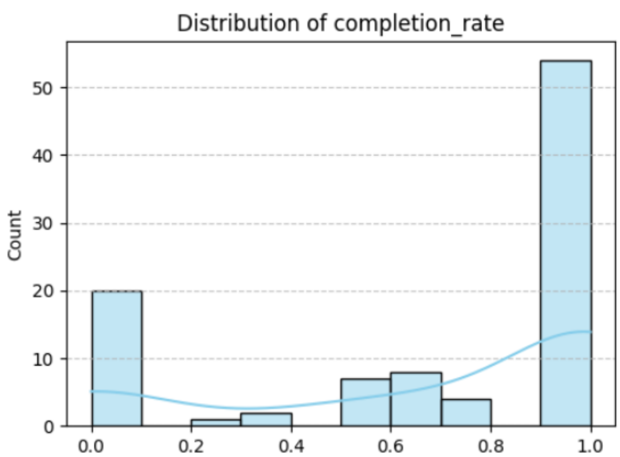

Fig. 3.

E. Distribution of Number of Tasks Planned (tasks_number)

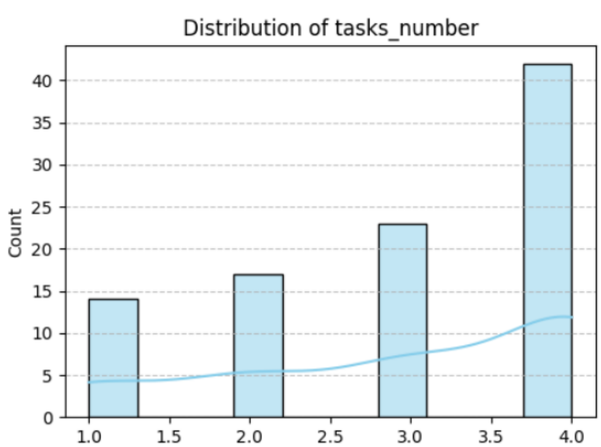

Fig. 4.

The histogram shows a relatively uniform distribution, with peaks at 2, 3, and 4 tasks. There are very few days where only 1 task was planned. The distribution is roughly symmetrical or slightly left-skewed.

F. Planning Streak Over Time

Fig. 5.

The planning streak shows an overall upward trend with significant fluctuations. There are periods where the streak increases steadily, followed by drops, indicating a break in the planning habit. At the beginning, there is an early period of low streaks, then a gradual increase to a peak, a reset, and another period of growth.

The resets in the streak is an effort to maintain consistency; there are occasional days where planning is missed. Several instances where the streak reaches a high point (around 10–30 days, then later to nearly 40 days) before dropping to 0.

G. Daily Completion Rate Over Time

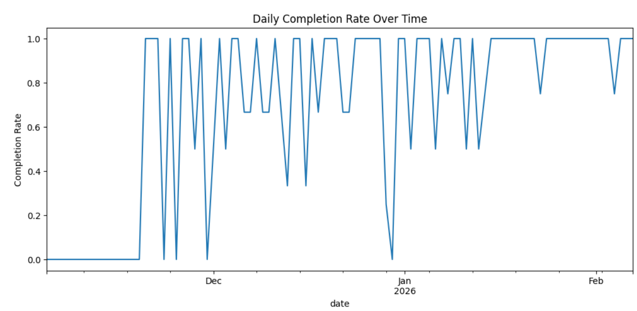

Fig. 6.

The daily completion rate fluctuates significantly between 0 and 1 (0% and 100%). There is not a clear, consistent upward or downward trend over the entire period.

The plot shows many days with 100% completion and also a noticeable number of days with 0% completion. This reinforces the bimodal distribution also seen on the histogram.

Notable Events: Periods of sustained high completion rates can be seen, along with rising planning streaks. There are also clusters of low completion rates, meaning less productive periods.

H. Daily Planning and Streak

Hypothesis 1 was tested using a point-biserial correlation to examine the relationship between daily planning and streak over time. Results revealed a significant positive association ($rpb = 0.514, p < 0.05$), p being 0.000001, rejecting the null

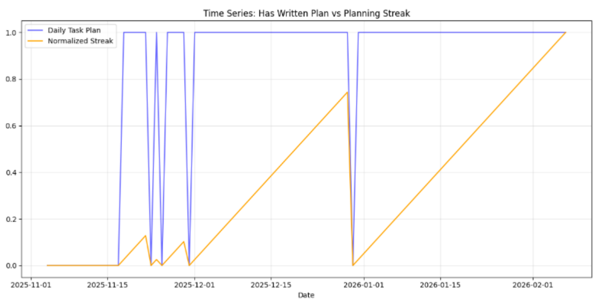

Fig. 7.

hypothesis and indicating that days with a written plan were associated with longer planning streaks.

I. Streak Length and Completion Rate

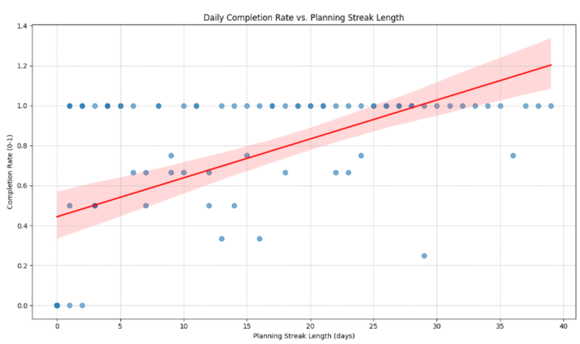

Fig. 8.

Hypothesis 2 examined the linear relationship between planning streak length and mean completion percentage using Pearson's correlation. A significant positive correlation was observed ($r = 0.514, p = 0.00070$), supporting the hypothesis that longer planning streaks are associated with higher daily completion rates.

J. Binomial Test: Backlog Completion for Planned Tasks

A binomial test to answer Hypothesis 3 indicated that the observed completion rate of 90.00% (18/20) was higher than the hypothesized rate of 50% ($p = 0.00020$).

V. DISCUSSION

This personal productivity analysis, centered on daily planning, task completion, and backlog management, reveals clear patterns and relationships that highlight the value of structured planning in achieving personal goals.

A key finding is the strong association between having a written daily plan and task completion rate. The point-biserial correlation between `has_written_plan` (binary: Yes/No) and `completion_rate` was 0.83 ($p < 0.05$), indicating a substantial positive relationship. Days with a written plan showed a median completion rate of 100%, compared to 0% on days without a plan. This suggests that externalizing tasks into a structured plan fosters clarity, commitment, and a tangible reference point for execution, shifting daily activity from reactive to intentional behavior. This finding supports Hypothesis 1.

Additionally, planning streak length (`planning_streak`) exhibited a moderate positive linear relationship with mean daily completion rate (`mean_completion_pct`), with Pearson $r = 0.514$ ($p < 0.001$). Longer consistent planning appears to compound benefits through habit formation, leading to improved self-discipline, more accurate task estimation, and a better understanding of personal productivity rhythms over time.

Other variables also showed positive correlations, even if not central to the main objectives. For example, the number of planned tasks (`tasks_number`) correlated strongly with completion rate ($r = 0.68$).

Regarding backlog management, the 20 backlog tasks—all of which were planned—achieved a 90% completion rate (18/20). A one-tailed binomial test against a neutral 50% baseline yielded $p = 0.00020$, indicating significantly better-than-chance performance. This supports the effectiveness of explicitly incorporating backlog items into daily plans. However, backlog tasks showed only weak correlations with planning streak ($r = 0.06$) and number of tasks ($r = 0.08$), suggesting that backlog inclusion does not automatically increase with longer streaks or higher task volume. Backlog items remained relatively few compared to daily regular tasks.

The analysis also evaluated the impact of task planning on maintaining a daily planning streak. In the 96-day period, streaks formed through consistent planning, with the longest reaching 39 days after initial drops to zero. The longest uninterrupted streak with 100% task completion lasted 11 days. For the personal objective of clearing 80–100% of backlog tasks, 90% (18/20) were accomplished through daily planning, falling within the target range. Among the most challenging backlog items were "Finish the 30th day of continuous journaling" and "Achieve the 90th day streak of DataCamp."

A. Limitations

While insightful, this study has several limitations:

- Self-report bias: All data were manually self-logged, making them susceptible to biased mood ratings and subjectivity in difficulty/motivation assessments.
- Single-subject design and small sample: The analysis is based on the researcher (N=1) over 96 days, limiting generalizability to other people or longer timeframes.
- Limited temporal scop: Data cover only November 2025–February 2026, missing seasonal, life-event, or long-term trends.
- Missing contextual variables: `mood_before`, `mood_after`, and `reason_task_outcome` were collected but dropped from the main aggregated dataset (`daily_agg`). Re-integrating them could provide new perspectives on how these factors affect planning and completion.

- Lack of unplanned backlog comparison: All backlog tasks were planned, preventing direct statistical comparison of completion rates with versus without planning. This made answering the corresponding research question difficult due to the absence of the necessary binary variation.
- Individual variability: Strong correlations observed here may not apply universally—some people complete tasks effectively without planning, while others plan but struggle with execution.

B. Recommendations for Future Work

- Collect richer task attributes (estimated vs. actual duration, task type: work/personal/learning, priority level).
- Include periodic qualitative reflections, especially on high/low completion days.
- Incorporate external factors (sleep quality, exercise, stress, major life events).
- Re-analyze `reason_task_outcome` to categorize barriers to completion.
- Extend data collection over multiple seasons/years and, ideally, across multiple individuals.
- Use digital tools with automatic timestamps or reminders to reduce self-report bias.

VI. CONCLUSION

Over 96 days, daily planning showed clear benefits. Early weeks had no planning and short, broken streaks. Only after treating planning seriously did consistent streaks and better execution appear. All three hypotheses were supported statistically, aligning with research on planning quality and habit formation

For Hypothesis 1 null: no significant relationship between creating daily plans and planning streak length was rejected. Point-biserial correlation showed a significant positive relationship p¡0.05: days with a written plan are associated with longer planning streaks. Hypothesis 2 null: planning streak length has no significant effect on daily task completion rate was rejected as well. Pearson correlation showed a significant positive relationship (%r = 0.514, p = 0.00070 ¡ 0.05%): longer streaks are associated with higher completion rates. Hypothesis 3 null: daily planning does not reduce backlog tasks was rejected using one-tailed binomial test that showed a significant positive association (%p = 0.00020 ¡ 0.05%): planned backlog tasks had a 90% completion rate, well above the 50% baseline (though limited by lack of unplanned comparison).

Writing tasks down every day created clarity and a sense of commitment the researcher did not have before. External structure is much needed than thought. Without a plan, entire days could pass with almost nothing accomplished. But once even a short streak is built, momentum kicked in—it helped follow through on harder tasks. The 90% backlog clearance is surprising. This taught me that procrastination isn't always about laziness—it's often about not giving the task a specific time and place in a day. Finally, seeing how quickly habits can change impacts. A few months of consistent effort turned planning from something resisted into something that felt natural and rewarding.

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