# Understanding Personal Procrastination Patterns: A Data-Driven Analysis of Task Completion and Distraction Behavior

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**Abstract—This study investigates personal procrastination and task completion behavior through a four-month self-tracking dataset consisting of 337 tasks across academic, thesis, community, and personal domains. The research examined temporal patterns of procrastination, the role of digital distraction, the influence of work context, and conditions associated with task completion outcomes. Descriptive statistics, chi-square tests, and Spearman rank-order correlations were applied to analyze relationships among distraction level, work context, day quality, and completion lag. Results indicate that procrastination occurs more frequently on weekdays than weekends, higher distraction levels are associated with longer completion lag, and working alone is linked to increased procrastination rates. Despite these patterns, overall task completion rates exceeded 98%, suggesting that delay often reflects postponed completion rather than abandonment. The findings extend existing procrastination research by providing longitudinal behavioral evidence within a single individual and highlight the practical importance of minimizing digital distractions and increasing structured accountability in daily productivity.**

**Index Terms—Procrastination, Self-tracking, Task Completion, Digital Distraction, Behavioral Data Analysis, Productivity Analytics, Chi-square Test, Spearman Correlation**

## I. INTRODUCTION

In modern academic life, understanding personal productivity patterns has become increasingly important for effective time management and goal achievement. University students face numerous competing demands across life domains such as academic works, community commitments, and personal responsibilities making consistent task completion challenging across contexts.

Procrastination represents a widespread challenge among students. A recent meta-analysis of 96 articles involving 55,477 participants found that the overall relationship between procrastination and academic performance is negative but the type of procrastination does matter when compared with academic performance, as active procrastination is positively related to academic performance, while passive procrastination is negatively related [1]. The rise of smartphones has intensified this challenge, with research demonstrating a strong connection between smartphone distraction and academic procrastination [2]. Although students engage in academic, community, and personal tasks, existing procrastination research has largely focused on academic activities, leaving unclear whether similar behavioral patterns occur across other life domains.

This study addresses this gap through self-tracking methods to examine task completion patterns across four life domains: academic coursework, thesis research, church commitments, and personal tasks. By analyzing 337 tasks over 4 months, the study addresses four research questions:

1) When does task procrastination occur most frequently?

2) What factors trigger distraction when working alone?

3) What factors are associated with delayed task completion?

4) What conditions are associated with successful task completion versus non-completion?

Although this study is exploratory in nature, inferential statistical tests were conducted to examine associations between selected variables. The following null and alternative hypotheses were tested:

$H_{01}$: There is no significant association between day category (weekday vs weekend) and procrastination status.
$H_{11}$: There is a significant association between day category (weekday vs weekend) and procrastination status.

$H_{02}$: There is no significant association between work context (working alone vs with others) and procrastination status.
$H_{12}$: There is a significant association between work context (working alone vs with others) and procrastination status.

$H_{03}$: There is no significant monotonic relationship between distraction level and completion lag.
$H_{13}$: There is a significant monotonic relationship between distraction level and completion lag.

$H_{04}$: There is no significant association between procrastination status and task completion outcome.
$H_{14}$: There is a significant association between procrastination status and task completion outcome.

This focus emerged from noticing repeated patterns of delayed completion in everyday productivity. These observations motivated a closer examination of the conditions that distinguish unfinished tasks from successfully completed ones. The study examines these patterns across multiple task domains to determine whether procrastination behaviors observed in academic research also appear in other areas of life. By tracking diverse tasks within a single individual, the study avoids differences that typically arise when comparing multiple participants, allowing clearer comparisons across contexts.

The objectives are to: (1) identify when procrastination most frequently occurs; (2) examine factors associated with distraction during solo work; (3) analyze patterns of delayed task completion; and (4) assess whether insights from academic procrastination research extend beyond educational settings. Through data collection and analysis, the study aims to identify productivity insights while exploring patterns that influence task completion and delayed completion.

This study analyzes personal task data collected over four months. Analyzing personal task data over time provides a detailed view of actual productivity behavior rather than relying solely on general surveys or perceptions. This allows closer examination of when and why tasks are completed or delayed in real-life contexts. Because the data comes from a single individual and relies on self-reporting, the findings cannot be generalized to a wider population. However, the design allows for detailed exploration of real-life productivity patterns across different types of tasks.

## II. LITERATURE REVIEW

This section reviews existing research related to the themes of this study: procrastination behavior among students, digital distractions and their academic consequences, and the role of work context in task completion. Each subsection examines relevant prior work, identifies their methods and findings, and highlights how this study relates to and extends from existing literature.

### *A. Procrastination Among University Students*

Procrastination refers to voluntarily postponing an intended course of action despite expecting to be worse off for this delay, and students are considered to be especially negatively affected. A meta-analysis of 96 articles involving 55,477 participants found that the overall relationship between procrastination and academic performance is negative, though the type of procrastination matters: active procrastination characterized by intentional delay and confidence in completing tasks on time is positively associated with academic performance, while passive procrastination marked by avoidance and inability to act is negatively associated [1]. Their analysis drew on studies sourced from the Web of Science database and used weighted correlation coefficients to synthesize findings. However, the authors acknowledged that significant heterogeneity existed across included studies, attributable to differences in geographic location, performance metrics, data collection methods, and the specific procrastination instruments used. Additionally, the meta-analysis was limited to academic performance as an outcome and drew exclusively from already-published self-report studies, leaving open the question of whether similar procrastination patterns emerge in non-academic domains. This distinction is important for the present study, as the repeated delay patterns observed in this dataset more closely align with passive procrastination behavior.

Rozental et al. recruited students from different universities in Sweden to participate in an anonymous online survey examining self-rated procrastination alongside measures of impulsivity, perfectionism, anxiety, depression, stress, and quality of life [3]. Their findings revealed that more severe cases of procrastination were associated with lower self-regulatory capacity, greater impulsivity, and considerably diminished well-being. The study usefully demonstrated that procrastination is not uniform but exists along a continuum, with more severe manifestations warranting targeted support. Despite these contributions, the authors noted key limitations: all measures relied on self-report, introducing the possibility of response and social desirability bias; and the cross-sectional design prevented any causal conclusions about how procrastination develops or changes over time. Because the study examined procrastination as a general trait rather than tracking task-level behavior, it also could not identify which specific daily conditions such as working alone versus with others, or time of day were associated with higher or lower procrastination in practice.

Farhadi Rad et al. conducted a descriptive-analytical cross-sectional study on 290 students across different academic fields at a medical sciences university in southern Iran [4]. Using standard validated questionnaires alongside descriptive statistics, t-tests, ANOVA, Pearson correlation coefficients, and multiple linear regression analyzed in SPSS, the study found that components of academic self-efficacy specifically effort, talent, and contextual confidence as well as six distinct components of emotional regulation difficulty, including difficulty performing purposeful behavior, lack of emotional awareness, limited access to regulation strategies, non-acceptance of emotional responses, difficulty in impulse control, and lack of emotional clarity, each significantly predicted academic procrastination. These findings suggest that both cognitive self-belief and the capacity to manage emotional states function as meaningful predictors of whether students delay or complete their academic responsibilities. However, the study carried notable limitations. Its cross-sectional design captured only a single point in time, making it impossible to draw causal conclusions or observe how these predictors fluctuate across days or tasks over a longer period. Furthermore, the study measured procrastination entirely through self-report questionnaire scales focused on academic tasks, meaning it could not observe whether or how these psychological factors actually manifested in real behavioral outcomes such as delayed completion in everyday life.

Collectively, these studies relied predominantly on self-report surveys and validated procrastination scales to measure procrastination levels. In contrast, the present study extends this approach by analyzing actual task completion behavior through longitudinal tracking over four months, offering a behavioral rather than perception-based view of procrastination.

*B. Digital Distraction and Task Completion*

The growing influence of smartphones has introduced significant challenges to sustained attention and task completion among students. Zhang et al. examined the relationship between smartphone distraction and academic anxiety and found that academic procrastination serves as a mediating variable between smartphone use and anxiety, with time management disposition acting as a moderating factor [2]. While the study provided valuable insight into the mechanisms connecting smartphone use to procrastination and anxiety, the authors identified several limitations: all variables were self-reported, raising concerns about common method bias; and the cross-sectional design could not establish causal direction. Critically, the study focused exclusively on academic anxiety as an outcome and did not examine whether and how distraction actually translated into reduced task completion rates in everyday practice. The present study addresses this gap by tracking distraction levels alongside actual task outcomes across 337 tasks bridging academic and non-academic domains.

Zhao and Li conducted a systematic review of empirical research on digital distractions in educational contexts, synthesizing findings from multiple studies on the causes, consequences, and prevention strategies of distraction in learning environments [5]. Their review found that digital distractions impair concentration, reduce task persistence, and fragment work sessions, with effects being stronger in unstructured, self-directed settings. Prevention strategies they identified such as device-free environments and time-blocking provide practical relevance for the recommendations of the present study. As a systematic review, however, Zhao and Li's work was limited by the scope of literature available for synthesis and noted that most included studies employed survey-based or experimental designs under controlled or semi-controlled conditions. The review also acknowledged that few studies tracked distraction longitudinally within individuals across varying real-life work contexts, and that findings were predominantly restricted to formal educational settings. This leaves unanswered how digital distraction operates across different life domains such as community or personal tasks or how it interacts with contextual factors like social presence during work. The present study contributes to this gap by providing behavioral data on distraction across multiple task types within a single individual over four months.

### *C. Work Context and Procrastination Reduction*

Work context has received comparatively less attention in procrastination research, despite its potential as a situational influence on task completion behavior. Koppenborg and Klingsieck conducted two vignette studies with student samples of 320 and 193 participants, respectively, using regression analyses and analyses of covariance to examine how group work structures affect procrastination [6]. They found that working in an interdependent group setting where each member's contribution was necessary for the group's collective outcome was associated with significantly lower procrastination and more positive emotional outcomes compared to working independently.

Their findings suggest that social accountability and shared responsibility can function as situational factors that counteract individual procrastination tendencies. However, the authors explicitly noted that their vignette methodology was a significant limitation: participants responded to hypothetical work scenarios rather than actual behavioral situations, which may not accurately reflect real-world decision-making around task delay. The experimental nature of the design also meant that the findings could not speak to whether these social effects persist across extended periods, across different task types, or in informal rather than structured group work arrangements. Additionally, procrastination was assessed through self-reported intentions in the vignette scenarios rather than through observed task completion behavior.

The findings of Koppenborg and Klingsieck closely parallel the observations in the present study, where task completion rates were consistently higher when working with others compared to working alone. The present study extends their work in two important ways: first, by examining the effect of work context using actual task completion data rather than hypothetical scenarios; and second, by demonstrating that this effect appears not only in structured academic group work but also in informal everyday contexts such as church commitments and personal tasks tracked over four months.

### *D. Gaps Addressed by This Study*

Taken together, the reviewed literature reveals a consistent pattern of methodological constraints that the present study is positioned to address. First, procrastination research has relied almost exclusively on self-report scales and cross-sectional survey designs, meaning behavioral manifestations of procrastination such as actual task completion rates and delayed completion frequencies remain largely unmeasured at the individual level over time [1], [3], [4]. Second, existing studies focus predominantly on academic contexts, providing limited evidence of whether procrastination behaviors and their predictors generalize to non-academic domains such as personal, thesis, or community responsibilities [1], [3], [4]. Third, digital distraction research confirms the negative role of smartphone use on student performance but has not examined how distraction levels vary across different work contexts: alone versus with others within a single individual [2], [5]. Fourth, work context research demonstrates that group work can reduce procrastination, but is based on vignette scenarios rather than real behavioral data and does not capture effects across informal task types or extended timeframes [6].

The present study addresses these gaps by: (1) tracking actual task completion and delayed completion behavior across 337 tasks over four months, rather than relying solely on self-report perceptions of procrastination; (2) examining procrastination-related patterns across four distinct task domains academic, thesis, church, and personal extending the scope of prior literature beyond purely educational settings; (3) linking self-reported distraction levels to observed task outcomes, while comparing distraction patterns between solo and group conditions; and (4) using behavioral data to test whether the social facilitation effects found in experimental research also appear in longitudinal productivity tracking. In doing so, the study offers a complementary perspective alongside existing survey-based and experimental approaches.

## III. METHODOLOGY

This chapter describes the exact procedures used to conduct this self-tracking study. It covers who participated, what data was collected and how it was measured, the tools used for recording, how the raw data was cleaned and prepared for analysis, and which statistical methods were applied to answer each research question.

### A. *Participants*

The sole participant in this study is the researcher themselves. This study follows a single-subject self-tracking design, which is appropriate when the goal is to understand behavioral patterns within one individual rather than make population-level generalizations.

- Subject: The researcher (student), serving as both the observer and the subject of observation.
- Profile: College student managing academic tasks, personal projects, and daily responsibilities.
- Age range: Late teens to mid-twenties (exact age withheld for privacy).
- No personally identifiable information beyond the above was collected or stored in the dataset.

Because this is a first-person self-report study, the researcher had full knowledge of all variables at the time of logging, which introduces the possibility of self-report bias.

### B. *Data Collection Methods*

#### a) *Variables Collected*

A total of 11 variables were logged per task entry. While 14 variables appear in the final dataset (cleaned_dataset.csv), only 11 were manually logged. The remaining 3 were derived during data preparation (see Section D).

| **Variable Name** | **Description** |
|---|---|
| date_created | The date the task was created or assigned. |
| date_complet ed | The date the task was actually completed (NaN if not completed). |
| task_id | Unique numeric identifier for each task entry. |
| task_name | Short text description of the task. |
| category | Type of task (e.g. academics, thesis, church, personal). |
| status | Final task outcome: Done, Missed, or In Progress. |
| when_worke d | Time of day slot when the task was worked on (e.g. morning (6am-12pm), afternoon (12pm-6pm), evening (6pm-10pm), night (10pm-6am). |
| notes | Text notes describing the reason or distraction type, if any occurred. |

| | |
|---|---|
| completion_days | Number of days passed from creation to completion. (0 = same day). |
| created_weekday | Day of the week the task was created (Monday–Sunday). |
| is_weekend | Representing whether a task was created during the weekend. Binary flag: 1 = task created on Saturday or Sunday, 0 = weekday. |
| work_alone_num | A binary variable indicating the work context of the task. Binary: 1 = worked on a task alone, 0 = worked with others present. |
| got_distracted_num | An ordinal variable measuring the intensity of distraction experienced while working on a task. 0 = no (stayed focused), 1 = yes-little (got distracted but recovered), 2 = yes-alot (constantly distracted, hard to focus). |
| day_quality_num | An ordinal variable reflecting the overall productivity level of the day. 0 = unproductive (procrastinated, didn't accomplish much), 1 = normal (average day, some work done), 2 = productive (got things done, felt good). |

*Table 1. Dataset variable names and descriptions.*

### *b) Logging Frequency*

Data was logged on a per-task basis, one row in the dataset corresponds to one task. Tasks were recorded at the time of creation or shortly after completion. The dataset contains 337 task entries collected over a continuous personal productivity tracking period for four months. The exact start and end dates of the collection period are encoded in the date_created column.

During the tracking period, additional contextual variables including when_worked, work_alone_num, got_distracted_num, and day_quality_num were introduced to enhance behavioral analysis. For entries recorded prior to their inclusion, retrospective was performed based on documented notes and task context. While this may introduce minor recall bias, the updates were limited to clearly interpretable cases to maintain data consistency

### *c) Tools and Apps Used*

- Notion: Primary task logging tool. Core task information, including task name, category, status, and date created was initially recorded using a calendar-based tracking system in Notion.
- Microsoft Excel: After export from Notion, the dataset was organized and expanded in Microsoft Excel. Additional contextual variables, including when_worked, work_alone_num, got_distracted_num, day_quality_num, date_completed, and explanatory notes, were input directly within the sheet to support subsequent analysis.
- Data analysis was conducted using Python 3.12.12 within a Jupyter Notebook environment. The following libraries were utilized:

    a. Pandas (2.2.2) for data cleaning and structured tabular manipulation

    b. NumPy (2.0.2) for numerical operations

    c. Matplotlib (3.10.0) and Seaborn (0.13.2) for statistical visualization

    d. SciPy (1.16.3) for inferential testing, including chi-square and Spearman correlation

    e. Statsmodels (0.14.6) for logistic regression modeling

## *C. Operational Definitions*

The following precise definitions were applied consistently throughout data collection. These definitions were predetermined to ensure consistent application throughout the tracking period.

| Variable | Operational Definition |
|---|---|
| Task Completion | A task is marked 'Done' when all required actions for that task have been completed to the researcher's satisfaction. Partial completion is recorded as 'In Progress.' |
| Missed Task | A task is marked 'Missed' if it was not completed by its intended date and was subsequently dropped or no longer pursued. Only 4 of 337 tasks received this status. |
| Delay (Completion Lag) | Delay was operationalized as the number of days between date_created and date_completed (completion_days). A value of 0 indicates same-day completion; values greater than 0 indicate multi-day completion. This measure reflects temporal postponement but does not distinguish between intentional scheduling and procrastinatory delay. |
| Procrastination (Composite Behavior Indicator) | Procrastination was operationalized as a task completed with completion_days > 0 AND either (a) distraction level greater than 0 or (b) day_quality_num = 0 (unproductive day). |
| Day Quality | A self-rated assessment of the researcher's overall day:  0 = unproductive (procrastinated, didn't accomplish much), 1 = normal (average day, some work done), 2 = productive (got things done, felt good). Rating was assigned at the end of the day based on overall productivity, mood, and energy. |
| Distraction Level | An ordinal rating of distraction experienced during work on a task: 0 = no (stayed focused), 1 = yes-little (got distracted but recovered), 2 = yes-alot (constantly distracted, hard to focus). |
| Working Alone | Binary variable: work_alone_num = 1 if the researcher was physically alone or in a private space when working on the task; 0 if others were present in the same space. |
| Distraction Type | Text note describing the specific cause of distraction (e.g. ''scrolling on phone', 'got tired halfway'). Recorded only when got_distracted_num >= 1. |
| Success | Binary variable: 1 = Done; 0 = Missed or In Progress. |

*Table 2. Operational definitions of key variables.*

### *D. Data Cleaning and Preparation*

The dataset was processed using a structured six-step data wrangling framework prior to analysis. Data cleaning and preparation were conducted in a dedicated preprocessing notebook before exporting the finalized dataset (cleaned_dataset.csv) for use in a separate analysis notebook.

1. Discovering
The raw Excel file (data_science_dataset.xlsx) was imported into Jupyter Notebook for initial exploration. The dataset structure was examined to identify:

- Numerical and categorical features
- Missing values
- Data types
- Potential duplicates

This step ensured familiarity with the dataset before transformation.

2. Structuring

Structural validation was performed to ensure dataset integrity:

- Checked for duplicate rows and index inconsistencies
- Verified absence of duplicate task IDs
- Standardized data types for all columns
- Converted date_created and date_completed to consistent date formats
- Removed time components from date_completed to align with date_created

3. Cleaning

Missing values were handled according to column type:

- date_completed: Missing entries corresponding to tasks marked “in progress” or “missed” were retained as NaT.
- Text columns (task_name, category, status, when_worked, notes) were filled with "None" where appropriate to preserve structural consistency.
- Numeric columns were not artificially filled when values were genuinely unavailable (e.g. unfinished tasks). Missing numeric values were left as NaN to allow pandas to handle them correctly during aggregation.

4. Enriching

New analytical variables were derived:

- completion_days: Calculated as the difference between date_completed and date_created.
- created_weekday: Extracted from date_created and converted to an ordered categorical variable.
- is_weekend: A binary indicator derived from created_weekday, where 1 represents Saturday or Sunday and 0 represents weekdays. This variable enables comparison of weekend versus weekday productivity patterns.
- work_alone_num, got_distracted_num, and day_quality_num: Converted from categorical labels into numeric encodings for statistical analysis.

5. Validating

To ensure structural and logical consistency, rule-based validation checks were performed on key variables. The following constraints were verified:

- Tasks marked as done were required to have a valid date_completed value.
- Tasks not marked as done were required to have completion_days recorded as NaN.
- completion_days values were verified to be non-negative.
- Ordinal variables (day_quality_num, got_distracted_num) were confirmed to contain only predefined scale values {0,1,2}.
- The binary variable work_alone_num was verified to contain only values {0,1}.

No violations were detected, indicating that the dataset met predefined logical consistency standards prior to analysis.

6. Publishing

The final set of 14 cleaned and validated variables was selected and exported as cleaned_dataset.csv.

Upon importing the cleaned dataset into the analysis notebook, minor consistency adjustments (e.g., reapplying fillna() where necessary) were performed to ensure compatibility with statistical operations. These adjustments did not alter the underlying task records.

### *E. Statistical Analysis Methods*

The analyses were organized around the four research questions. The following statistical methods and visualization types were applied:

| **Research Question** | **Statistical Method** | **Visualization** | **Rationale** |
|---|---|---|---|
| RQ1: When does task procrastination occur most frequently? | Proportion of procrastinated tasks calculated across days of the week and weekend vs. weekday categories; Chi-square test of independence were conducted to test $H_{01}$ | Bar charts, line charts | To examine temporal patterns and compare procrastination frequency across categorical time groups |
| RQ2: What factors trigger distraction when working alone? | Category-level comparisons were conducted to examine differences in | Bar charts | To determine whether working alone is associated |

| | | | |
|---|---|---|---|
| | distraction levels and procrastination proportions across work contexts (alone vs. with others). Chi-square test of independence were conducted to test $H_{02}$. | | with higher distraction and higher procrastination risk. |
| RQ3: What factors are associated with delayed task completion? | Descriptive statistics of completion_days; category-level mean comparison; Spearman rank-order correlation was conducted to test $H_{03}$. | Bar charts, frequency table | To assess whether distraction, day quality, and work context are associated with longer completion lag |
| RQ4: What conditions are associated with successful task completion versus non-completion? | Category-level comparison of success rates; Chi-square test of independence were conducted to test $H_{04}$. | Bar charts | To compare contextual variables between successful and non-completed tasks and assess outcome reliability |

*Table 3. Statistical methods and visualizations per research question.*

Both descriptive statistics and selected inferential tests (chi-square and Spearman correlation) were conducted. Logistic regression was attempted but failed to converge due to quasi-separation resulting from the high baseline completion rate. Inferential findings should therefore be interpreted cautiously.

### *F. Mathematical Formulation of Statistical Tests*

To ensure methodological transparency, the following statistical formulations were applied:

1. Chi-Square Test of Independence

The chi-square statistic was computed using:

$$X^2 = \sum \frac{(O - E)^2}{E}$$

where:

- X2 is the chi-square test statistic
- Σ is the summation operator (it means “take the sum of”)
- *O* is the observed frequency
- *E* is the expected frequency

The expected frequency was calculated as:

- *E = (Row Total × Column Total) / Grand Total*

The chi-square test evaluates whether two categorical variables are statistically independent. If the p-value is less than the significance level ($\alpha = 0.05$), the null hypothesis of independence is rejected. In this study, the chi-square test was applied to contingency tables comparing procrastination status across weekday vs weekend categories and work context (alone vs with others).

2. Spearman Rank-Order Correlation

The Spearman correlation coefficient (ρ\rhoρ) was computed using:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

where:

- *d = difference between paired ranks*
- *n = number of paired observations*

Spearman correlation is a non-parametric measure used to determine the strength and direction of a monotonic relationship between two ordinal or continuous variables. Values of ρ range from −1 to +1. Spearman correlation was applied to examine the relationship between distraction level and completion_days.

3. Logistic Regression (Attempted)

Logistic regression models the probability of success using:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$$

where:

- *$p$ = probability of task success*
- *$X_k$ = predictor variables*
- *$\beta_k$ = regression coefficients*

However, due to quasi-separation caused by the extremely high completion rate (>98%), the logistic regression model failed to converge. Therefore, results from this model are interpreted cautiously.

4. Significance Level

All hypothesis tests were evaluated at:

$$\alpha = 0.05$$

A p-value less than 0.05 indicates statistical significance and supports rejection of the null hypothesis.

5. Cramér's V

In addition to reporting chi-square statistics and p-values, effect size was calculated using Cramér's V to measure the strength of association between categorical variables:

$$V = \sqrt{\frac{x^2}{n\,(k-1)}}$$

where:

- *$X^2$ = chi-square statistic*
- *$n$ = total sample size*
- *$k$ = the smaller of (number of rows − 1) or (number of columns − 1)*

Cramér's V ranges from 0 to 1, where values closer to 0 indicate weaker associations and values closer to 1 indicate stronger associations. Effect sizes were interpreted using conventional guidelines (0.10 = small, 0.30 = medium, 0.50 = large).

## IV. RESULTS

### *A. Overall Dataset Section*

| | completion_days | got_distracted_num | day_quality_num |
|---|---|---|---|
| count | 328.000000 | 333.000000 | 337.000000 |
| mean | 0.304878 | 0.681682 | 1.246291 |
| std | 1.009908 | 0.832796 | 0.646782 |
| min | 0.000000 | 0.000000 | 0.000000 |
| 25% | 0.000000 | 0.000000 | 1.000000 |
| 50% | 0.000000 | 0.000000 | 1.000000 |
| 75% | 0.000000 | 1.000000 | 2.000000 |
| max | 14.000000 | 2.000000 | 2.000000 |

*Table 4. Summary Statistics*

Table 4 shows that the dataset consisted of 337 tasks, of which 328 had valid completion lag values. Tasks that were marked as "In Progress" or "Missed" did not have completion lag values and were excluded from calculations involving completion_days. The mean completion lag was 0.30 days (SD = 1.01), with a median of 0 days. The 75th percentile was also 0 days, indicating that at least three-quarters of tasks were completed on the same day they were created. However, the maximum completion lag reached 14 days, producing a positively skewed distribution. These results suggest that while most tasks were completed promptly, a small number of delayed tasks contributed to extended completion times. The mean distraction level was 0.68 (SD = 0.83), indicating generally low-to-moderate distraction intensity. The mean day quality rating was 1.25 (SD = 0.65), suggesting that most days were rated between normal and productive.

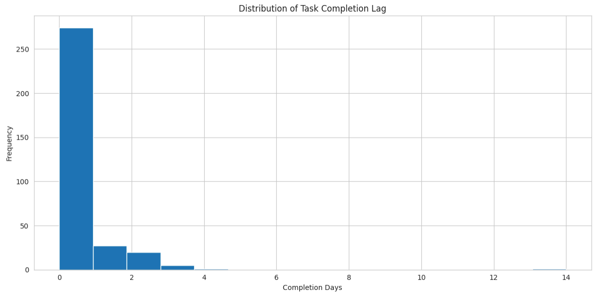



*Figure 1. Distribution of Task Completion Lag (Histogram)*

Figure 1 shows that the distribution of completion_days is highly right-skewed. The majority of tasks were completed on the same day (0 days), while a small number of tasks extended beyond one day, with a maximum lag of 14 days.

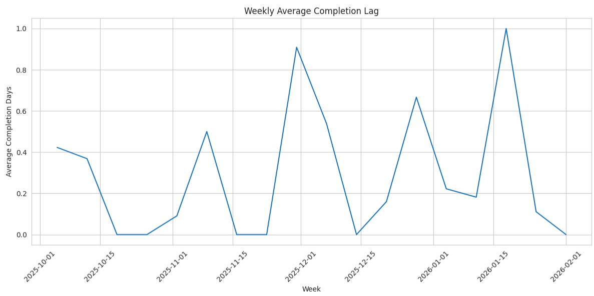



*Figure 2.Weekly Average Completion Lag Over Time*

Figure 2 presents weekly fluctuations in average completion lag. Most weeks maintained low average delay values, with occasional spikes indicating periods of longer task completion times.

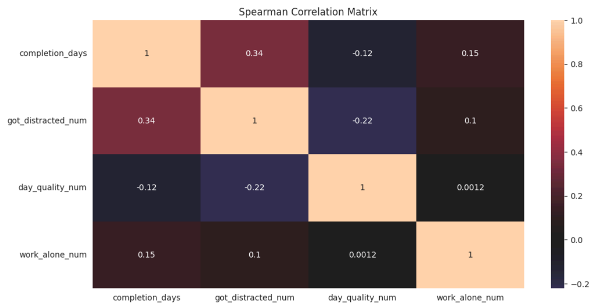



*Figure 3. Spearman Correlation Matrix*

Figure 3 displays the Spearman correlation matrix among completion lag, distraction level, day quality, and work context. A moderate positive correlation ($\rho = 0.34$) was observed between distraction level and completion lag, while day quality showed a weak negative relationship with delay.

### *B. RQ1 – When Does Procrastination Occur Most Frequently?*

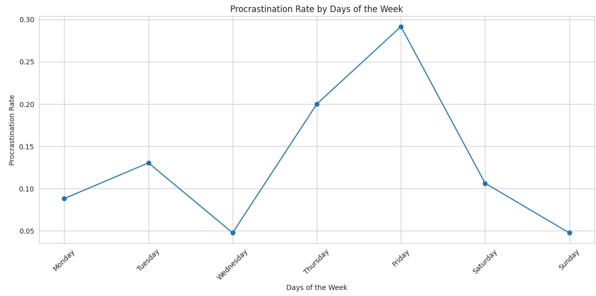



*Figure 4. Procrastination Rate by Days of the Week*

Figure 4 illustrates variation in procrastination rates across days of the week. Friday exhibited the highest procrastination rate, while Wednesday and Sunday showed the lowest rates.

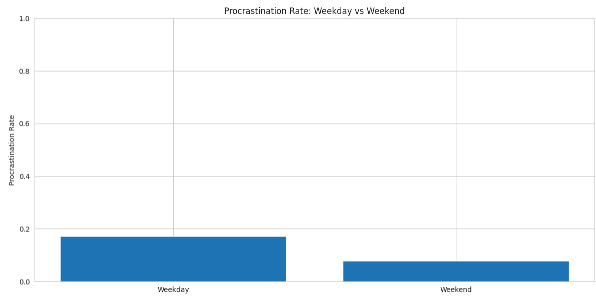



*Figure 5. Procrastination Rate: Weekday vs Weekend*

Figure 5 compares procrastination rates between weekdays and weekends. Procrastination occurred more frequently on weekdays than on weekends.

| | |
|---|---|
| Chi-square | 8.3531 |
| p-value | 0.0039 |
| Cramér’s V | 0.1574 |

*Table 5. RQ1 Chi-square Test*

Table 5 shows that the chi-square test indicated a statistically significant association between day category and procrastination status ($\chi^2 = 8.35$, $p = 0.0039$), suggesting that procrastination rates differed meaningfully across time categories. The effect size, measured using Cramér’s V, was 0.16, indicating a small association between day category and procrastination behavior. Therefore,

$H_{11}$ is supported, indicating a significant association between day category and procrastination status.

### *C. RQ2 – What factors trigger distraction when working alone?*

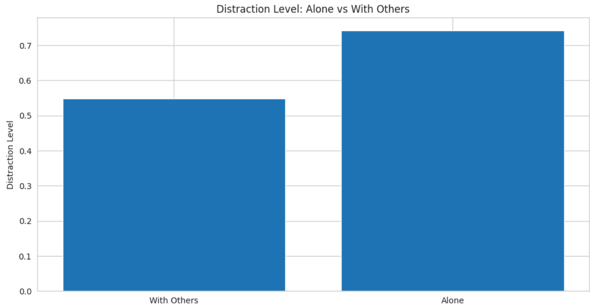



*Figure 6. Average Distraction Level: Alone vs With Others*

Figure 6 shows that average distraction levels were higher when working alone compared to working with others.

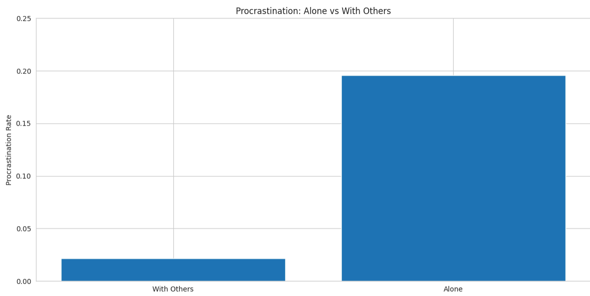



*Figure 7. Procrastination Rate: Alone vs With Others*

Figure 7 demonstrates that procrastination rates were substantially higher when tasks were completed alone than when others were present.

| | |
|---|---|
| Chi-square | 14.8721 |
| p-value | 0.00012 |
| Cramér’s V | 0.2101 |

*Table 6. RQ2 Chi-square Test*

Table 6 shows that the chi-square test revealed a significant association between working alone and procrastination ($\chi^2 = 14.87$, $p < 0.001$). Cramér’s V was 0.21, suggesting a small-to-moderate effect size. Therefore, $H_{12}$ is supported, indicating a significant association between work context and procrastination status.

### *D. RQ3 – What factors are associated with delayed task completion?*

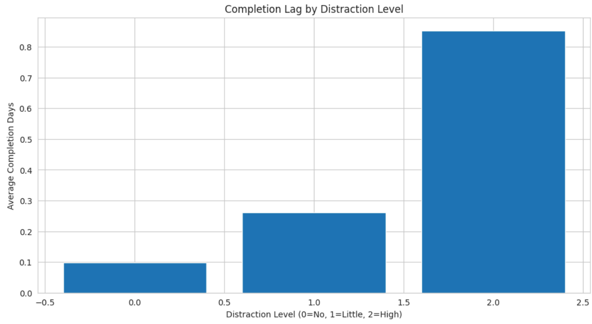



*Figure 8. Completion Lag by Distraction Level*

Figure 8 shows a clear upward trend in completion lag as distraction level increases. Tasks with high distraction (2) had the longest average completion lag.

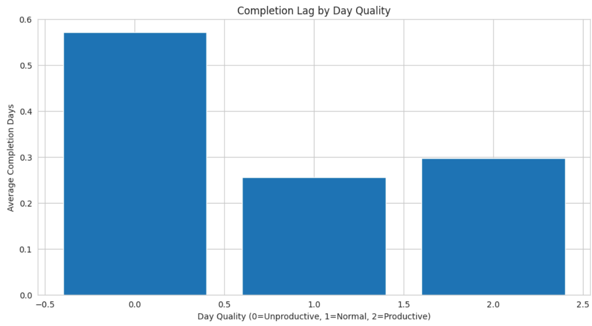



*Figure 9. Completion Lag by Day Quality*

Figure 9 indicates that tasks completed on unproductive days had longer average completion lag compared to normal or productive days.

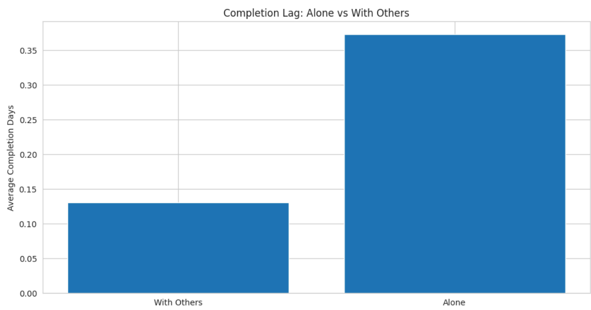



*Figure 10. Completion Lag: Alone vs With Others*

Figure 10 shows that tasks completed alone had longer average completion lag than those completed with others present.

| **Note** | **Frequency** |
|---|---|
| none | 12 |
| Scrolling on phone | 8 |
| kept checking social | 5 |

| | |
|---|---|
| media | |
| overwhelmed with the task, scrolling on phone | 5 |
| phone kept distracting me | 4 |
| got bored halfway | 3 |
| spaced out multiple times | 3 |
| got tired halfway | 3 |
| daydreaming a lot | 2 |
| got bored, phone kept distracting me | 1 |
| spaced out multiple times, scrolling on phone | 1 |
| kept checking social media, spaced out | 1 |
| got bored | 1 |
| daydreaming a lot, scrolling on phone | 1 |
| got tired, scrolling on phone | 1 |
| spaced out | 1 |
| tired | 1 |
| phone notifications | 1 |

*Table 7. Most Frequently Reported Distraction Notes Others*

Table 7 presents the most frequently reported distraction notes among delayed tasks. Phone-related distractions (e.g., scrolling, checking social media, notifications) appeared most frequently.

| | |
|---|---|
| Spearman | 0.3403 |
| p-value | 2.45e-10 |

*Table 8. RQ3 Spearman Test*

Table 8 shows that the Spearman correlation analysis revealed a moderate positive relationship between distraction level and completion lag ($\rho = 0.34$, $p < 0.001$) therefore, $H_{13}$ is supported, indicating that higher distraction levels are associated with longer completion times.

*E. RQ4 – What conditions are associated with successful task completion versus non-completion?*

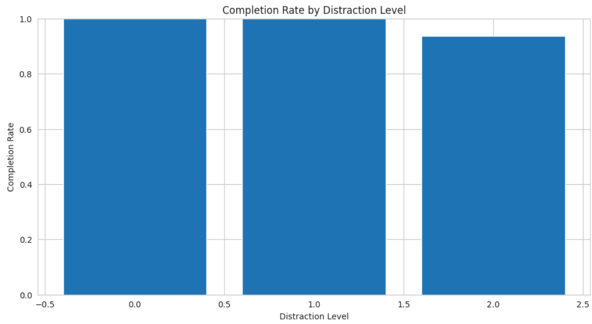



*Figure 11. Completion Rate by Distraction Level*

Figure 11 shows that completion rates remained high across distraction levels, though slightly lower at the highest distraction level.

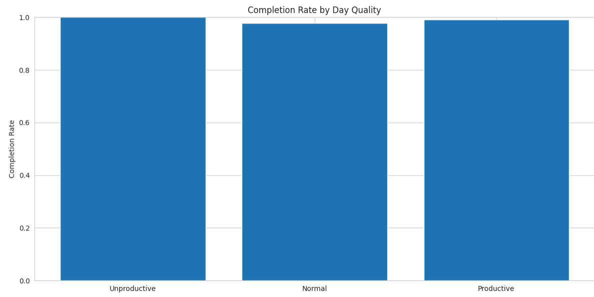



*Figure 12. Completion Rate by Day Quality*

*Figure 12 demonstrates minimal variation in completion rate across day quality categories, with completion remaining above 97% in all cases.*

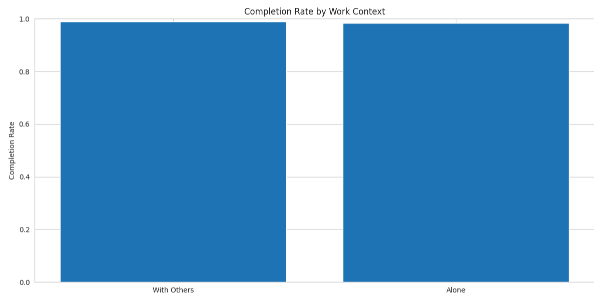



*Figure 13. Completion Rate by Work Context*

Figure 13 indicates negligible differences in completion rates between working alone and working with others.

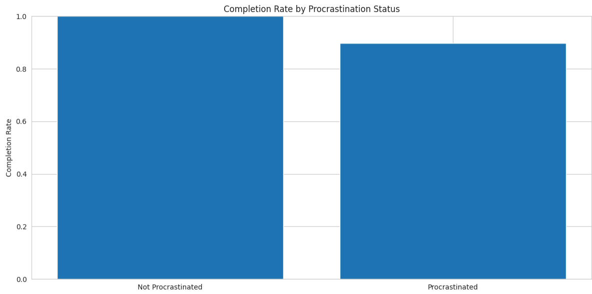


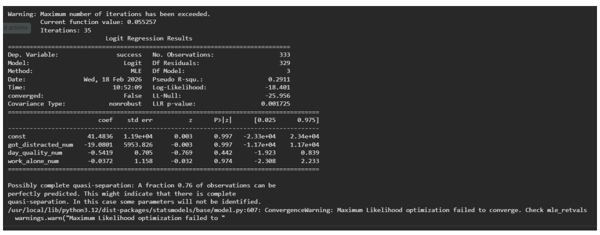

*Figure 14. Completion Rate by Procrastination Status*

Figure 14 shows that non-procrastinated tasks had a 100% completion rate, while procrastinated tasks had a lower completion rate (approximately 89.8%).

| | |
|---|---|
| Chi-square | 16.0535 |
| p-value | 0.00033 |
| Cramér's V | 0.2183 |

*Table 9. RQ4 Chi-square Test*

Table 9 shows that the chi-square test of independence examine the association between procrastination status and task completion outcome. The results indicated a statistically significant association, $\chi^2 = 16.05$, $p < 0.001$, with Cramér's V = 0.22, indicating a small-to-moderate association. Therefore, $H_{14}$ is supported, indicating a significant association between procrastination status and task completion outcome..



```
Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.055257
         Iterations: 35
                           Logit Regression Results
==============================================================================
Dep. Variable:                success   No. Observations:                  333
Model:                          Logit   Df Residuals:                      329
Method:                           MLE   Df Model:                            3
Date:                Wed, 18 Feb 2026   Pseudo R-squ.:                  0.2911
Time:                        10:52:09   Log-Likelihood:                -18.401
converged:                      False   LL-Null:                       -25.956
Covariance Type:            nonrobust   LLR p-value:                  0.001725
======================================================================================
                         coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------------
const                 41.4836   1.19e+04      0.003      0.997   -2.33e+04    2.34e+04
got_distracted_num   -19.0801   5953.826     -0.003      0.997   -1.17e+04    1.17e+04
day_quality_num       -0.5419      0.705     -0.769      0.442      -1.923       0.839
work_alone_num        -0.0372      1.158     -0.032      0.974      -2.308       2.233
======================================================================================

Possibly complete quasi-separation: A fraction 0.76 of observations can be
perfectly predicted. This might indicate that there is complete
quasi-separation. In this case some parameters will not be identified.
/usr/local/lib/python3.12/dist-packages/statsmodels/base/model.py:607: ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

*Figure 15. Logistic Regression Output*

Figure 15 shows that the Logistic regression analysis did not converge due to quasi-separation, reflecting the extremely high baseline completion rate in the dataset.

## V. DISCUSSION

### *A. Interpretation of Results*

This study examined patterns of procrastination, distraction, and task completion across 337 tasks tracked over four months. Several consistent behavioral patterns emerged.

The support for $H_{11}$ confirmed a statistically significant, though small, association between day category and procrastination rates. The highest procrastination rates were observed during weekdays, particularly toward the end of the week, while weekends showed lower procrastination rates. This pattern may reflect differences in cognitive load and obligation density. Weekdays were associated with structured academic and thesis responsibilities, which may have increased perceived pressure and task aversion. In contrast, weekends may have allowed more autonomy in scheduling, reducing resistance to task initiation.

The support for $H_{12}$ indicated a statistically significant association between work context and procrastination rates, with a small-to-moderate effect size. Tasks completed while working alone exhibited higher procrastination proportions compared to tasks completed in the presence of others. However, this effect requires careful interpretation. The reduced procrastination observed in group contexts may not reflect improved self-regulation, but rather deadline-driven urgency or shared accountability. Many collaborative work sessions occurred under time pressure, suggesting that external deadlines may partially explain the effect.

Consistent with the support for $H_{13}$, distraction level was positively associated with longer completion lag. Tasks completed on highly distracted days required more time between creation and completion. This finding aligns with digital distraction literature suggesting that fragmented attention reduces sustained task engagement. In this dataset, phone and social media use emerged as the dominant distraction sources, reinforcing prior findings that smartphone behaviors disrupt productivity.

Although $H_{14}$ was supported, overall task completion rates remained extremely high (>98%). The association between procrastination status and completion outcome was statistically significant, with a small-to-moderate effect size. While procrastination was associated with longer delays and a lower completion rate compared to non-procrastinated tasks, most delayed tasks were ultimately completed. This indicates that delay did not necessarily translate into task abandonment, but rather into extended completion lag.

Taken together, the results suggest that procrastination in this dataset functioned more as temporal postponement accompanied by distraction rather than complete task avoidance.

### *B. Comparison to Related Work*

The findings both align with and extend prior research.

Consistent with the meta-analysis by de Vries et al. [1], delay behavior in this dataset resembles passive procrastination, characterized by postponement accompanied by distraction rather than strategic delay. However, unlike many prior studies relying on self-report scales, this study examined actual behavioral completion patterns over time.

The observed relationship between distraction and completion lag supports findings by Zhang et al. [2], who identified academic procrastination as linked to smartphone distraction. While Zhang et al. focused on anxiety outcomes, this study demonstrates how distraction manifests behaviorally as increased time-to-completion.

The effect of work context partially supports Koppenborg and Klingsieck [6], who found that group work reduces procrastination. However, the present findings suggest that this reduction may be influenced by deadline pressure rather than purely by social facilitation. This nuance highlights the importance of distinguishing between structured accountability and reactive urgency.

Unlike many prior cross-sectional studies [3][4], this study captured within-individual fluctuations over time, offering behavioral evidence rather than trait-based measurement.

### *C. Limitations*

Several limitations must be acknowledged.

First, this is a single-subject study. The findings cannot be generalized beyond the researcher without replication.

Second, the dataset relied partly on self-report measures, including distraction level and day quality. Although logged consistently, subjective ratings may reflect perception bias.

Third, the number of missed tasks was extremely small (n = 4). This limited the ability to perform robust inferential modeling. Logistic regression failed to converge due to quasi-separation, indicating insufficient variability in completion outcomes. Given the extremely high base completion rate and limited outcome variability (n = 4 missed tasks), multivariate modeling was not statistically appropriate.

Fourth, additional contextual variables were introduced partway through the tracking period and retrospectively coded for earlier entries. Although care was taken to maintain consistency, minor recall bias may exist.

Finally, delay does not always imply procrastination. Some multi-day tasks may have been structurally designed to span multiple days, which complicates interpretation of completion lag.

### *D. Recommendations and Future Work*

Future research could expand this design to multiple participants to examine whether similar weekday patterns and distraction effects emerge across individuals.

Additional variables could strengthen the model, including:

- Task difficulty
- Task estimated duration
- Deadline proximity (days until due date)
- Emotional state at task start
- Objective phone usage metrics

Future studies may also distinguish between reactive deadline-driven productivity and proactive self-regulated productivity to clarify whether social presence truly reduces procrastination or simply compresses work into urgent windows.

For students, practical implications include minimizing phone access during solo work sessions and intentionally incorporating structured accountability mechanisms outside of deadline pressure.

## VI. CONCLUSION

This study examined personal procrastination, distraction, and task completion patterns through a four-month self-tracking dataset containing 337 tasks. The purpose was to determine when procrastination occurs most frequently, what factors are associated with distraction, how delay relates to completion lag, and which conditions are linked to successful task completion.

The statistical analyses supported the hypotheses that procrastination rates differ across weekday categories, that distraction level is associated with longer completion lag, and that work context is associated with procrastination proportions. However, the observed effect sizes were small to small-to-moderate, indicating that while these factors are meaningfully related to procrastination behavior, they explain only part of the variability in task outcomes. Procrastination occurred more frequently during weekdays than weekends. Higher distraction levels were associated with longer time-to-completion, with phone and social media use emerging as the most common distraction sources. Tasks completed while working alone exhibited higher procrastination proportions compared to tasks completed in the presence of others, although this pattern may reflect deadline-driven urgency rather than purely social facilitation.

Despite observed delays, overall task completion rates remained extremely high (>98%), suggesting that procrastination in this dataset more often manifested as postponed completion rather than total abandonment. While procrastination was associated with lower completion probability, most delayed tasks were ultimately completed.

On a personal level, the analysis revealed that distraction, particularly digital distraction, plays a measurable role in extending task duration. It also showed that external structure, such as working alongside others or approaching deadlines, was associated with lower procrastination proportions. Importantly, delay did not necessarily equate to failure; most tasks were eventually completed even when procrastination occurred.

These findings can be applied in daily life by intentionally reducing phone access during solo work sessions, incorporating structured accountability mechanisms, and recognizing that delay patterns often reflect attentional fragmentation rather than inability. Future studies could expand this design across multiple individuals and incorporate objective behavioral measures such as app usage tracking, task difficulty ratings, or deadline proximity indicators.

In conclusion, this self-tracking study demonstrates that procrastination is better understood as a situational behavioral pattern influenced by distraction, work context, and temporal structure rather than a fixed personality trait. By analyzing real behavioral data over time, this project contributes a behavioral perspective to existing survey-based procrastination research while offering personalized insight into everyday productivity dynamics.

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