UNIVERSITÀ DEGLI STUDI DI MILANO

Invisible Labor for Women: A Statistical Learning Approach

Statistical Learning

MSc in Data Science for Economics

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Abstract

This paper analyzes the unequal division of unpaid (hidden) work, in particular, how it bears disproportionately on women. Although the unevenness has been fairly commonly acknowledged, there has not been much quantitative investigation of the structural determinants of this unevenness. Our objective is to identify socio-demographic and labour market-related determinants accounting for the gendering of unpaid work. We utilized data from the American Time Use Survey. We performed principal component analysis, clustering, various linear regression models, and classification techniques such as Random Forests and XGBoost. Our findings indicate both apparent differences and the challenge of explaining intricate social behavior with statistical models.

Keywords: Unpaid labor, gender inequality, time use, classification, regression, PCA, clustering, social data analysis

Contents

1 Introduction

Invisible labor has emerged as a hotly debated topic in academic scholarship as well as in the public sphere, especially with respect to its unequal effect on women in domestic settings. Invisible labor can generally be described as the unpaid, unseen, and undervalued work that goes into household maintenance and household running, much of which can be outsourced theoretically for compensation. Classic work by Margaret Reid defined such activities as those that, while not always performed by hired help, are nevertheless "market-replaceable"—that is, they can be performed by someone else for compensation. These tasks typically include cooking, cleaning, grocery shopping, caring for children and elderly relatives, and the myriad forms of "mental load" involved in household management, such as planning, organizing, and anticipating family needs.

While earlier studies have documented significant gender disparities in the performance of invisible labor, with women generally shouldering a greater share, the patterns and predictors of such labor remain insufficiently understood—especially when factors such as race, age, and family structure are considered. Recent discussions have expanded the concept of invisible labor to encompass not just direct caregiving or household tasks, but also the cognitive and emotional management required to keep a household running, often termed the "mental load."

The current study examines the characteristics of hidden labor in the United States with data from the American Time Use Survey (ATUS), a large national representative dataset quantifying how individuals spend time on different daily activities. We measure invisible labor primarily by Reid's operationalization of "market-replaceable" labor, augmenting this with a broader definition to encompass cognitive activities related to household management, as much as the data allow.

Our analysis is exploratory in nature and seeks to answer several research questions related to invisible labor and its distribution across gender, race, age, and family composition. To address these questions, we employ both unsupervised (e.g., clustering, principal component analysis) and supervised learning methods (e.g., regression models), preceded by thorough data preprocessing and exploratory data analysis. The structure of this report is as follows: Section 2 describes the dataset and data handling procedures; Section 3 presents exploratory analyses; Section 4 and 5 detail the unsupervised and supervised learning results, respectively; and Section 6 discusses the implications, limitations, and future research directions.

2 Data and Preprocessing

The U.S. Bureau of Labor Statistics' American Time Use Survey (ATUS), in place since 2003, is the principal source of nationally representative time-use data on Americans' time allocation to various activities on a given day. ATUS employs a stratified, random sample design and collects rich 24-hour time diaries from thousands of respondents annually for all activities done between 4 a.m. yesterday morning and 4 a.m. on the interview day. The survey queries a broad set of activities, including paid work, domestic work, care for children or other relatives, leisure, education, and personal care, and collects extensive demographic information on each respondent and household.

We use data for the 2023 ATUS release in this project, which has detailed time-use data for 8,548 respondents and 43 variables, and constitutes one of the strongest and most recent datasets in which to examine daily patterns of activity among U.S. citizens. The survey's cross-sectional design and high response quality make it especially well-suited to investigate household work patterns and gender, e.g., measuring invisible and unpaid work. ATUS respondents are asked to provide the exact number of minutes spent on a large range of activities, which provides fine-grained detail that is essential for statistical learning analyses.

Number of respondents	8,548
Number of variables	43

Variable Selection. The variables used in the analysis fall into three broad groups:

Demographic Categorical Variables

Variable	Description
SEX	Gender (Male/Female)
RACE4	Race/ethnicity
sp race4	Race/ethnicity of spouse/partner
EDUC	Education level
SPEDUC	Education level of spouse/partner
EMPSTAT	Employment status
SPEMPSTAT	Employment status of spouse/partner
DAY	Day of the week
HH CHILD	Presence of children in household
MARST	Marital status
DIFFANY	Any difficulty with daily activities
ECPRIOR	Prior elder care provided
MULTJOBS	Has more than one job
FULLPART	Full/part time employment status
FAMINCOME	Family income bracket
SPOUSEPRES	Presence of spouse or partner

Demographic Numerical Variables

Variable	Description
AGE	Age of respondent
SPAGE	Age of spouse/partner
HH SIZE	Household size
HH NUMKIDS	Number of children in household
HH NUMADULTS	Number of adults in household
AGEYCHILD	Age of youngest child
UHRSWORKT	Hours worked per week
UHRSWORKT_DAILY_MIN	Hours worked per day in minutes
EARNWEEK	Weekly earnings
SPEARNWEEK	Weekly earnings of spouse/partner
SPUSUALHRS	Usual hours worked per week by spouse/partner

Time Use Variables

Variable	Description
BLS_CAREHH	Care for household members (min/day)
BLS_CARENHH	Care for non-household members (min/day)
BLS_HHACT	Household activities (min/day)
BLS_PURCH	Purchasing goods/services (min/day)
BLS_COMM	Communication/electronic device usage (min/day)
BLS_EDUC	Education activities (min/day)
BLS_FOOD	Food prep, eating, cleanup (min/day)
BLS_LEIS	Leisure and sports (min/day)
BLS_PCARE	Personal care activities (min/day)
BLS_SOCIAL	Socializing, relaxing, leisure (min/day)
BLS_WORK	Work and work-related activities (min/day)

Following well-established definitions and the theoretical concept of unpaid work, I eventually defined invisible work as the additive sum of four time-use indicators: `BLS_CAREHH`, `BLS_CARENHH`, `BLS_HHACT`, and `BLS_PURCH`. Thus, we are including the direct care labor (both for household and non-household individuals), ordinary home activities, as well as purchasing activity. Where possible, we also measured variables that measure indirectly the "mental load" of household decisions, without included direct measures within the data.

All categorical variables were re-coded to descriptive labels. For example, binary variables having original coding of 0/1 in the data (such as gender) were re-labeled for interpretational purposes. Any uninformative answers (such as “Don’t know,” “Refused,” or “Not sure”) were re-coded to missing values (`NA`).

For the majority of analyses, the sample was restricted to those survey participants who were living in a partnered relationship (married or cohabiting), and we focused primarily on heterosexual couples. While other family formations would be interesting to study, they fall outside the scope of the present analysis. Each usage time is a composite of multiple ATUS activity codes. Breakouts for each of these composites are provided in the following tables.

Personal Care (BLS_PCARE)

Sub-variable	Description
BLS_PCARE_SLEEP	Sleeping
BLS_PCARE_GROOM	Grooming
BLS_PCARE_HEALTH	Health-related self care
BLS_PCARE_ACT	Personal activities
BLS_PCARE_TRAVEL	Travel related to personal care

Eat and Drinking (BLS_FOOD)

Sub-variable	Description
BLS_FOOD_FOOD	Eating and drinking
BLS_FOOD_TRAVEL	Travel related to eating and drinking

Household Activities (BLS_HHACT)

Sub-variable	Description
BLS_HHACT_HWORK	Housework
BLS_HHACT_FOOD	Food preparation and cleanup
BLS_HHACT_LAWN	Lawn and garden care
BLS_HHACT_HHMGMT	Household management
BLS_HHACT_INTER	Interior maintenance, repair, and decoration
BLS_HHACT_EXTER	Exterior maintenance, repair, and decoration
BLS_HHACT_PET	Animals and pets
BLS_HHACT_VEHIC	Vehicles
BLS_HHACT_TOOL	Appliances, tools, and toys
BLS_HHACT_TRAVEL	Travel related to household activities

Purchasing Goods and Services (BLS_PURCH)

Sub-variable	Description
BLS_PURCH_CONS	Consumer goods purchases
BLS_PURCH_GROC	Grocery shopping
BLS_PURCH_PROF	Professional and personal care services
BLS_PURCH_BANK	Financial services and banking
BLS_PURCH_HEALTH	Medical and care services
BLS_PURCH_PCARE	Personal care services
BLS_PURCH_HHSERV	Household services
BLS_PURCH_HOME	Home maintenance, repair, decoration, and construction (not done by self)
BLS_PURCH_VEHIC	Vehicle maintenance and repair services (not done by self)
BLS_PURCH_GOV	Government services
BLS_PURCH_TRAVEL	Travel related to purchasing goods and services

Caring for Household Members (BLS_CAREHH)

Sub-variable	Description
BLS_CAREHH_KID	Caring for and helping household children
BLS_CAREHH_KIDOTHER	Caring for and helping household children (except activities related to education and health)
BLS_CAREHH_KIDEDUC	Activities related to household children's education
BLS_CAREHH_KIDHEALTH	Activities related to household children's health
BLS_CAREHH_ADULT	Caring for and helping household adults
BLS_CAREHH_TRAVEL	Travel related to caring for and helping household members

Caring for Non-Household Members (BLS_CARENHH)

Sub-variable	Description
BLS_CARENHH_KID	Caring for and helping non-household children
BLS_CARENHH_ADULT	Caring for and helping non-household adults
BLS_CARENHH_ADULTCARE	Caring for non-household adults
BLS_CARENHH_ADULTHELP	Helping non-household adults
BLS_CARENHH_TRAVEL	Travel related to caring for and helping non-household members

Work and Work-Related Activities (BLS_WORK)

Sub-variable	Description
BLS_WORK_WORKING	Working
BLS_WORK_WORKREL	Work-related activities
BLS_WORK_OTHER	Other income-generating activities
BLS_WORK_SEARCH	Job search and interviewing
BLS_WORK_TRAVEL	Travel related to work

Educational Activities (BLS_EDUC)

Sub-variable	Description
BLS_EDUC_CLASS	Attending class
BLS_EDUC_HWORK	Homework and research
BLS_EDUC_TRAVEL	Travel related to education

Organizational, Civic, and Religious Activities (BLS_SOCIAL)

Sub-variable	Description
BLS_SOCIAL_RELIG	Religious and spiritual activities
BLS_SOCIAL_VOL	Volunteering (organizational and civic activities)
BLS_SOCIAL_VOLACT	Volunteer activities
BLS_SOCIAL_ADMIN	Administrative and support activities
BLS_SOCIAL_SOCSERV	Social service and care activities (except medical)
BLS_SOCIAL_MAINTEN	Indoor and outdoor maintenance, building, and cleanup activities
BLS_SOCIAL_CULTURE	Participating in performance and cultural activities
BLS_SOCIAL_ATTEND	Attending meetings, conferences, and training
BLS_SOCIAL_CIVIC	Civic obligations and participation
BLS_SOCIAL_TRAVEL	Travel related to organizational, civic, and religious activities

Leisure and Sports (BLS_LEIS)

Sub-variable	Description
BLS_LEIS_SOC	Socializing, relaxing, and leisure
BLS_LEIS_SOCCOM	Socializing and communicating
BLS_LEIS_SOCCOMEX	Socializing and communicating (except social events)
BLS_LEIS_ATTEND	Attending or hosting social events
BLS_LEIS_SPORT	Sports, exercise, and recreation
BLS_LEIS_RELAX	Relaxing and leisure
BLS_LEIS_TV	Watching TV
BLS_LEIS_ARTS	Arts and entertainment (other than sports)
BLS_LEIS_PARTSPORT	Participating in sports, exercise, and recreation
BLS_LEIS_ATTSPORT	Attending sporting or recreational events
BLS_LEIS_TRAVEL	Travel related to leisure and sports

Communication (BLS_COMM)

Sub-variable	Description
BLS_COMM_TELE	Telephone calls (to or from)
BLS_COMM_MSG	Household and personal messages
BLS_COMM_MSGMAIL	Household and personal mail and messages
BLS_COMM_MSGEMAIL	Household and personal e-mail and messages
BLS_COMM_TRAVEL	Travel related to telephone calls

Other Activities (BLS_OTHER)

Sub-variable	Description
BLS_OTHER	Other activities not elsewhere classified

A more detailed examination of the distributions, patterns, and interrelationships of these variables will be presented in the Exploratory Data Analysis (EDA) section that follows.

3 Exploratory Data Analysis

Because the American Time Use Survey (ATUS) uses a complex sampling design, each respondent is assigned a person-level weight (WT06). This weight accounts for several factors:

- **Probability of selection**: some individuals have a higher or lower chance of being chosen for the survey.
- **Nonresponse adjustment**: certain groups are less likely to respond, so weights compensate for these differences.
- **Post-stratification to population totals**: weights ensure that the final dataset matches U.S. population totals for key demographics like age, sex, and race/ethnicity.

In practice, the WT06 weight indicates the number of people in the U.S. population represented by each respondent.

These weights must be used on all summary statistics, tables, and figures. Otherwise, results would be biased toward over- or under-represented groups and would fail to reflect national trends. All of this section's analyses are therefore weighted accordingly in order to produce valid, population-level inferences about invisible labor and related time use patterns.

Before analyzing the distribution of invisible labor and time use, we first examine the demographic composition of the analytic sample. This serves two purposes: 1.to confirm that, after weighting, the sample closely mirrors the U.S. adult population, and (2) to provide context for interpreting subsequent findings on invisible labor. To this end, we present both visual and tabular summaries of key demographic variables, including gender, race/ethnicity, education, marital status, household income, and presence of children in the household. Donut charts offer an at-a-glance comparison of the major demographic categories, while accompanying tables provide detailed weighted frequencies and percentages for each group.

Figure 1: Weighted distributions of key demographic variables in the analytic sample. Each donut chart represents the survey-weighted proportion of respondents in each category, using ATUS WT06 weights.

Table 1: Distribution of Gender (Weighted)

SEX	Weighted N	Weighted %
Female	50,571,332,986	51.1
Male	48,466,638,141	48.9

*A*fter the application of survey weights, the gender split in the sample is almost perfectly balanced: 51.1distribution, so there is no gender skew in the weighted data. Any gendered differences discovered later are therefore not likely to be the result of sample imbalance.

Table 2: Distribution of Education Level (Weighted)

EDUC	Weighted N	Weighted %
College degree +	36,505,468,699	36.9
HS diploma, no college	27,940,466,850	28.2
Less than HS diploma	12,632,066,687	12.8
Some college	21,959,968,891	22.2

*E*ducational level is dispersed across the scale: 36.9% of respondents hold college or higher degree, 28.2% possess a high school diploma with no college, 22.2% some college, and a scant 12.8% no high school diploma. This distribution is in line with national data and allows meaningful analysis by educational strata.

Table 3: Distribution of Marital Status (Weighted)

MARST	**Weighted N**	**Weighted %**
Divorced	9,333,743,281	9.4
Married - spouse absent	1,492,698,945	1.5
Married - spouse present	48,822,454,748	49.3
Never married	32,422,374,836	32.7
Separated	1,720,817,942	1.7
Widowed	5,245,881,375	5.3

*N*early half of all adults in the sample are married and living with spouse (49.3%). Another 32.7% were never married, but the remaining categories (divorced, widowed, separated, or married but not living together) add up to 18

Table 4: Distribution of Households with Children (Weighted)

HH_CHILD	**Weighted N**	**Weighted %**
No	64,081,336,448	64.7
Yes	34,956,634,679	35.3

*J*ust 35.3% of respondents reside in childbearing households, com- compared to 64.7% of those without. This has immediate consequences for the study of invisible labor, as child-rearing forms a central element. Estimates of unpaid work must clearly incorporate this split.

Table 5: Distribution of Family Income (Weighted)

FAMINCOME	Weighted N	Weighted %
Less than $5,000	1,461,512,452	1.5
$5,000 to $7,499	674,708,188	0.7
$7,500 to $9,999	875,821,732	0.9
$10,000 to $12,499	1,745,168,540	1.8
$12,500 to $14,999	1,609,881,071	1.6
$15,000 to $19,999	2,160,483,253	2.2
$20,000 to $24,999	3,325,027,980	3.4
$25,000 to $29,999	3,253,292,519	3.3
$30,000 to $34,999	4,201,525,289	4.2
$35,000 to $39,999	4,563,769,371	4.6
$40,000 to $49,999	6,412,357,246	6.5
$50,000 to $59,999	7,221,214,221	7.3
$60,000 to $74,999	10,108,668,756	10.2
$75,000 to $99,999	13,368,793,617	13.5
$100,000 to $149,999	16,672,690,585	16.8
$150,000 and over	21,383,056,308	21.6

sample covers the full spectrum of U.S. family incomes, though there is a strong skew toward the higher end: 21.6% of the sample have household incomes of $150,000 or more. Lower incomes are nevertheless well covered, which helps enable robust analysis of socioeconomic variation in invisible labor.

Together, these summary statistics and visualizations confirm that, after proper weighting, the ATUS sample is well representative of the U.S. population for substantial demographic characteristics. This provides a strong empirical foundation for the subsequent analysis of invisible labor trends and distributions.

3.1 Invisible Labor Variable Construction

Before analyzing time-use patterns by gender, we briefly review how the primary measure of invisible (unpaid) labor was constructed for this study. Guided by existing literature and operational definitions in the ATUS, we define *unpaid labor* as the sum of time spent in the following activity categories:

- Household Activities (`BLS_HHACT`)
- Purchasing Goods and Services (`BLS_PURCH`)
- Caring for Household Members (`BLS_CAREHH`)
- Caring for Non-Household Members (`BLS_CARENHH`)

Expressed mathematically, for each respondent:

$$\text{Unpaid Labor (min/day)} = \text{BLS\_HHACT} + \text{BLS\_PURCH} + \text{BLS\_CAREHH} + \text{BLS\_CARENHH}$$

This composite variable captures the total daily minutes devoted to unpaid and largely invisible forms of labor, as operationalized in our study.

3.2 Gender Differences in Time Use

To observe the distribution of time use by gender, we move to mean daily minutes (with 95% confidence intervals) spent on a range of categories of activity, for example the constructed unpaid labor variable and all of the ATUS major time-use domains. The following figures present side-by-side comparisons of women and men for each activity type

Figure 2: Mean daily minutes spent on unpaid labor by gender. Women spend approximately 1.5 hours more per day on unpaid labor than men.

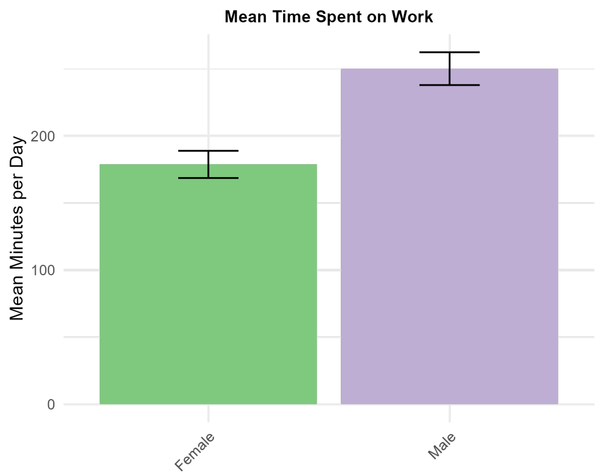

Figure 3: Mean daily minutes spent on paid work by gender. Men spend significantly more time on paid work than women.

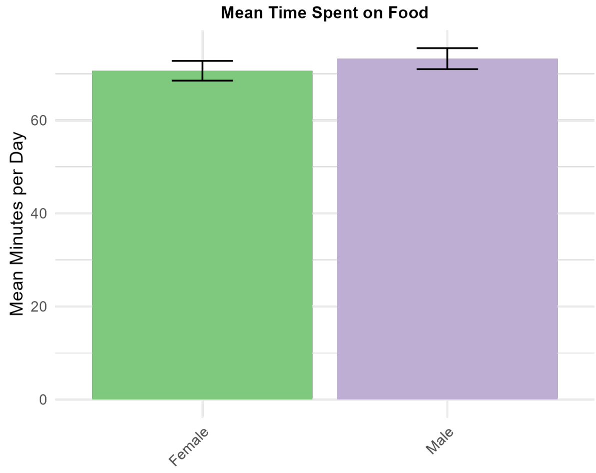

Figure 4: Mean daily minutes spent on food-related activities by gender. Men and women spend roughly the same amount of time on eating, drinking, and related activities.

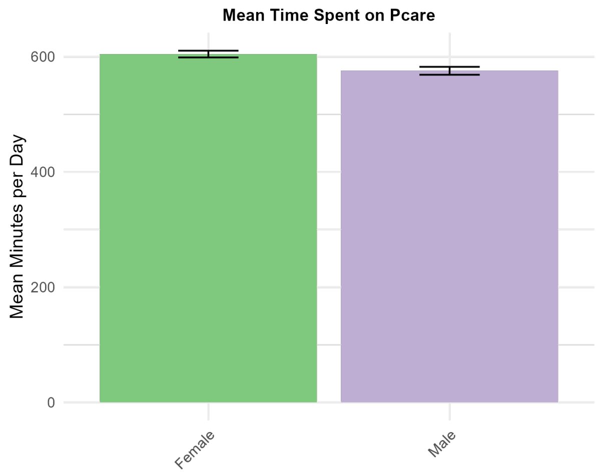

Figure 5: Mean daily minutes spent on personal care by gender. Women and men spend approximately the same amount of time on personal care, with women only slightly higher.

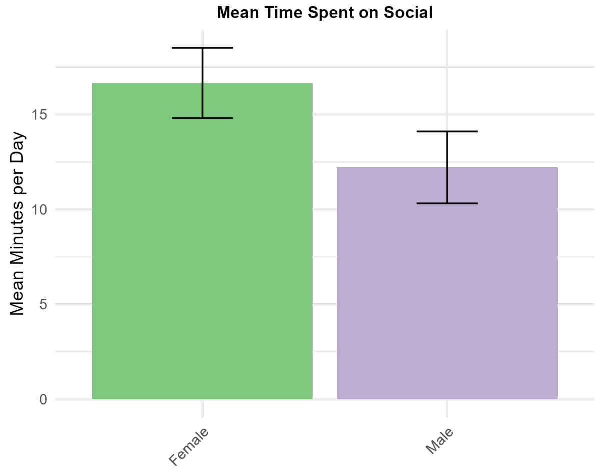

Figure 6: Mean daily minutes spent on social activities by gender. Women spend more time socializing than men.

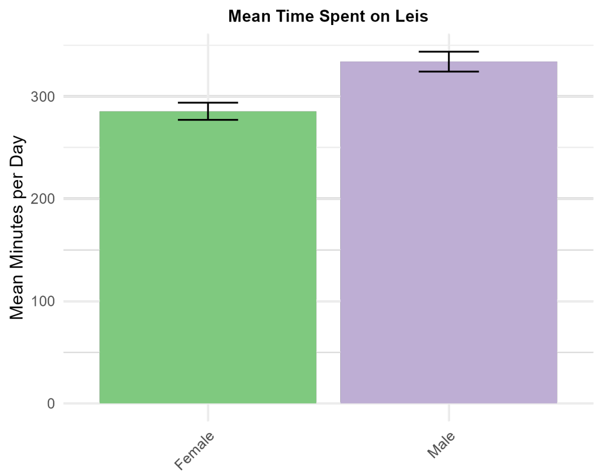

Figure 7: Mean daily minutes spent on leisure and sports by gender. Men spend more time on leisure activities than women.

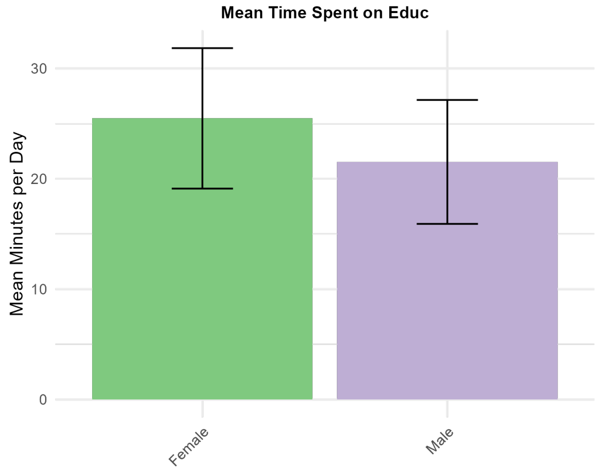

Figure 8: Mean daily minutes spent on education by gender. Women spend slightly more time on education-related activities than men.

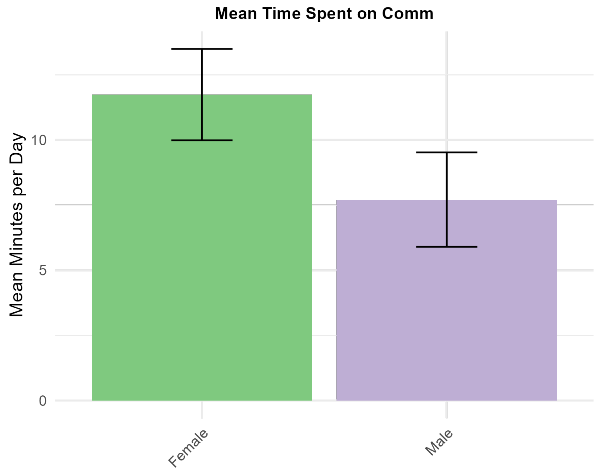

Figure 9: Mean daily minutes spent on communication (calls, email, messaging) by gender. Women spend a little more time on communication activities than men.

These visualizations set the stage for more detailed analysis, highlighting broad gender differences in invisible labor and other key aspects of daily life.

Unpaid Labor by Gender and Presence of Children

The presence of children under 18 in the household is correlated with a substantial increase in daily unpaid work for both women and men, but the impact is significantly higher for women. As can be seen from Figure 10, women do significantly more unpaid work than men regardless of family structure. When there are children, women's mean daily unpaid work augments by almost 70 minutes, and men's by approximately 30 minutes. This sharp divergence underscores the chronic unequal distribution of household responsibilities.

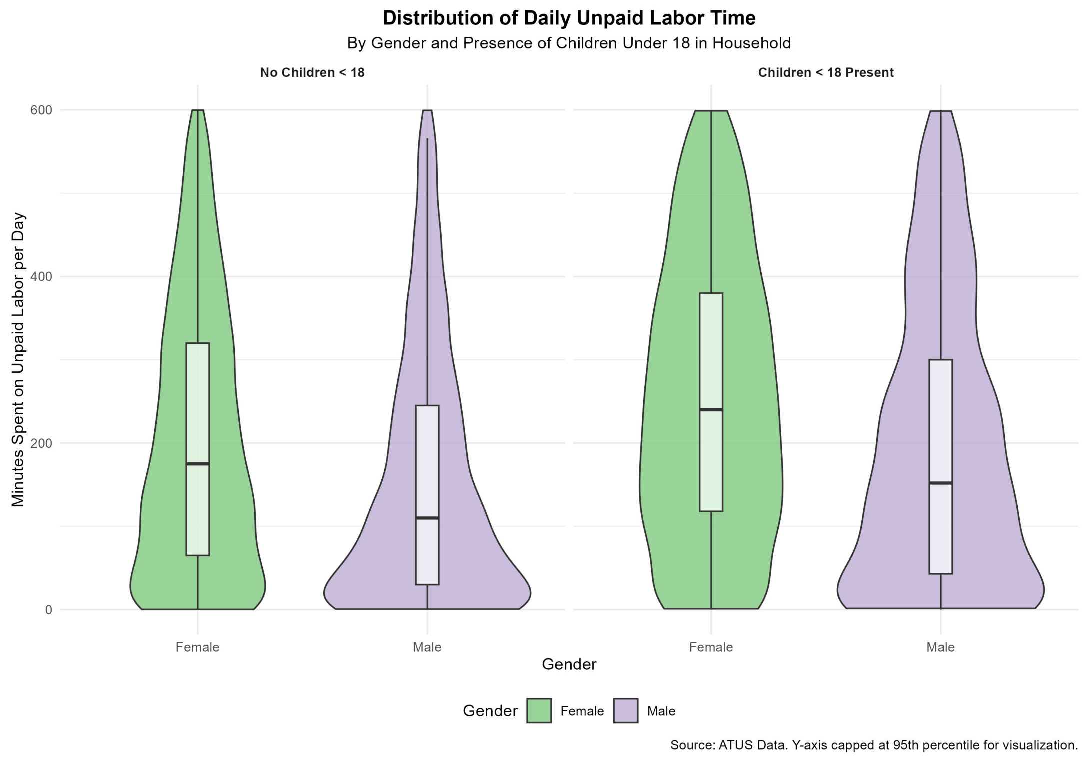

Figure 10: Distribution of daily unpaid labor time by gender and presence of children under 18 in the household. Y-axis capped at 95th percentile for visualization. Source: ATUS Data, weighted estimates.

Children	Gender	Mean	Median	90th Percentile
No	Female	208.9	164.0	480.0
No	Male	144.5	90.0	385.0
Yes	Female	276.8	230.0	600.0
Yes	Male	173.2	110.0	465.0

Table 6: Weighted mean, median, and 90th percentile of daily unpaid labor (minutes) by gender and presence of children under 18. Source: ATUS data with WT06 weights.

Unpaid Work by Employment Status and Gender

Figure 11 shows the distribution of unpaid work time for unpaid work done on a daily basis by gender and labor force status. Women collectively across all categories work more in unpaid work than men. People not in the labor force or working but absent from work have the most amount of time performing unpaid work, showing the extent to which absence from paid work is associated with greater domestic and care responsibilities. Even among those with employment, women do much more unpaid work than men, revealing long-standing gender disparities not corrected by simple employment.

Table 7 brings these results together, presenting mean, median, and 90th percentile figures of daily unpaid labour minutes by labor status. Women in every labor category have a greater average per day of unpaid work than men. Overall, lower paid employment is linked with more time spent on unpaid activities, but the gender gap remains large in all groups.

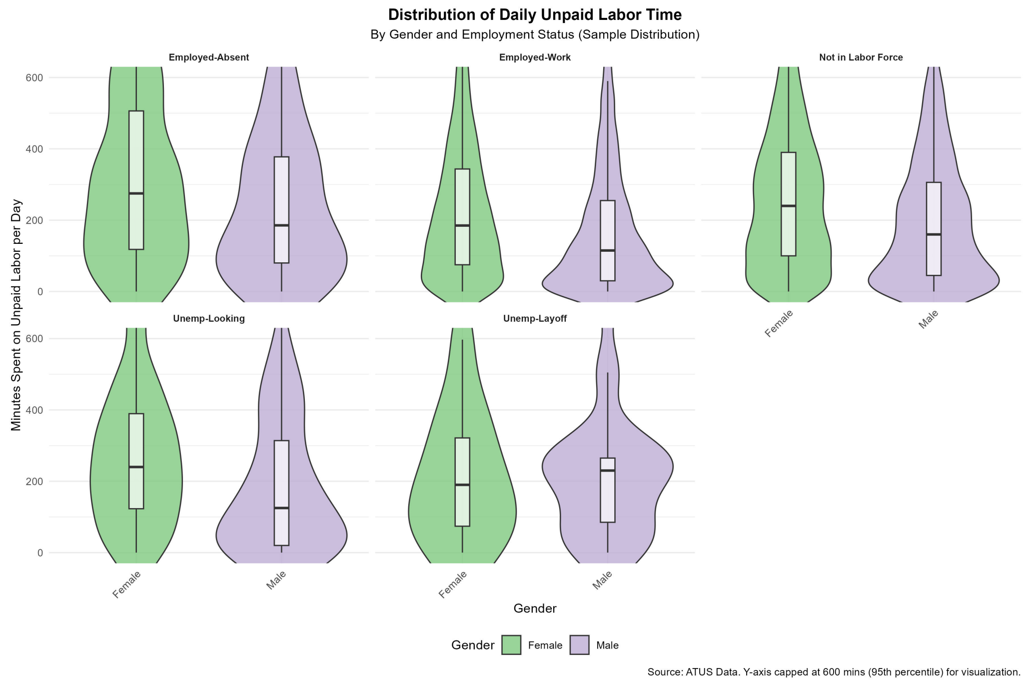

Figure 11: Distribution of daily unpaid labor time by gender and employment status. Source: ATUS data, weighted.

Table 7: Unpaid Work by Employment StatusMinutes per day, weighted estimates

Employment Status	**Mean**	**Median**	**90th Percentile**
Employed - absent	252.5	181.0	610.0
Employed - at work	169.6	117.0	430.0
Not in labor force	237.8	195.0	531.0
Unemployed - looking	219.5	180.0	509.0
Unemployed - on layoff	157.8	50.0	505.0

Source: ATUS data with survey weights (WT06).

Unpaid Work by Full-Time vs. Part-Time Status

Not unexpectedly, those employed part-time work a lot more hours in unpaid la- bor—such as caregiving and household chores—versus individuals with full-time employment. The divergence is clear for women and men, but the gender difference exists regardless of working hours: women systematically spend more time on unpaid work than men in both employment groups.

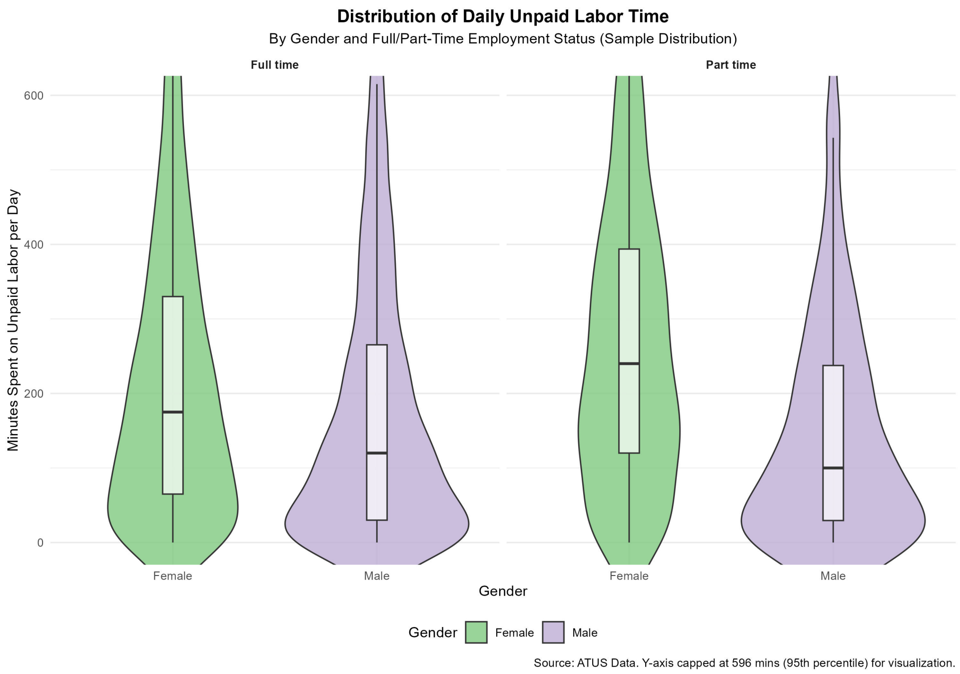

Figure 12: Distribution of daily unpaid labor time by gender and full-/part-time employment status. Source: ATUS Data (weighted, y-axis capped at 95th percentile for visualization).

The summary statistics confirm the visual pattern: those working part time report a much higher average and median daily commitment to unpaid labor compared to those in full-time positions. The difference is substantial, and again, women consistently spend more time than men.

Employment Status	Mean	Median	90th Percentile
Full time	165.3	110.0	420.0
Part time	203.5	142.0	495.0

Table 8: Unpaid work by full-/part-time status (minutes per day, weighted estimates). Source: ATUS data with survey weights (WT06).

3.3 Unpaid Labor by Age Group and Gender

Before moving to more advanced analyses, we examine how unpaid labor varies with age and gender. Age is a critical determinant of daily routines and family responsibilities, so we expect systematic differences in unpaid work over the life course.

Figure 13 shows the trend in average daily unpaid labor time by age and gender. The associated summary table provides mean, median, and 90th percentile estimates by age group and gender, calculated with survey weights.

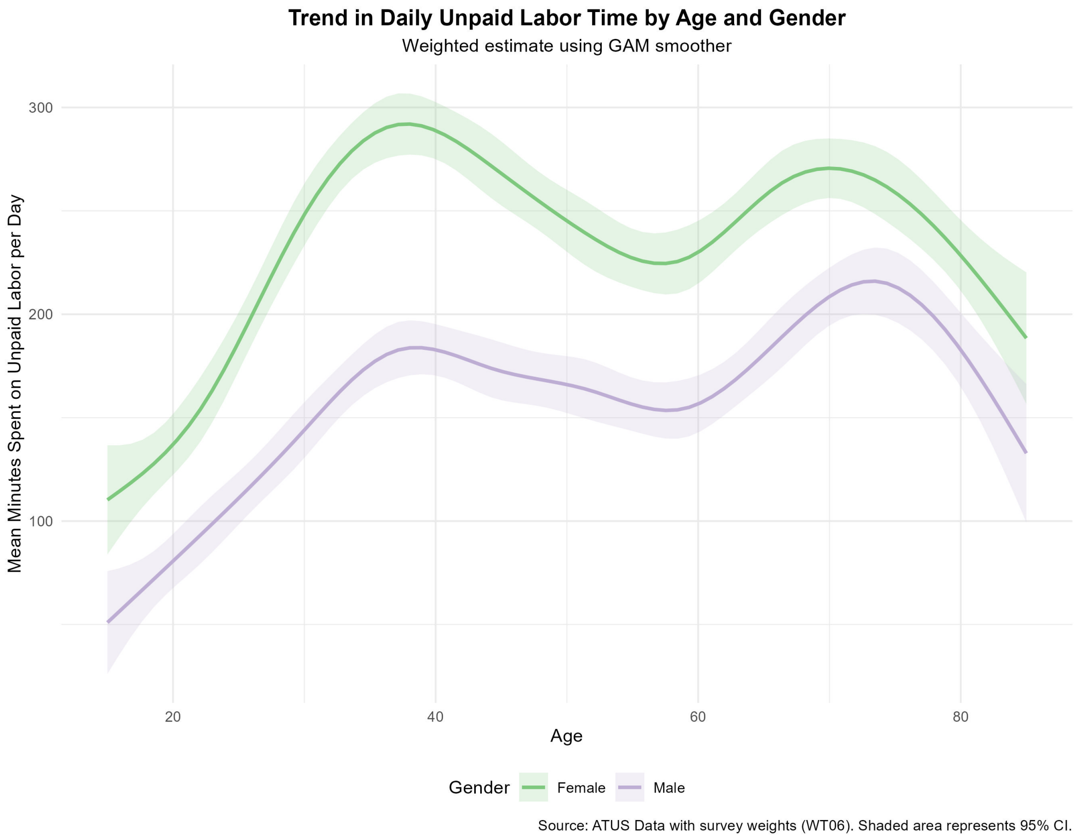

Figure 13: **Trend in Daily Unpaid Labor Time by Age and Gender.** Weighted mean minutes per day spent on unpaid labor, by age and gender. The solid lines represent means, and shaded areas show 95% confidence intervals (GAM smoother). Source: ATUS data with survey weights (WT06).

Table 9: Unpaid Work by Age Group and GenderMinutes per day, weighted estimates

Gender	**Age Group**	**Mean**	**Median**	**90th Percentile**
Female	15–24	139.2	93.0	365.0
Female	25–34	241.4	188.0	540.0
Female	35–44	275.5	233.0	600.0
Female	45–54	252.8	195.0	550.0
Female	55–64	235.4	188.0	555.0
Female	65+	250.8	235.0	500.0
Male	15–24	81.7	35.0	210.0
Male	25–34	136.1	80.0	380.0
Male	35–44	186.1	130.0	482.0
Male	45–54	166.9	113.0	423.0
Male	55–64	152.3	100.0	405.0
Male	65+	196.1	150.0	450.0

Source: ATUS data with survey weights (WT06).

There is also a clear gender and age gradient in unpaid labor. In each age group, women spend a much larger amount of time doing unpaid labor compared to men. Unpaid labor time rises extremely between the ages of 15 and 44, peaking for women ages 35–44 (arguably the time period of family and childbearing responsibilities). Men and women each have a relatively decline in unpaid work following midlife, with a modest rise at older ages (65+), perhaps because of retirement and improved availability for home and caregiving duties. The gender difference persists throughout life, though somewhat diminishing at older ages.

3.4 Unpaid Labor by Race/Ethnicity and Gender

Social expectations and cultural background are of great importance in influencing unpaid labor household trends. Since the population in the U.S. is heterogeneous, it is important to identify how time spent doing unpaid work varies by race and ethnicity. Since the original ATUS race codes are too specific for this use, so we created more aggregate categories: *White*, *Black/African American*, *Hispanic/Latino*, *Asian*, and *Other/Mixed*. The *Other/Mixed* group consists of multiracial individuals and those not fitting the major categories.

The following figure displays mean daily minutes spent on unpaid labor by gender, across race/ethnicity groups. Across all categories, women consistently spend more time on unpaid labor than men.

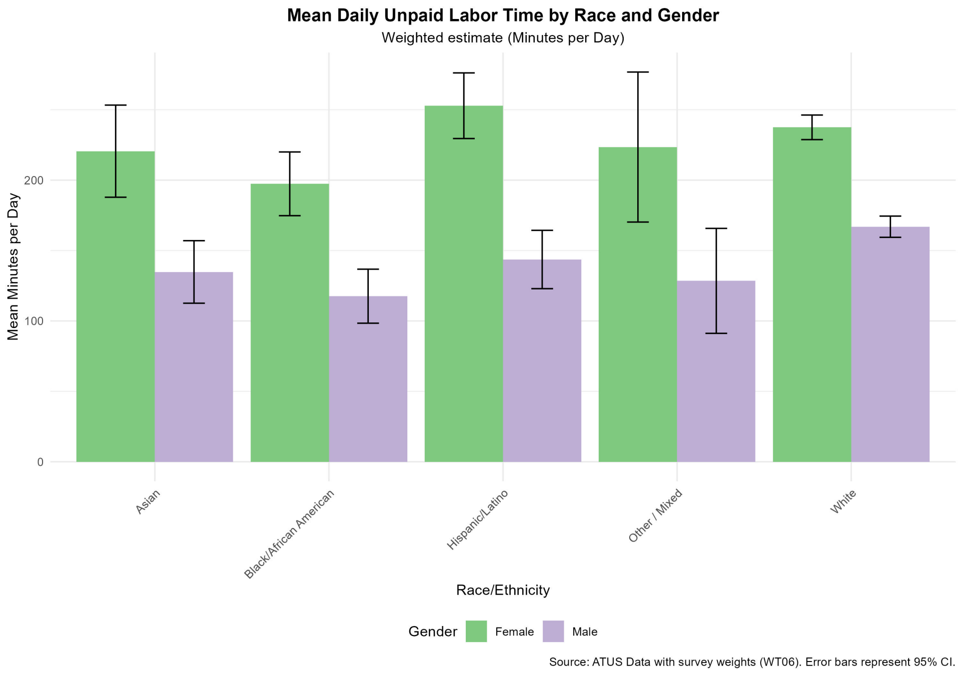

Figure 14: Mean Daily Unpaid Labor Time by Race/Ethnicity and Gender.
Source: ATUS Data with survey weights (WT06). Error bars represent 95% confidence intervals.

Table 10: Unpaid Work by Race/Ethnicity and GenderMinutes per day, weighted estimates

Gender	**Race/Ethnicity**	**Mean**	**Median**	**90th Percentile**
Female	Asian	220.6	160.0	530.0
Female	Black/African Am.	197.4	140.0	460.0
Female	Hispanic/Latino	252.9	210.0	566.0
Female	Other / Mixed	223.5	211.0	487.0
Female	White	237.5	195.0	510.0
Male	Asian	134.8	85.0	360.0
Male	Black/African Am.	117.6	61.0	345.0
Male	Hispanic/Latino	143.6	70.0	420.0
Male	Other / Mixed	128.5	90.0	261.0
Male	White	166.9	110.0	435.0

Source: ATUS data with survey weights (WT06).

Next, we examine the **gender gap** in unpaid labor for each racial/ethnic group. The plot below shows the difference in mean daily unpaid work between women and men. The largest gap is found among Hispanic/Latino respondents, while the smallest is observed among White and Black/African American groups.

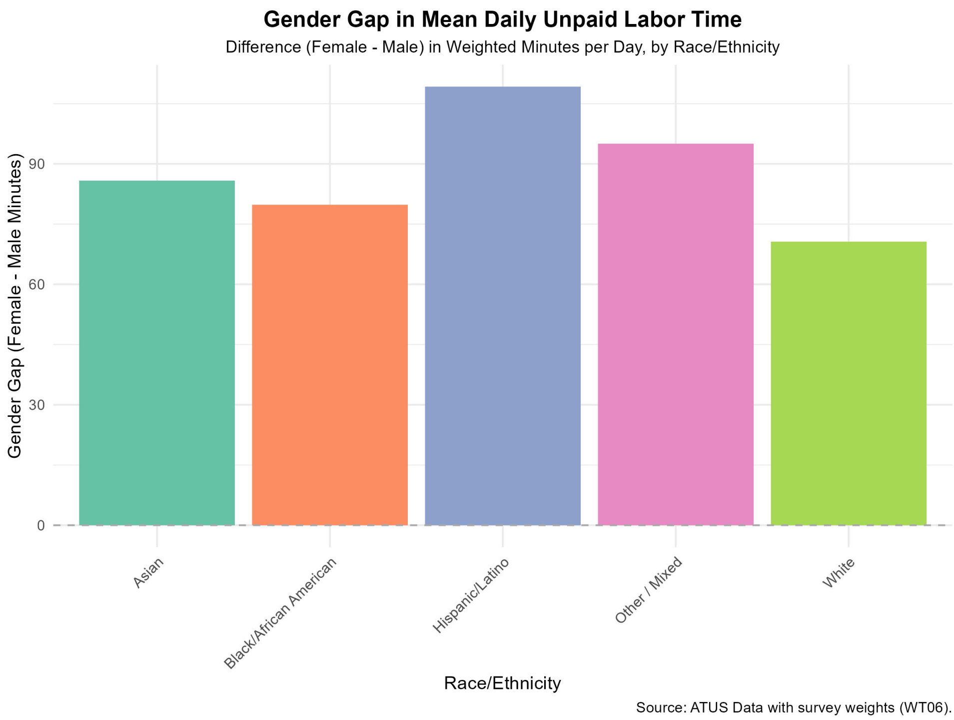

Figure 15: Gender Gap in Mean Daily Unpaid Labor Time by Race/Ethnicity. Difference (Female - Male) in weighted minutes per day. Source: ATUS Data with survey weights (WT06).

Table 11: Gender Gap in Mean Daily Unpaid Labor Time by Race/Ethnicity
Difference (Female - Male) in weighted minutes per day

Race/Ethnicity	**Gender Gap (Female - Male)**
Asian	85.8
Black/African American	79.8
Hispanic/Latino	109.2
Other / Mixed	95.0
White	70.6

Source: ATUS data with survey weights (WT06).

While women do more unpaid work than men in all racial/ethnic groups, the size of the gender gap is not equal. Hispanic/Latino women do over 100 minutes of additional unpaid labor every day compared to their male equivalents, with the gap is weaker for Black/African American and White respondents. This emphasizes how both gender and cultural forces intersect to produce household labor divisions.

3.5 Gender Gap in Unpaid Labor: Interracial vs. Same-Race Couples

To further deconstruct the determinants of unpaid work, we examine whether the gender gap in unpaid labor time differs between interracial couples and same-race couples. Given cultural blending and potential negotiation of home roles within mixed marriages, some difference would be expected.

Figure 16 shows the gender gap in mean daily unpaid labor time (female minus male) for partnered individuals, comparing interracial and same-race couples. The difference is not dramatic, but the gender gap is slightly larger in interracial couples compared to same-race couples. This suggests that, if anything, cross-racial partnerships may reinforce rather than reduce traditional gender asymmetries in unpaid work, at least on average.

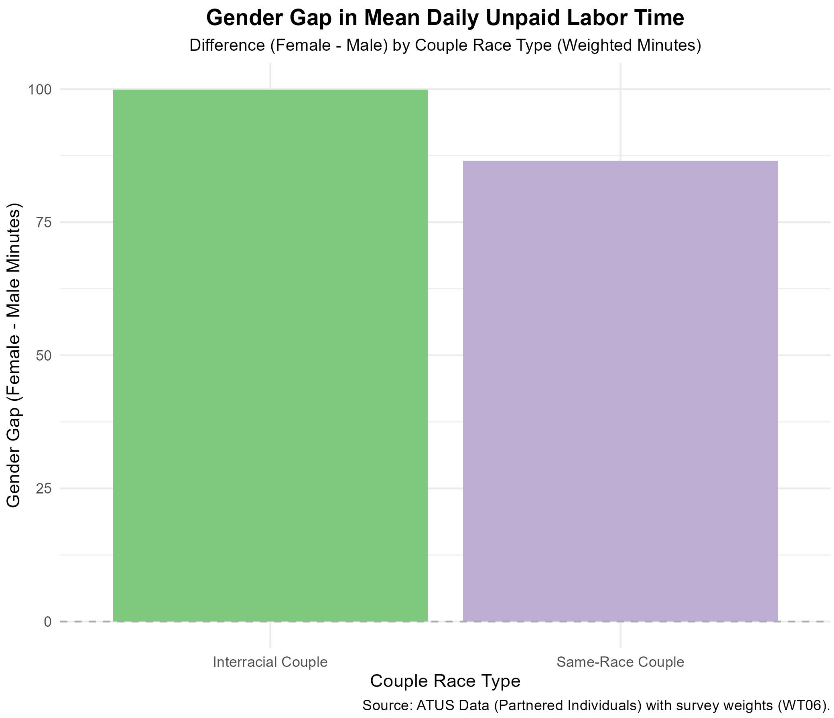

Figure 16: Gender gap (female minus male) in mean daily unpaid labor time by couple race type (interracial vs. same-race couples). Source: ATUS Data (Partnered Individuals) with survey weights (WT06).

Table 12: Gender Gap in Mean Daily Unpaid Labor Time by Couple Race Type

Couple Race Type	**Gender Gap (Female - Male)**
Interracial Couple	99.3
Same-Race Couple	85.5

Difference (Female - Male) in weighted minutes per day. Source: ATUS Data (Partnered Individuals) with survey weights (WT06).

3.6 Unpaid Labor by Women's Weekly Earnings

In order to determine whether women's unpaid work varies across income classes, we consider mean unpaid daily labor time by weekly earnings group. Surprisingly, the amount of unpaid women's work does not vary significantly by earnings. No matter how much women are paid, their unpaid work load is still persistently high.

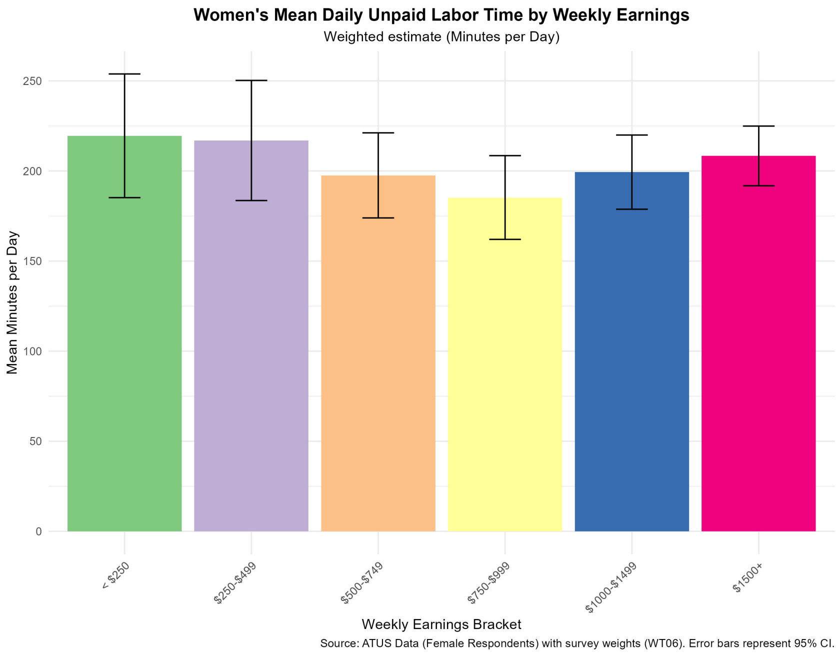

Figure 17: Women's Mean Daily Unpaid Labor Time by Weekly Earnings Bracket. Source: ATUS Data (Female Respondents) with survey weights (WT06). Error bars represent 95% CI.

Table 13: Women's Mean Daily Unpaid Labor Time by Weekly Earnings

Weekly Earnings Bracket	**Mean (Minutes)**	**Std. Error**	**N (Unweighted)**
¡ $250	219.5	17.5	164
$250-$499	216.9	17.0	266
$500-$749	197.5	12.0	352
$750-$999	185.3	11.9	336
$1000-$1499	199.4	10.5	457
$1500+	208.3	8.5	588

Source: ATUS data (Female Respondents) with survey weights (WT06).

3.7 Unpaid Labor by Marital Status and Gender

We then examine if marital status is associated with differences in unpaid work time based on gender. It's no secret that married individuals spend more time on unpaid labor, likely reflecting the greater burdens of household management, potential child-rearing, and household duties shared. Standout is the reality that unmar- married women continue to do far more unpaid work than unmarried men, and that married men do nearly as much unpaid work as unmarried women.

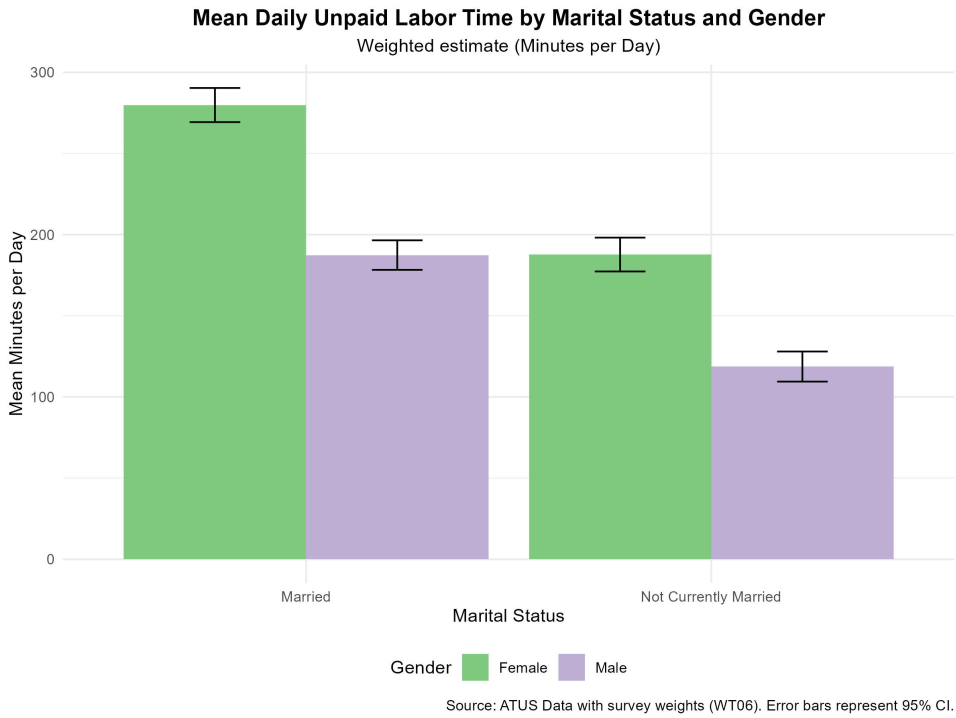

Figure 18: Mean Daily Unpaid Labor Time by Marital Status and Gender
Weighted estimates (Minutes per Day)

Table 14: Mean Daily Unpaid Labor by Marital Status and Gender
Weighted estimates (Minutes per day)

Gender	Marital Status	Mean Minutes	Std. Error
Female	Married	279.8	5.4
Female	Not Currently Married	187.7	5.3
Male	Married	187.4	4.6
Male	Not Currently Married	118.7	4.7

Source: ATUS data with survey weights (WT06).

3.8 Unpaid Labor by Partner Presence in Household

We also examine if the presence of a spouse or partner at home is associated with unpaid labor time. As expected, the availability of spouse or partner is associated to increasing unpaid work, particularly by women, because the number of domestic tasks it shares and caregiving responsibilities rise. Even when there is no partner, women spend significantly more time doing unpaid work than men.

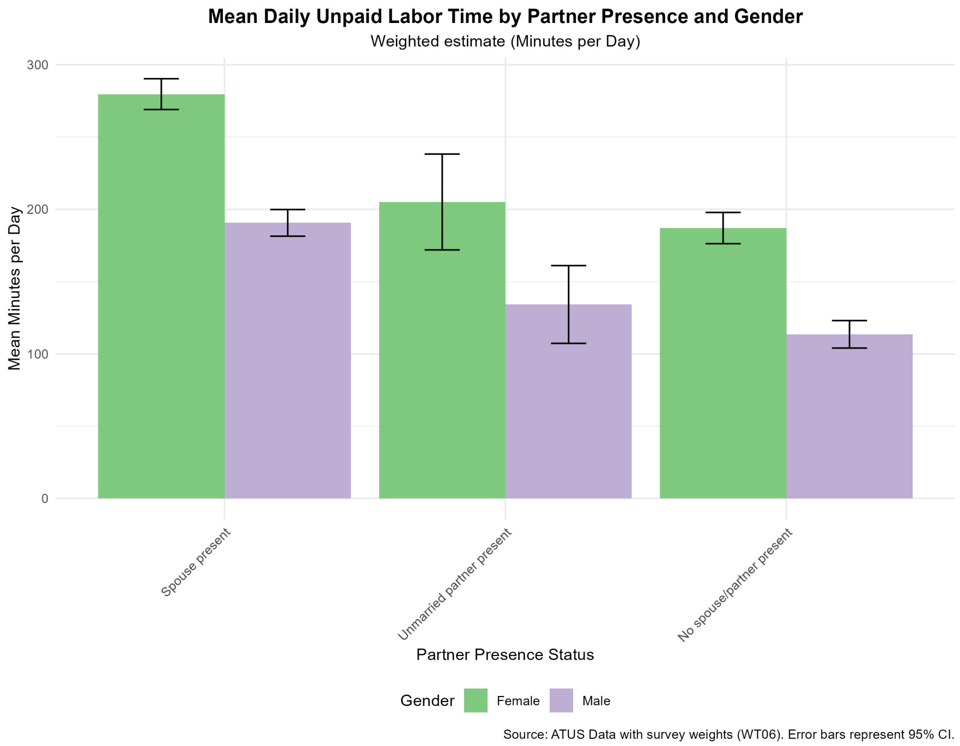

Figure 19: Mean Daily Unpaid Labor Time by Partner Presence and Gender
Weighted estimate (Minutes per Day)

Table 15: Mean Daily Unpaid Labor by Partner Presence and Gender
Weighted estimates (Minutes per day)

Gender	Partner Presence	Mean Minutes	Std. Error
Female	Spouse present	279.7	5.4
Female	Unmarried partner present	205.1	16.9
Female	No spouse/partner present	187.0	5.5
Male	Spouse present	190.6	4.7
Male	Unmarried partner present	134.2	13.7
Male	No spouse/partner present	113.5	4.9

Source: ATUS data with survey weights (WT06).

3.9 Composition and Relationship of Paid and Unpaid Labor by Gender

In this section, we explore two critical dimensions: the composition of unpaid labor activities by gender, and the relationship between time spent on paid versus unpaid work for men and women.

Composition of Mean Daily Unpaid Labor Time by Gender Figure 20 breaks down unpaid work into its main components: care for members of the household, care for non-members of the household, household tasks, and buying goods/services. The results are not unexpected—women not only work more time on unpaid work in total, but the greatest percentage of that time is on household tasks and care. Men spend less time overall, with the same distribution pattern, but all categories lower across the board for men.

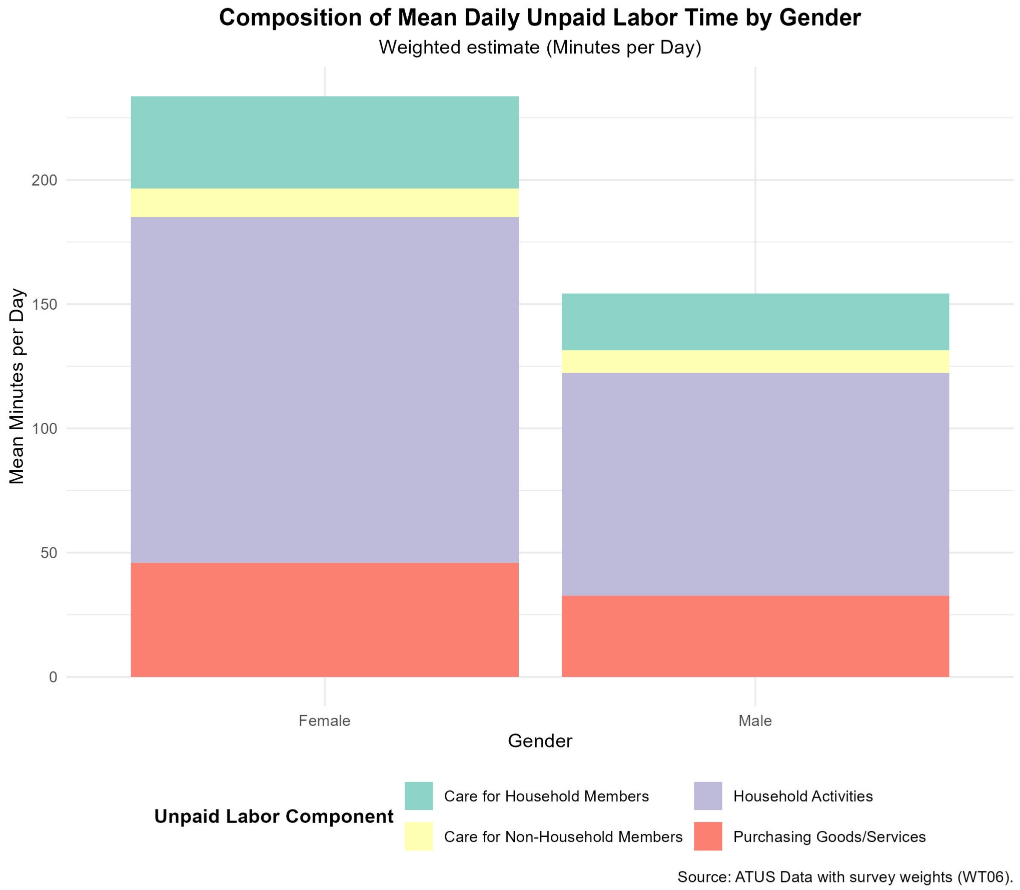

Figure 20: Composition of Mean Daily Unpaid Labor Time by Gender. Source: ATUS Data with survey weights (WT06).

Relationship Between Paid Work and Unpaid Labor Time by Gender Figure 21 examines the relationship between paid work minutes and unpaid work using a smoothed trend by gender. As expected, higher paid work is associated with less unpaid work. However, women consistently have more unpaid work time than men at any level of paid work. The graph also shows that the majority of individuals report zero minutes in paid or unpaid work, which reflects the heterogeneity in the labor force—some individuals only do paid work, while others engage in no paid labor at all.

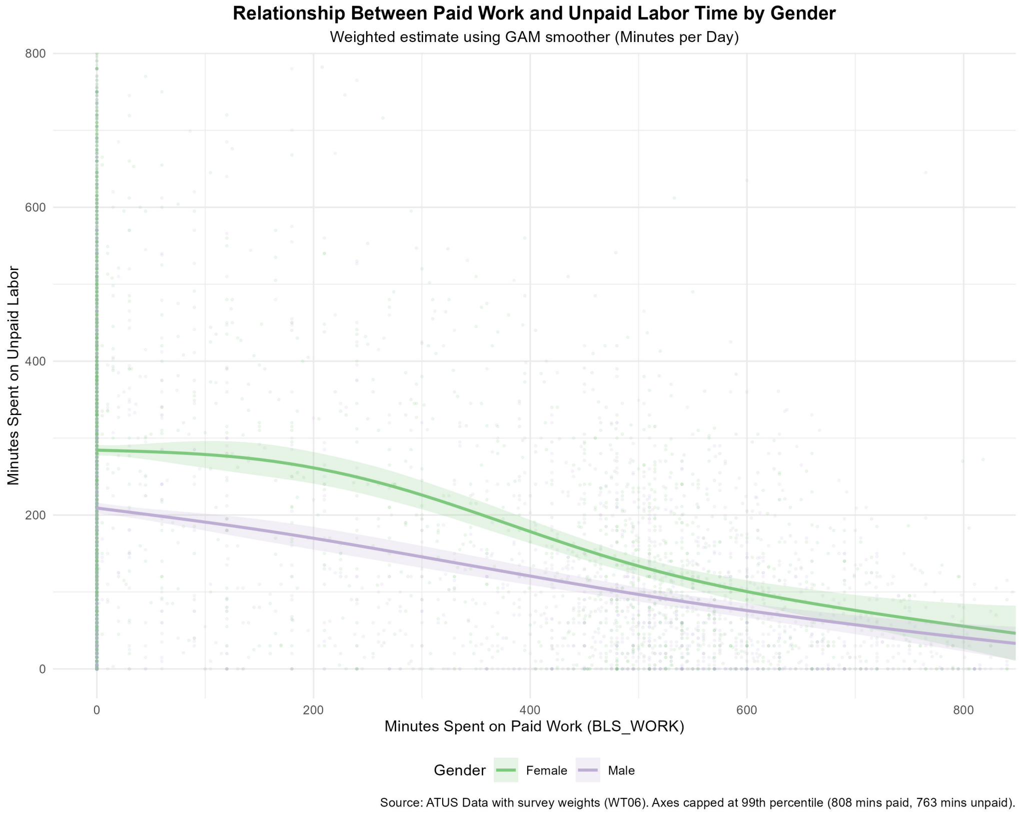

Figure 21: Relationship Between Paid Work and Unpaid Labor Time by Gender. Source: ATUS Data with survey weights (WT06).

3.10 Summary Statistics and Correlation of Time Use Variables

Here we present a descriptive portrait of how individuals spend their day on big activities, based on weighted ATUS estimates. The summary statistics that follow act as a point of reference to interpret later analysis. Time spent on paid work, unpaid labor, leisure, and personal care fill waking hours in a way that is unsurprisingly not different from what is conventionally supposed. Paid work and unpaid labor are strongly negatively correlated—more of one almost always suggests less of the other. The density plots show the strongly right-skewed distributions for most categories of time-use (with most indicating little to zero time spent on activities like education, socializing, or commuting). Such trends reflect the trade-offs inherent in time allocation.

Table 16: Summary Statistics for Time Use Variables

Time Use Category	**Mean**	**Std. Error**	**Median**	**N (Unweighted)**
Unpaid Labor	194.8	2.7	135.0	8,548
Comm	9.8	0.6	0.0	8,548
Educ	23.5	2.2	0.0	8,548
Food	71.9	0.8	60.0	8,548
Leis	309.1	3.3	262.0	8,548
Pcare	590.2	2.3	570.0	8,548
Social	14.5	0.7	0.0	8,548
Work	213.8	4.1	0.0	8,548

Source: ATUS data with survey weights (WT06). N is the unweighted count of non-missing observations.

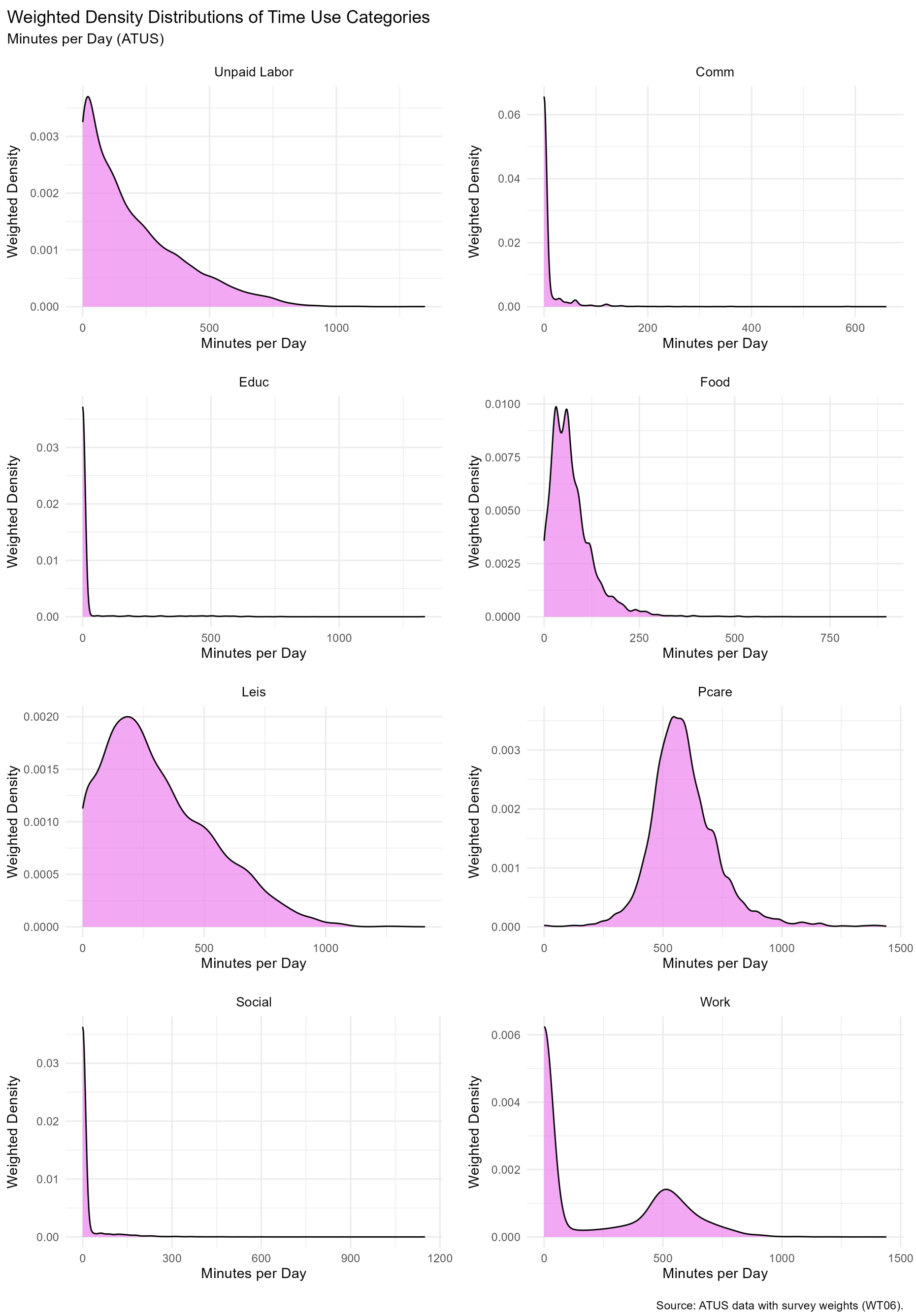

Figure 22: Weighted Density Distributions of Time Use Categories (Minutes per Day, ATUS)

Distribution Shapes: The density plots in Figure 22 demonstrate that most people report zero minutes for many time-use categories on any given day (notably commuting, education, and socializing), with only a minority engaging substantially in these activities. In contrast, personal care, leisure, and unpaid labor show much broader distributions.

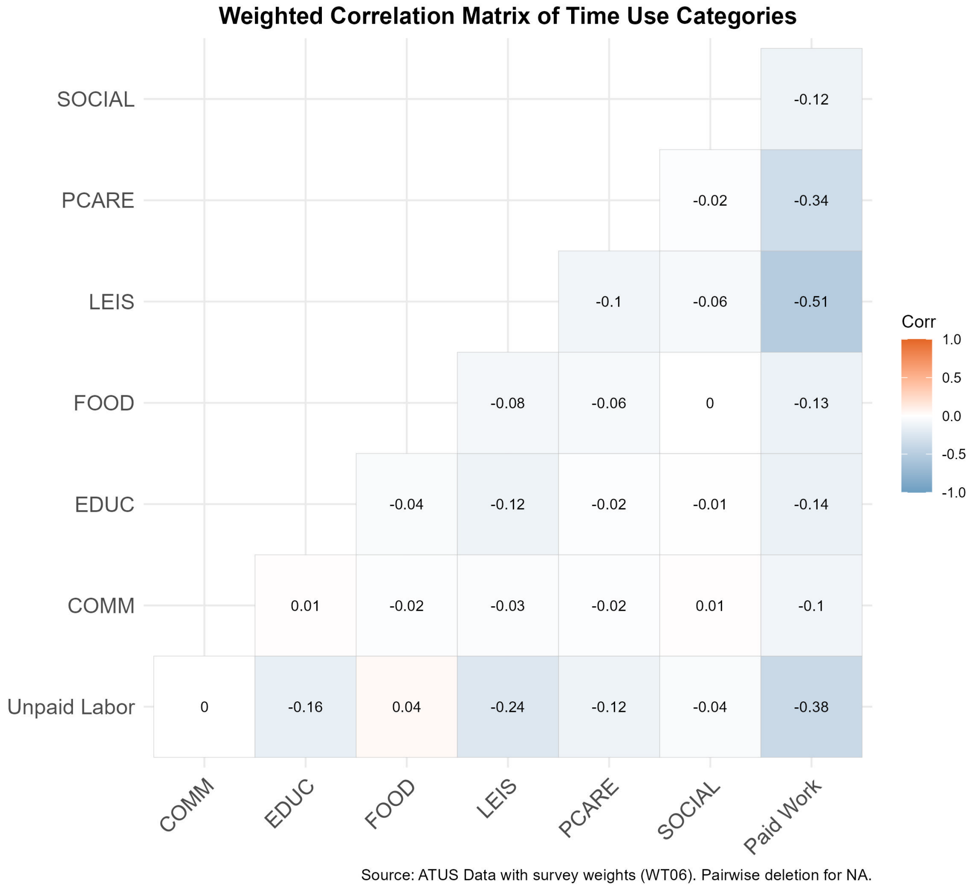

Figure 23: Weighted Correlation Matrix of Time Use Categories

Correlation Patterns: The heatmap in Figure 23 confirms that paid work is most negatively correlated with both unpaid labor ($r = -0.38$) and leisure ($r = -0.51$), which is entirely logical—time spent working for pay means less time for everything else. Personal care also drops as paid work increases, while all other categories show only weak or negligible relationships.

3.11 Distributions and Correlations of Numerical Demographic Variables

In order to comprehend the background traits of respondents, we analyze the distributions and correlations among leading numerical demographic indicators like age, household size, number of adults and children, income, and working hours. These indicators provide key background for making sense of patterns in unpaid work and other time use outcomes.

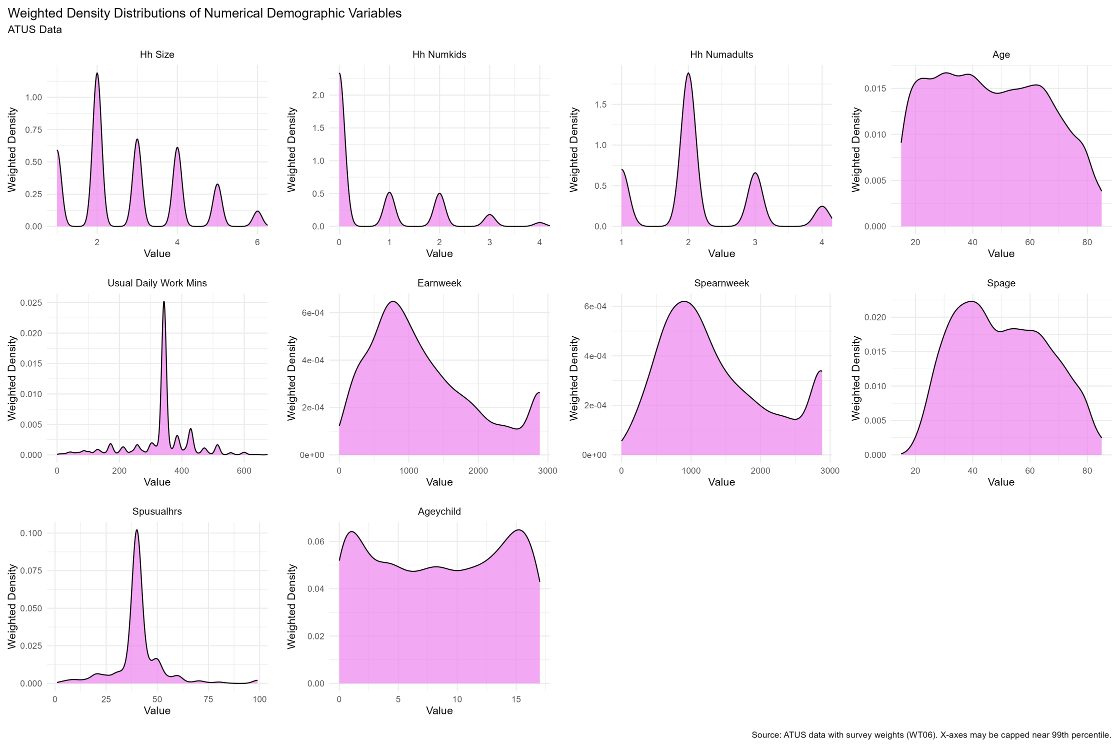

Figure 24: Weighted density distributions of numerical demographic variables. Most variables are right-skewed, with household and earnings variables showing substantial variation and notable spikes at conventional values (e.g., household size, usual work hours). Source: ATUS data with survey weights (WT06).

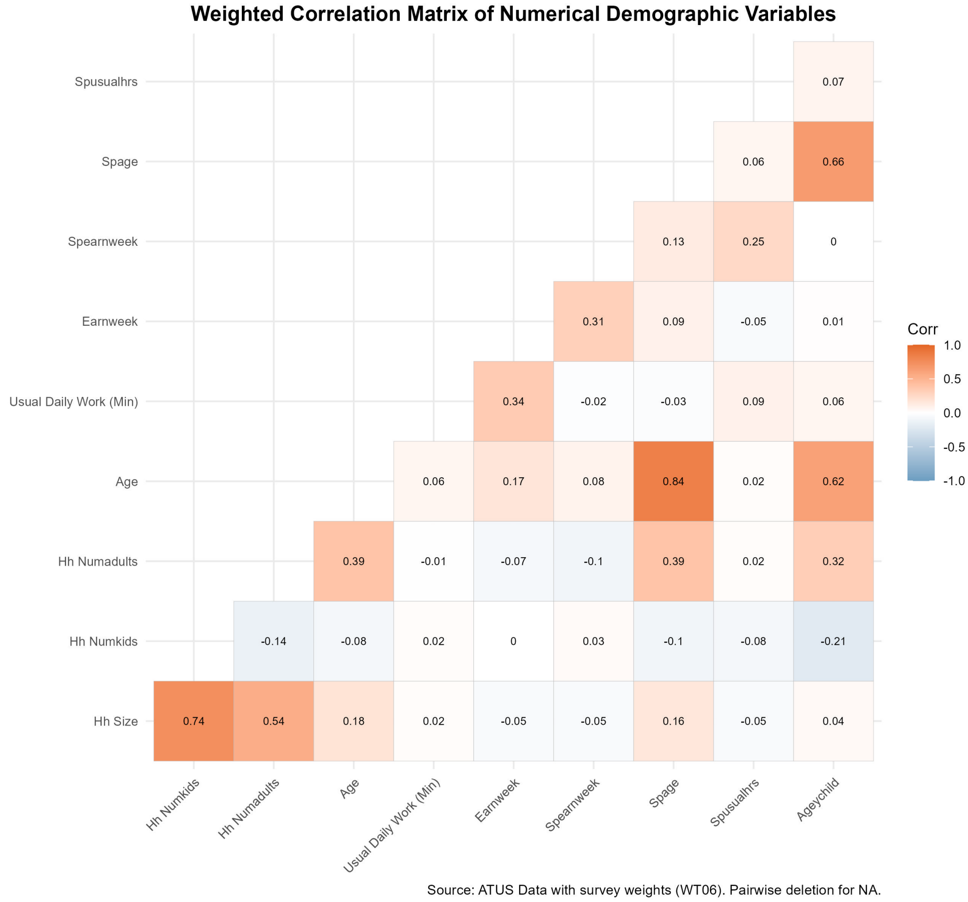

Figure 25: Weighted correlation matrix for numerical demographic variables. Strong positive correlations are observed between variables that logically move together, such as respondent and spouse's age, number of adults and household size, and earnings and work hours. As expected, the number and age of children are associated with household size and adult variables. Source: ATUS data with survey weights (WT06).

Key Takeaway:

The demographic factors have high levels of variation and anticipated associations: age is highly related to spouse's age and number of children; earnings are related with regular working hours. Such correlations determine the internal validity of the data and highlight the value of including demographic controls in analysis of unpaid labor.

4 Unsupervised Learning

4.1 Data Preparation and Preprocessing

Proper data preparation was a valuable step to unsupervised learning on time-use data. In order to concentrate on the household division of labor processes, we limited our analytic sample to couples, those who were presently residing with a partner, married or not or unmarried.

Number of partnered respondents	4,915
Number of variables	8

All eight variables were thoroughly investigated using weighted density plots. As per tradition in such survey data, distributions were highly right-skewed, with huge numbers of respondents reporting no or little time for some activities and a minority reporting exceptionally high values. Communication, specifically, had high outlier behavior. In order to reduce distortion from outlier values, all time-use variables were truncated at the 99th percentile. This method successfully dampened the excess influence of outliers while retaining the complete set of usual daily functioning. In individuals with extremely strong skew—i.e. communication, education, socialization, and unpaid work—a logarithmic transformation was applied to compress the upper tails further. All variables were subsequently standardized (z-scored) for the sake of comparison, such that vari- ables on larger raw scales would not overshadow the results of principal component or cluster analysis. Interestingly, there were no missing values on the main time-use variables for partnered sample of respondents. It allays all fears of impu- station or data gaps and enhances the validity of further analyses.

The log transformation: $\log(x + 1)$

Table 17: Summary statistics of time-use variables after capping, transformation, and standardization

Variable	**Min**	**1st Qu.**	**Median**	**Mean**	**Max**
BLS_COMM	-0.42	-0.42	-0.42	0.00	3.22
BLS_EDUC	-0.13	-0.13	-0.13	0.00	8.18
BLS_FOOD	-1.39	-0.71	-0.21	0.00	3.66
BLS_LEIS	-1.52	-0.79	-0.12	0.00	2.55
BLS_SOCIAL	-0.41	-0.41	-0.41	0.00	3.07
BLS_WORK	-0.64	-0.64	-0.64	0.00	2.60
unpaid_labor	-2.73	-0.22	0.31	0.00	1.08
BLS_PCARE	-4.68	-0.59	-0.06	0.00	3.34

After applying capping, log transformation (where needed), and standardization, all eight time-use variables have means very close to zero, with ranges consistent with a standard deviation of one. Table 17 provides summary statistics for each variable, confirming that the dataset is well-prepared for principal component and cluster analysis.

4.2 Latent Dimensions of Couples' Time Allocation: PCA Results

Research Question:
What are the key latent dimensions of couples' time allocation across work, domestic labor, and leisure?

Principal Component Analysis (PCA) was conducted on eight standardized time-use variables for all partnered individuals (married or cohabiting). The scree plot (Figure 26) shows that the first four principal components explain about 62% of the total variance (PC1: 20%, PC2: 16%, PC3: 13%, PC4: 13%). This falls within the expected range for social science, where explained variance is typically lower than in the physical sciences.[1]

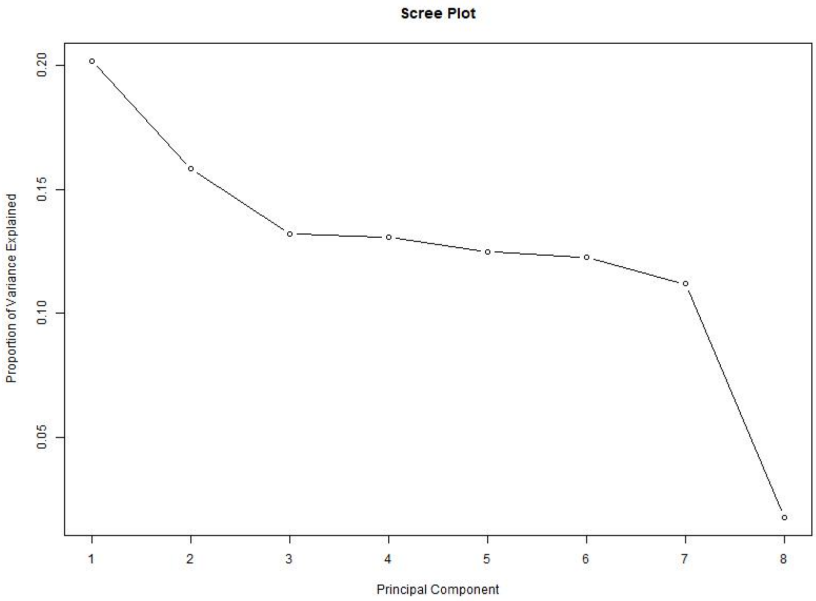

Figure 26: Scree plot showing proportion of variance explained by each principal component.

The variable contribution plot (Figure 27) indicates which time-use variables are most influential for each principal component, while the PCA biplot (Figure 28) visually summarizes the relationships between variables and the primary axes of variation.

[1]In social research, extracted factors often explain only 50–60% of the total variance; the decision on how many components to retain depends on theoretical and practical interpretability, not arbitrary thresholds.

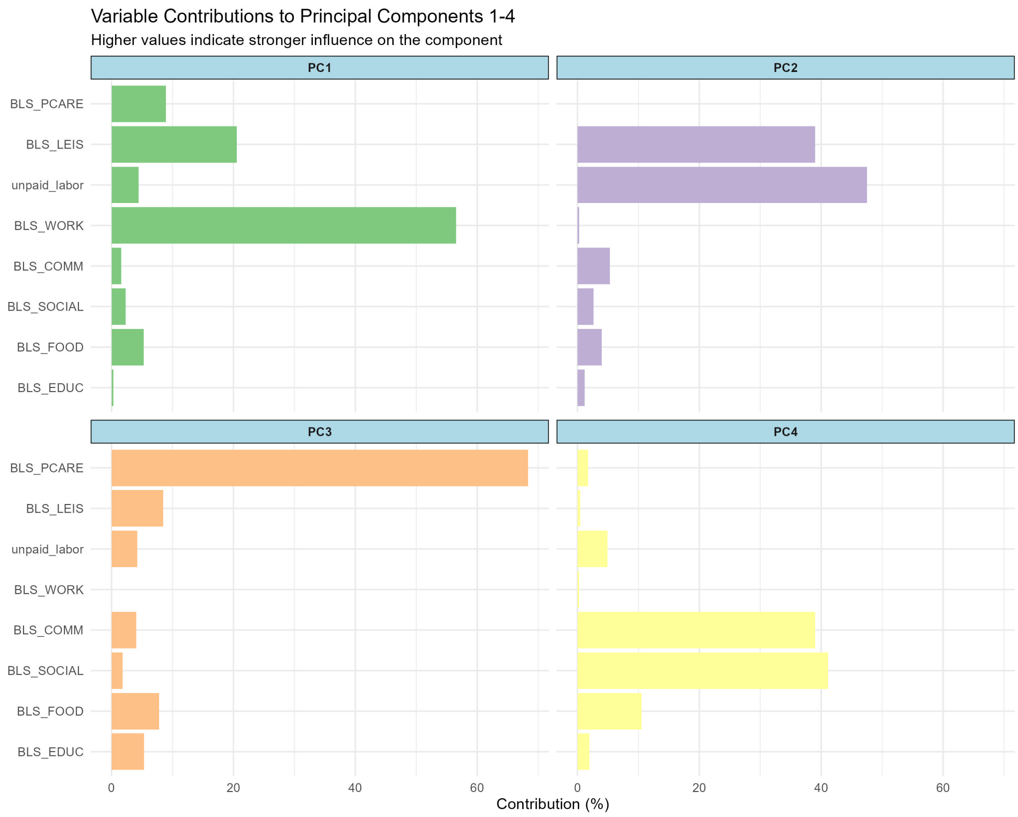

Figure 27: Variable contributions (% variance explained) to the first four principal components.

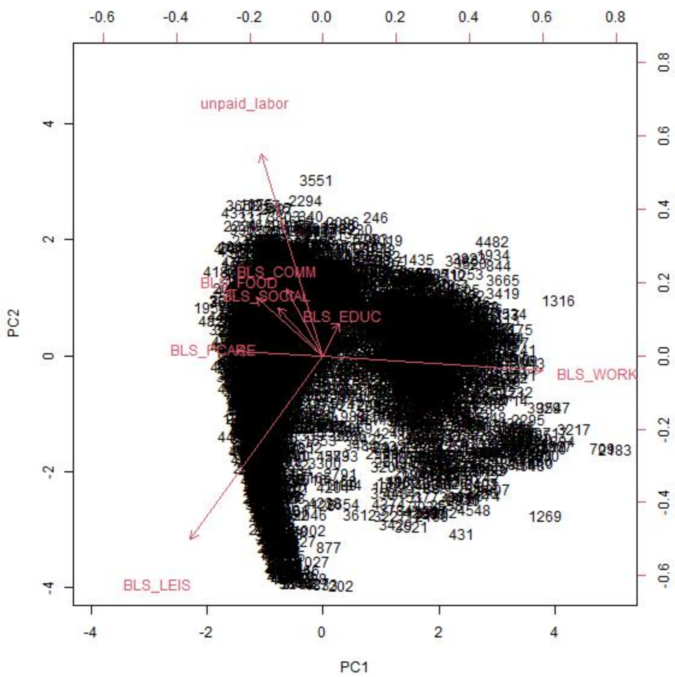

Figure 28: PCA biplot: Projection of individuals and time-use variables onto the first two principal components.

Interpretation of the Components

- **PC1 (Paid Work vs. Leisure):** Distinguishes those who allocate more time to paid work (positive direction) versus those who prioritize leisure, personal care, and food (negative direction). This axis essentially separates work-oriented from leisure-oriented lifestyles.
- **PC2 (Unpaid Labor & Social Engagement):** Dominated by unpaid labor (housework, caregiving), with additional loadings from socializing and communication. High PC2 scores identify individuals with heavy unpaid/domestic and social obligations.
- **PC3 (Personal Care Focus):** Primarily reflects unusually high investment in personal care, independent of other activities.
- **PC4 (Communication vs. Other Activities):** Contrasts time spent on communication/socializing with other domains of daily life.

Summary and Sociological Implications:
These results show that couples' time use is organized along several dis- tinct dimensions—namely, the paid work-leisure tradeoff, domestic division of responsibility for unpaid work, and the extent of engagement in personal care and social activ- ities. The suggestion that the first two predictors combined account for more than a third of the variance reflects the significance of work-leisure and domestic division in determining everydaily life. As is standard in time-use studies, no single "dominant" pattern appears; instead, the analysis confirms that contemporary couples navigate a rich, multi-dimensional world shaped by older and newer roles. That multidimensionality also explains why social science unsupervised learning typically yields only imperfectly "clean" or highly separated clusters—human time use is simply too diverse and circumstance-sensitive for neat typologies.

4.3 Work–Life Balance Profiles: Cluster Analysis Results

Research Question:
Which distinct work–life balance profiles emerge among partnered individuals based on their daily time-use patterns?

To identify distinct work–life balance profiles, we applied **K-means clustering** on the PCA-transformed time-use variables.

Determining the Number of Clusters. The optimal number of clusters was selected based on the elbow method (Figure 29) and silhouette analysis (Figures 31 and 30). The elbow plot suggested a bend around $k = 3$, and silhouette scores peaked at $k = 3$ (average silhouette width ≈ 0.32).

According to Kaufman and Rousseeuw's guidelines, silhouette scores between 0.26 and 0.50 indicate a ***weak but potentially meaningful structure***. This is common in social science data, where human behavior is inherently noisy and sharp clustering boundaries are rare. Thus, an average silhouette width of ≈ 0.32 is acceptable in this context.

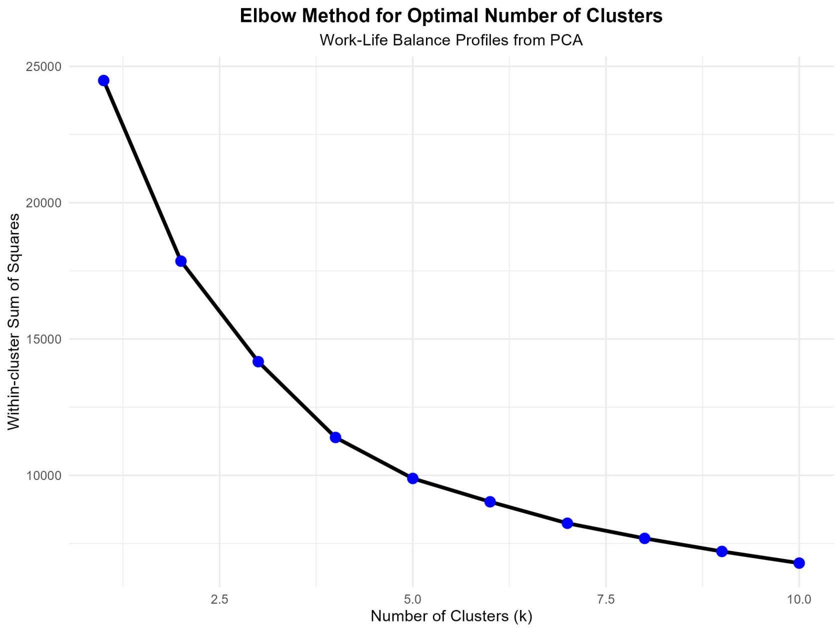

Figure 29: Elbow method: Within-cluster sum of squares for different numbers of clusters.

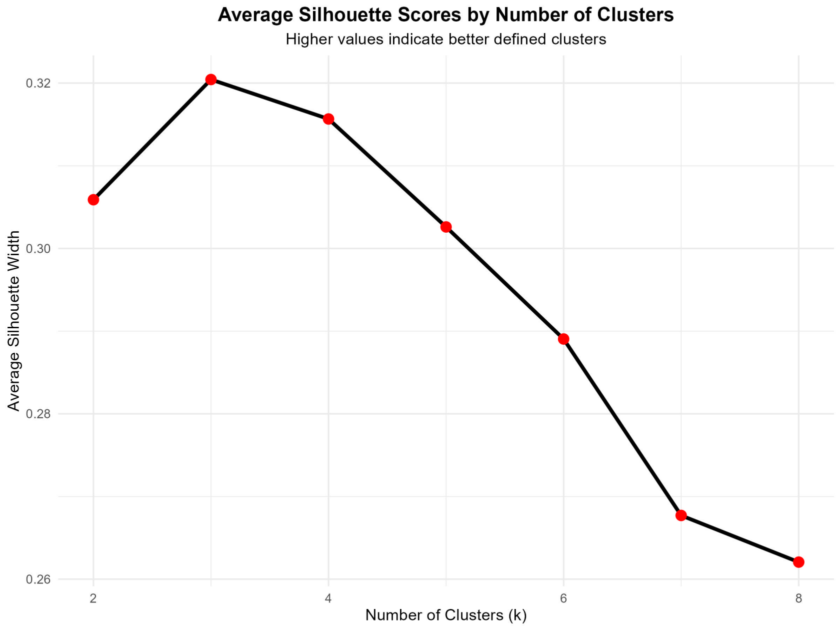

Figure 30: Average silhouette scores by number of clusters.

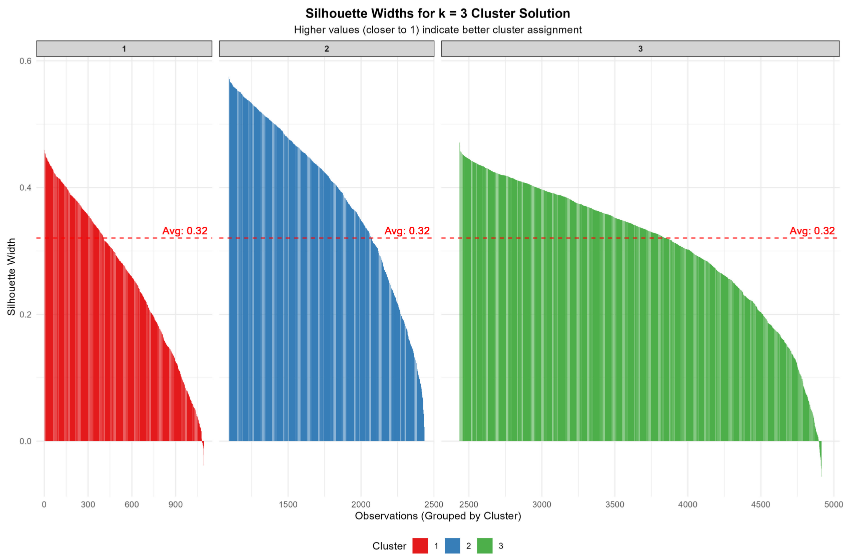

Figure 31: Silhouette plot for the selected 3-cluster solution ($k = 3$).

Moreover, while a two-cluster solution ($k = 2$) might offer a simpler interpretation (mainly separating "work-centered" and "leisure-centered" individuals), it achieved a lower average silhouette score. Therefore, we proceeded with $k = 3$ to capture richer and more nuanced profiles of time use.

Cluster Profiles. The radar charts (Figure 32) visualize the time-use patterns across the three clusters:

- **Profile 1 (1095 individuals):** Characterized by **low paid work hours** and **moderate unpaid labor**, with **high personal care** and **leisure** time. This group appears more *leisure-oriented*, possibly including part-time workers, retirees, or individuals prioritizing non-work activities.

- **Profile 2 (2480 individuals):** Displays **moderate paid work hours**, **high unpaid labor**, and **moderate leisure**. These individuals combine significant household/domestic responsibilities with some labor market engagement — resembling a *dual burden* profile, often linked to work–family juggling.

- **Profile 3 (1340 individuals):** Shows **high paid work hours** and **lower unpaid labor and leisure time**. This profile represents a *work-centered* group — individuals investing heavily in the labor market with limited time left for unpaid domestic work or leisure.

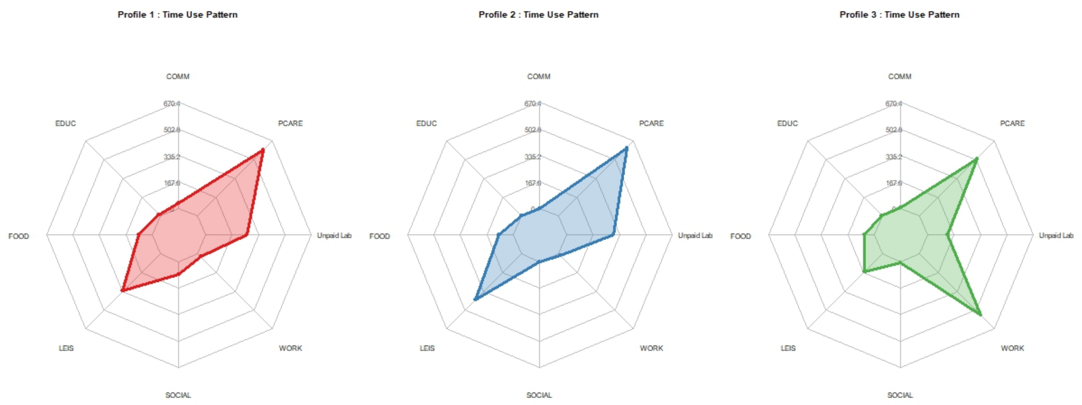

Figure 32: Radar charts illustrating time-use patterns across the three identified profiles.

Finally, the clusters are visualized in the PCA space (Figure 33), showing partial but not complete separation — consistent with moderate silhouette scores.

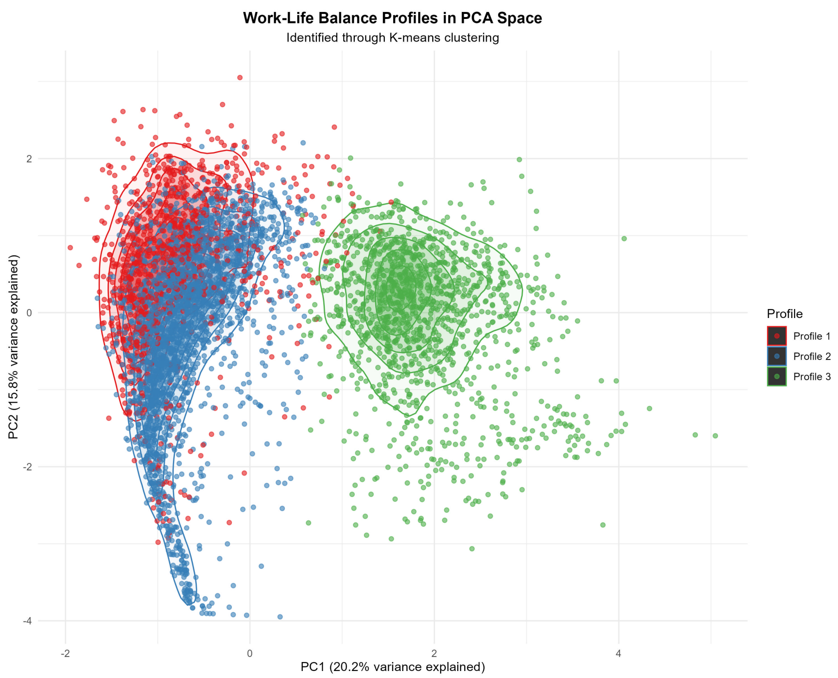

Figure 33: Scatterplot of individuals in the PCA space colored by cluster membership.

Summary: The unsupervised clustering reveals three interpretable but partially overlapping work–life balance profiles among partnered individuals. Although cluster compactness is not strong — a known issue in real-world human behavioral data — the patterns provide sociologically meaningful insights into the diversity of time allocation strategies among couples.

4.4 Gendered Division of Labor Across Work–Life Balance Profiles

Research Question:
What distinct patterns of gendered division of labor can be identified among couples based on time use?

To answer this question, we examined the gender distribution within the three work–life balance profiles identified by clustering, and analyzed differences in average daily minutes spent on key activities.

Gender Composition Across Clusters
Figure 34 presents the proportion of men and women in each cluster:

- Profile 1, characterized by higher leisure time, has a majority of women (61%).
- Profile 2, reflecting a moderate balance of paid work and unpaid labor, shows nearly equal representation of men and women (50% each).
- Profile 3, dominated by intensive paid work, has a higher proportion of men (60%).

This distribution suggests that women are more likely to be found in profiles associated with greater unpaid labor and leisure time, while men are overrepresented in the profile emphasizing paid work.

Figure 34: Proportion of gender within work–life balance profiles.

Gendered Time Allocation Within Clusters
Figure 35 shows the average daily minutes spent on the activities used in the PCA, broken down by gender and cluster. Clear patterns emerge:

- Across all profiles, women consistently spend substantially more time than men on unpaid labor activities.
- Men consistently spend more time on paid work, especially pronounced in Profile 3.

- Leisure time favors men in Profile 1 and Profile 3, where they allocate slightly more time to leisure activities compared to women.
- Personal care time is relatively balanced between genders, although women spend slightly more time in Profiles 1 and 2.

These findings reinforce the persistence of a traditional gendered division of labor across different work–life balance profiles.

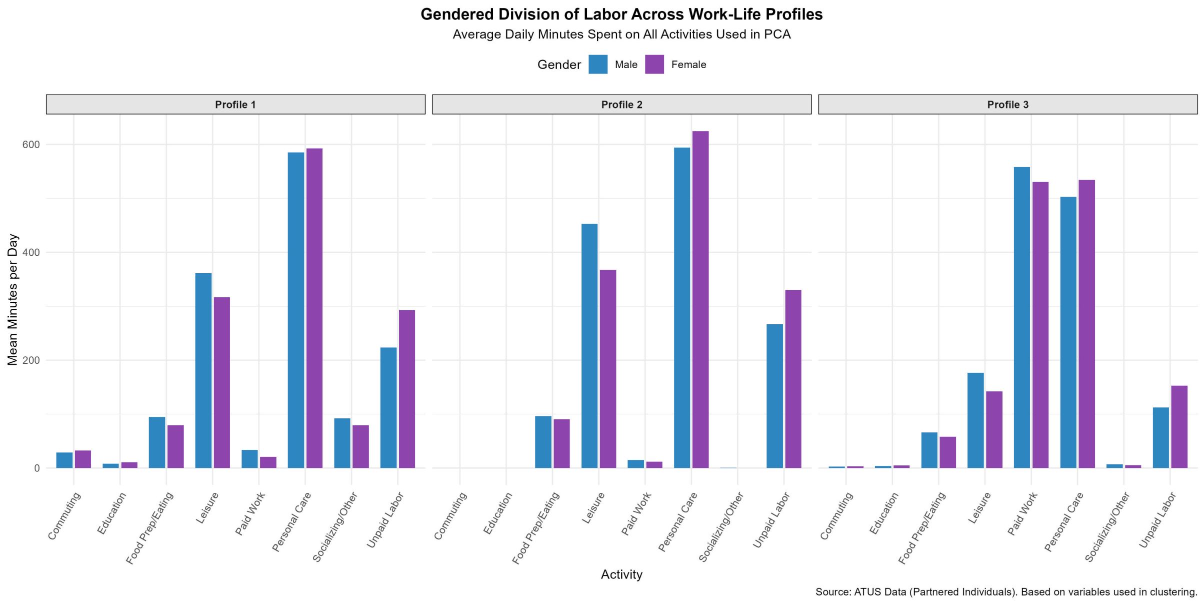

Figure 35: Average daily minutes spent by gender across activities, for each work–life balance profile.

Summary:

While clustering revealed meaningful differences in work–life balance profiles, gender disparities remained visible across all groups. Women consistently shouldered more unpaid labor responsibilities, even in profiles where overall time allocation patterns differed. Conversely, men predominated in paid work commitments. These results underscore that, despite diverse patterns of time use among partnered individuals, traditional gender inequalities in domestic labor persist.

4.5 Influence of Household Structure on Couples' Time Use

Research Question:
How does household or family structure – for example, having children – influence couples' time-use patterns?

We investigated whether the presence of children under 18 years old significantly influenced daily time allocation among partnered individuals across the identified work–life balance profiles.

Results Overview:

- The distribution of households with and without children varies across profiles (Figure 36). Profile 3 shows the highest proportion of households with children (47%), followed by Profile 2 (31%) and Profile 1 (24%).

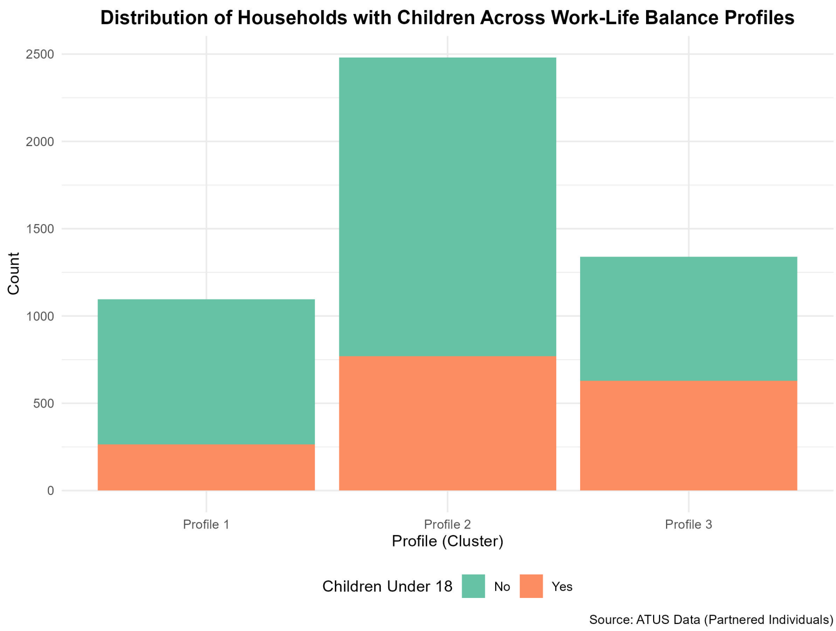

Figure 36: Distribution of households with and without children across work-life balance profiles.

- Average time-use patterns by parental status within each cluster are shown in Figure 37. While some differences exist—particularly a modest increase in unpaid labor and a slight decrease in leisure time among individuals with children—the overall patterns within clusters remain relatively stable.

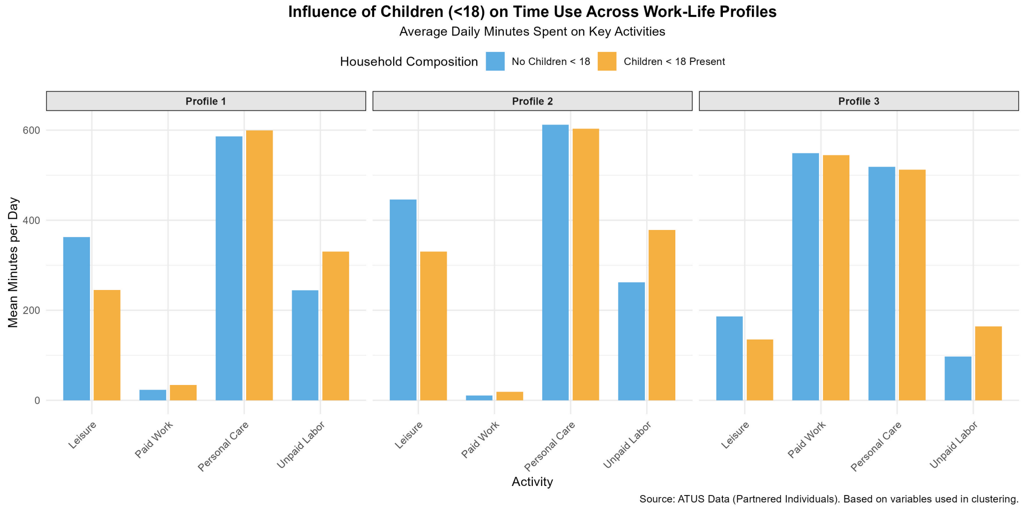

Figure 37: Influence of having children under 18 on average daily minutes spent on key activities, by cluster.

Interpretation:

While the presence of children appears to shift time allocation somewhat—reducing leisure time and increasing unpaid labor—these shifts are not substantial enough to redefine the underlying time-use profiles. In other words, household structure acts more as a *modifying factor* within profiles rather than a primary driver of profile membership.

Specifically:

- In Profile 1 (moderate workers), individuals with children spend slightly more time on unpaid labor and slightly less on leisure, but overall time-use remains broadly similar.
- In Profile 2 (domestic-focused), the pattern is consistent: the presence of children is associated with a moderate rise in unpaid labor.
- In Profile 3 (career-focused), individuals without children unsurprisingly report higher paid work and leisure times, while those with children report greater unpaid labor.

Summary:

The influence of household structure (presence of children) on couples' time-use patterns is detectable but relatively modest. Family composition refines but does not radically alter the main behavioral profiles captured by clustering.

4.6 Family Income Distribution Across Work-Life Balance Profiles

Research Question:
How does household economic situation influence work-life balance profiles?

To investigate the relationship between household income and the work-life balance profiles identified through clustering, we analyzed the distribution of family income groups within each cluster. The results are displayed in Figure 38.

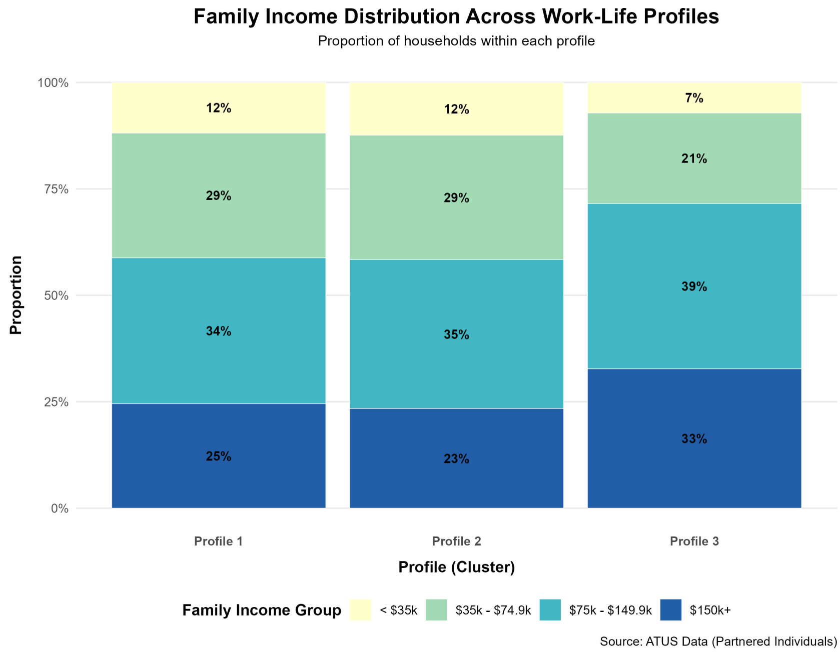

Figure 38: Family income distribution across work-life balance profiles. Proportions of households within each profile by income group.

Findings:

- **Profile 3** is notably more affluent than Profiles 1 and 2. Approximately 33% of Profile 3 households reported incomes above $150,000, compared to about 25% in Profile 1 and 23% in Profile 2.
- In addition, Profile 3 has a higher proportion of households in the $75,000–$149,999 income bracket (around 39%), relative to Profiles 1 (34%) and 2 (35%).
- Conversely, Profiles 1 and 2 include a larger share of households in the $35,000–$74,999 and more than $35000 income brackets.

Interpretation:

These results suggest that economic resources partly differentiate work-life balance profiles. Higher-income households are more heavily represented in Profile 3, which is also characterized by distinct time-use patterns emphasizing higher paid work and lower unpaid labor. Nevertheless, the differences, while clear, are moderate rather than extreme. This indicates that while income contributes to shaping work-life arrangements, it does not wholly determine them, reflecting the complex social realities of partnered individuals.

Thus, household income appears to influence couples' time-use profiles, but it is only one of multiple factors driving variation in work-life balance patterns.

5 Supervised Learning

5.1 Handling Missing Data

Prior to any modeling being conducted, we initially examined the prevalence of missing data across all variables in the dataset. The majority of missingness arose from variables that did not relate to certain individuals based on household composition. Specifically, those with no spouse or partner (`SPOUSEPRES = "No spouse/partner present"`) had missing values for all spouse-related variables. Similarly, those with no children in the household (`HH_CHILD = "No"`) had missing values for child-related variables.

These values are not really "missing" statistically but structurally non-applicable. To address this, we employed logical rules to attribute such values to `NA` or a neutral label (N̈ot Applicable¨) where necessary. The variable groups impacted were:

- **Spouse-related variables**: `SPSEX`, `sp_race4`, `SPEDUC`, `SPEMPSTAT`, `SPEARNWEEK`, `SPAGE`, `SPUSUALHRS`, and `SPUSUALHRS_DAILY_MIN`.
- **Children-related variables**: `HH_NUMKIDS` and `AGEYCHILD`.

We then computed the change in missing value counts after this step to confirm that artificial missingness had been removed correctly.

Table 18: Change in Missing Values After Logical Recoding

Variable	Change in Missing Count
HH_NUMKIDS	+6,219
SPSEX	–3,633
SPEDUC	–3,633
SPEMPSTAT	–3,633

As can be seen in Table 18, missingness in variables such as `HH_NUMKIDS` increased—through more precise encoding of structural missingness—while that in spouse variables decreased due to reclassification of incorrectly labeled values.

This preprocessing step ensured that the imputation phase would only operate on reasonable, truly missing values, thereby increasing our models' robustness.

5.2 Removing Variables with Excessive Missingness

Following recoding the logically missing values, we assessed the overall completeness of the dataset. As is the general rule of thumb in the literature, variables with more than 50% missing data are usually considered too sparse to retain, as imputation in those cases would more often rely on noise than information.

We computed the missing value percentage for each variable and deleted those with values over 50%. These deleted variables were ones that could not be used for reliable modeling or inference in the subsequent steps.

Table 19: Variables Removed Due to >50% Missing Values

Variable Name
WHYABSNT
HH_NUMKIDS
AGEYCHILD
SPEARNWEEK
SPUSUALHRS_DAILY_MIN

This filtering step led to the removal of five variables. Their exclusion ensures that the subsequent imputation stage remains stable and avoids artificially generated correlations from sparsely populated features.

5.3 Multiple Imputation with MICE

After removing structurally missing and high-missingness variables, we proceeded to impute the remaining missing values using the `mice` package in `R`, which stands for *Multivariate Imputation by Chained Equations*. This package is widely regarded in the literature as one of the most flexible and statistically sound frameworks for handling missing data in complex survey and observational datasets. It is particularly well-suited to settings where missingness is non-monotonic and variables are of mixed types (e.g., numeric, categorical, ordinal).

To prepare the data for imputation, we first converted all `character` variables into `factor` type. This left us with three core variable classes:

- `factor`: 20 variables
- `integer`: 15 variables
- `numeric`: 4 variables

We then assigned variable-specific imputation methods using a tailored method vector. These were chosen based on the type and number of levels of each variable, as summarized in Table 20. Specifically, we used predictive mean matching for numeric variables, logistic regression for binary factors, and polytomous regression for categorical factors with more than two levels. For certain variables known to have complex or nonlinear missing patterns (e.g., earnings and working hours), we applied decision tree-based methods (`cart`) to improve imputation quality.

Table 20: Imputation Methods by Variable Type

Variable Type	Imputation Method
`numeric`	Predictive Mean Matching (`pmm`)
`binary factor`	Logistic Regression (`logreg`)
`multi-level factor`	Polytomous Regression (`polyreg`)
`custom`	CART Decision Trees (`cart`) for selected variables

In order to further refine the imputation plan, we constructed an individual predictor matrix. This matrix excluded the outcome variable (outcome variable: `unpaid_labor`) as a predictor and avoided self-prediction for all variables. The imputation was conducted using 20 imputations (`m = 20`), with each having 5 iterations, and convergence diagnostics revealed stable results across chains. Finally, we created a `long`-format version of the imputed dataset for pooled model analysis. This imputed data will be used in all subsequent modeling steps.

5.4 Baseline Linear Model Construction

With the imputed datasets complete, we proceeded to construct the baseline supervised model. This model was designed to estimate unpaid labor (`unpaid_labor`) as a function of a set of demographic, employment, and household variables. The model was not intended as a predictive tool, but rather to assess the strength and direction of association between covariates and unpaid labor time.

As we used multiple imputation via the `mice` package, we obtained 20 complete datasets. Each of these was treated as an independent draw from the posterior distribution of the missing data. To respect the survey design and ensure unbiased estimation, we applied the ATUS-provided weights (`WT06`) within each imputed dataset using the `svydesign()` function from the `survey` package.

The baseline model took the form of a survey-weighted linear regression, estimated separately on each imputed dataset and later combined using Rubin's rules via `MIcombine()`.

The explanatory variables included in this baseline model were:

- **Demographics:** `SEX`, `AGE`, `RACE4`, `EDUC`
- **Employment:** `EMPSTAT`, `FULLPART`, `UHRSWORKT_DAILY_MIN`, `EARNWEEK`
- **Household context:** `HH_SIZE`, `SPOUSEPRES`, `HH_CHILD`

These variables were selected after excluding those with high missingness or problematic collinearity, to avoid unstable model estimates during imputation or pooling.

The model specification is written as:

$$\begin{aligned} \text{unpaid\_labor}_i = \beta_0 &+ \beta_1 \cdot \text{SEX}_i + \beta_2 \cdot \text{AGE}_i + \beta_3 \cdot \text{RACE4}_i + \beta_4 \cdot \text{EDUC}_i \\ &+ \beta_5 \cdot \text{EMPSTAT}_i + \beta_6 \cdot \text{FULLPART}_i + \beta_7 \cdot \text{UHRSWORKT\_DAILY\_MIN}_i \\ &+ \beta_8 \cdot \text{EARNWEEK}_i + \beta_9 \cdot \text{HH\_SIZE}_i + \beta_{10} \cdot \text{SPOUSEPRES}_i + \beta_{11} \cdot \text{HH\_CHILD}_i + \varepsilon_i \end{aligned} \tag{1}$$

For each imputed dataset, the linear model was estimated using `svyglm()`, and the results were combined to yield pooled coefficients, standard errors, and t-statistics. In addition, we computed pseudo R^2 values for each fitted model by comparing the deviance of the fitted model with that of a null (intercept-only) model. The distribution of pseudo R^2 across the 20 imputations was summarized and visualized to assess the model's overall explanatory power.

The pooled results and summary statistics are presented in the following subsection.

5.5 Pooled Results and Model Fit

We estimated the baseline linear model across 20 imputed datasets and combined the results using Rubin's rules. Table 26 (see Appendix or Results section) summarizes the pooled coefficients, standard errors, confidence intervals, t-statistics, and p-values for each explanatory variable. Variables were sorted by absolute t-value to highlight those with the strongest statistical association with unpaid labor.

Without interpreting the direction or size of these coefficients at this stage, we observe that a number of demographic and household variables (e.g., `SEX`, `HH_CHILD`, `SPOUSEPRES`) showed consistently strong and statistically significant effects across imputations. The pooled model intercept and a few employment characteristics were also significant.

To assess model fit, we computed a pseudo-R^2 statistic for each imputed dataset. This measure reflects the proportional reduction in deviance between the fitted model and a null (intercept-only) model. The average pseudo-R^2 across the 20 imputations was:

Average pseudo-R^2: 0.163

The distribution of pseudo-R^2 values across imputations was as follows:

Table 21: Summary Statistics of Pseudo-R^2 Values Across Imputations

Statistic	**Value**
Minimum	0.161
1st Quartile	0.162
Median	0.163
Mean	0.163
3rd Quartile	0.164
Maximum	0.165

The relatively tight range of pseudo-R^2 values confirms that variation across the imputed datasets is limited, and the model's explanatory power is consistent. This also reinforces that our imputation process yielded plausible and stable complete datasets.

A more nuanced interpretation of coefficients and model structure will follow once the final model is selected and refined.

5.6 Feature Engineering and Enhanced Linear Model

The baseline model, while descriptive, reflected constraints in registering intricate interac-conflicts between demographic and socioeconomic characteristics. For instance, the presence of children presumably operates on unpaid work differently according to gender, race, or work status. In order to improve these subtle relationships, we conducted focused feature engineering.

Feature Engineering Strategy

We created interaction terms and transformations to reflect heterogeneity in the predictors' effects. Specifically:

- **Quadratic term for age**: Centered age (AGE_c) and its square (AGE_c^2) were included to capture non-linear age effects.
- **Gender-specific interactions**: Dummies were created for gender $\times$ race, gender $\times$ education, gender $\times$ employment status, and gender $\times$ household composition (e.g., `Male_WithChild`, `Female_WithSpouse`).
- **Child and employment interactions**: For example, `Unemployed_WithChild` captures the effect of being both unemployed and a parent.
- **Derived socio-economic metrics**:
  - `LOG_EARN`: Log-transformed earnings to account for skewness.
  - `WORK_HH_RATIO`: Ratio of daily work hours to household size as a proxy for time burden.
  - `FREE_TIME_PROXY`: Minutes remaining in the day after accounting for work time.
- **Categorical groupings**:
  - `AGE_GROUP`: Age brackets.
  - `EARN_CATEGORY`: Earnings segmented into categories.
  - `HOUSEHOLD_TYPE`: Combinations of child and spouse presence (e.g., Married with children, Single parent).

All numeric predictors were standardized for model stability. This enhanced dataset was used to re-run the survey-weighted linear regression over all 20 imputed datasets.

Model Results and Improvement

The enhanced model achieved an average pseudo-R^2 of **0.184**, improving upon the base model's **0.163**. This increase in explanatory power indicates that the added engineered features provided additional structure and helped capture more of the variation in unpaid labor across individuals.

These enhancements usually result from the inclusion of interaction effects (e.g., gender combined with employment status, education, and parenthood), quadratic terms (e.g., age squared), and standardized continuous predictors (e.g., weekly earnings, working hours per household member). These enhancements allow the model to better reflect the intricacy of unpaid labor allocation as it occurs in the real world, where unpaid labor allocation is influenced by intricate combinations of demographic and household factors.

Compared to the base model, the enhanced specification more accurately identified high-burden individuals—particularly those facing overlapping social roles, such as unemployed parents or low-educated men. Several newly engineered features emerged as statistically significant predictors, further supporting the hypothesis that unpaid labor is shaped by intersectional factors.

A full summary of pooled coefficient estimates, standard errors, and significance levels is available in Table 27

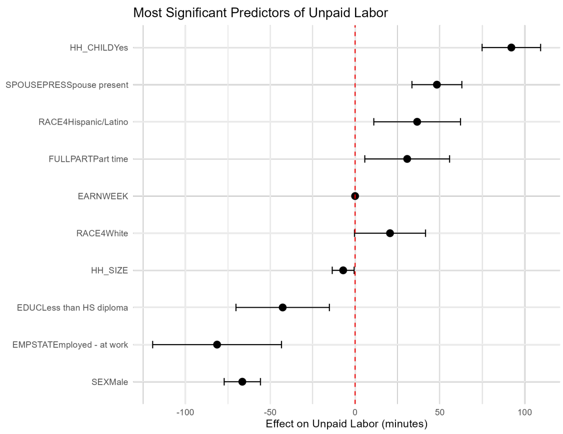

Figure 39: *
Top Predictors: Base Model

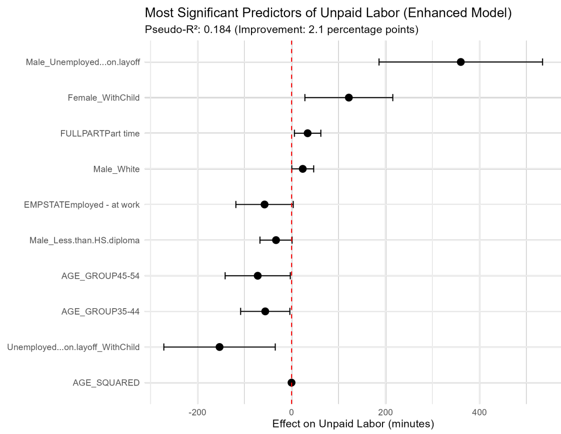

Figure 40: *
Top Predictors: Enhanced Model

Figure 41: Comparison of most significant predictors of unpaid labor between the base and enhanced models.

5.7 Model Transformation and Comparative Evaluation

Despite notable improvement in explanatory power through feature engineering, residual diagnostics revealed that the enhanced model's assumptions—particularly normality of residuals—remained questionable. To address this, we explored transforming the dependent variable `unpaid_labor` to reduce right-skewness and stabilize variance.

Transformation Strategy

Two common transformations were applied:

- **Logarithmic transformation:** $\log(\texttt{unpaid\_labor} + 1)$
- **Square root transformation:** $\sqrt{\texttt{unpaid\_labor}}$

Each transformation was applied across the 20 imputed datasets. Survey-weighted linear regression models were re-estimated using the same explanatory variables as the enhanced model. Residual distributions were inspected, and pseudo-R^2 values were computed for comparison.

Comparative Evaluation of Model Fit

Table 22 summarizes the pseudo-R^2 results for each model specification. The square root transformation yielded the best performance, with a pseudo-R^2 of **0.188**, outperforming both the base model (0.163) and the enhanced model (0.184). In contrast, the log-transformed model performed worse, indicating an unsuitable transformation for this outcome.

Transformation	Pseudo-R^2	Improvement (p.p.)
Original (untransformed)	0.163	0.0
Enhanced features	0.184	+2.1
Log transformation	0.137	−2.6
Square root transformation	**0.188**	**+2.5**

Table 22: Comparison of Model Performance by Transformation

Residual Diagnostics of Best Model

Figure 44 displays the residual histogram and Q-Q plot for the square root-transformed model. The distribution is notably more symmetric, and the Q-Q plot indicates a closer alignment with normality compared to previous models—justifying its selection.

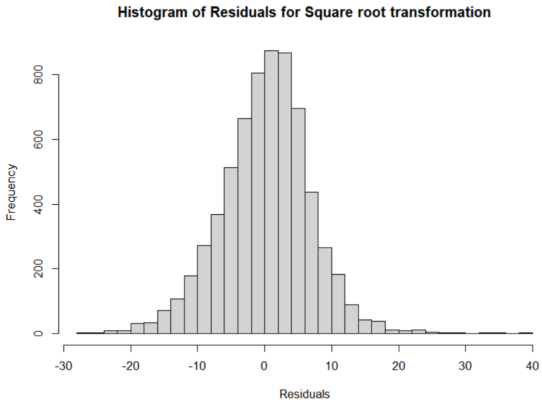

Figure 42: *
Histogram of Residuals

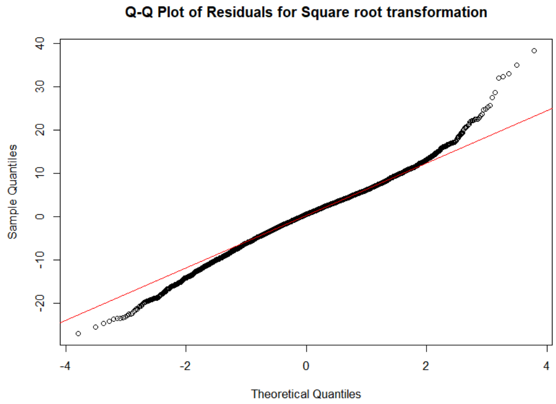

Figure 43: *
Q-Q Plot of Residuals

Figure 44: Residual diagnostics for the best-performing model (square root transformation).

Based on these findings, we proceed using the square root-transformed model as the final specification for further interpretation and policy relevance. Summary tables for this model are provided in Appendix.

Attempted Two-Part Model (Zero-Inflated Structure)

To account for the large number of zero values in the unpaid labor variable (approximately 16.3%), we briefly explored a two-part modeling strategy. The first part estimated the probability of engaging in any unpaid labor using a weighted logistic regression, while the second part modeled the amount of unpaid labor (conditional on participation) using a Gamma regression with a log link. However, this approach yielded poor fit in both stages and failed to outperform the square root-transformed linear model. One likely reason is that the zeros in the data may not reflect distinct structural absence (i.e., true non-participation), but rather variation in short reference periods or reporting inconsistencies—limiting the interpretability and predictive power of the two-part framework. For these reasons, we do not pursue this approach further.

5.7.1 Handling Outliers in Unpaid Labor

Visual inspection of the unpaid labor variable revealed the presence of extreme outliers. As shown in Figure 45, the distribution is right-skewed with several high-end values. A total of **111 outliers** were identified, accounting for approximately **1.3%** of the sample. The maximum recorded value was an implausible **1,350 minutes per day**—equivalent to over 22 hours of unpaid labor.

To mitigate the influence of these extreme cases, we applied *winsorization* at both the 95th and 99th percentiles. This involved capping all values above these thresholds to the corresponding percentile value and generating square root-transformed versions of these capped variables (`sqrt_unpaid_w95` and `sqrt_unpaid_w99`). This approach retains the overall shape of the distribution while reducing the disproportionate leverage of high-end values on model estimates.

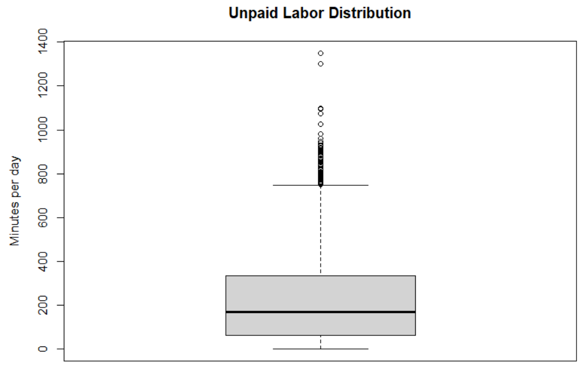

Figure 45: Boxplot showing distribution and outliers in unpaid labor (minutes/day).

5.7.2 Winsorization and Final Model Evaluation

After identifying and quantifying outliers in the unpaid labor variable, we applied *winsorization* at both the 95th and 99th percentiles to reduce their influence. These capped variables were then square-root transformed, aligning with our earlier finding that the square root model offered the best performance in terms of residual normality and R^2.

We re-estimated the model using these transformed outcomes and calculated their pseudo-R^2 values. The 95% winsorized model achieved an average R^2 of **0.186**, while the 99% version yielded a slightly better value of **0.187**. These are on par with the original square root model ($R^2 = 0.188$), suggesting that winsorization provides robustness without substantial loss of fit.

Table 23 summarizes the performance of all models evaluated, highlighting how transformations and outlier handling impacted explanatory power.

Table 23: Comparison of Model Pseudo-R^2 Across Specifications

Transformation	**Pseudo-R^2**	**Improvement**
Original (untransformed)	0.163	—
Enhanced features	0.184	+2.08 percentage points
Log transformation	0.137	–2.62 percentage points
Square root transformation	0.188	+2.47 percentage points
95% Winsorized + Sqrt	0.186	+2.3 percentage points
99% Winsorized + Sqrt	0.187	+2.4 percentage points

In conclusion, the **square root-transformed model**—with or without winsorization—consistently performed best. It offered the highest explanatory power and improved residual normality compared to other specifications. This model will therefore be used in the final interpretation of results.

Key Takeaways

The square root-transformed model shows some statistically significant predictors of unpaid labor participation. Male and on layoff, female with children, and part-time employee were consistently found to have a higher level of unpaid labor even when transformed. Being full-time employed, male, or lower education is, however, predictive of lower unpaid labor.

The term in squared age is still significant, indicating a non-linear relationship between age and unpaid work, although the practical size of this effect is small. Importantly, although some coefficients achieve statistical significance, the model as a whole must be read with caution: the aim here is not exact prediction, but to bring to light patterns that can be useful for wider social analysis.

5.8 Classification Analysis: Predicting Unpaid Labor Classes

Motivation and Approach

While the linear models provided some inferential insights, their predictive performance was limited—particularly in capturing the variance in unpaid labor allocation. To explore whether we could better predict unpaid labor patterns, we reframed the task as a multi-class classification problem.

Specifically, we categorized individuals into three distinct classes based on the number of unpaid labor minutes per day:

- **Underworked**: < 30 minutes/day
- **Normal**: 30 to 240 minutes/day
- **Overworked**: > 240 minutes/day

We then trained two supervised classification models—Random Forest (RF) and Extreme Gradient Boosting (XGBoost)—on 10 and 20 imputed datasets respectively. Models were fine-tuned using cross-validation, and performance was evaluated on test splits pooled across imputations.

5.9 Classification Results

Random Forest achieved a mean classification accuracy of $\mathbf{0.528 \pm 0.009}$, while **XGBoost** achieved a slightly lower average of $\mathbf{0.517 \pm 0.004}$. Final accuracies on the combined test set were:

- **Random Forest:** 0.515
- **XGBoost:** 0.523

These results suggest that both models struggle to classify unpaid labor intensity accurately, likely due to overlapping feature profiles across groups and class imbalance.

Confusion Matrices

XGBoost Confusion Matrix (Final Test Set):

Prediction \ Reference	**Normal**	**Overworked**	**Underworked**
Normal	329	185	137
Overworked	257	459	80
Underworked	19	6	5

Table 24: Confusion matrix for XGBoost classifier

Random Forest Confusion Matrix (Final Test Set):

Prediction \ Reference	**Normal**	**Overworked**	**Underworked**
Normal	214	129	84
Overworked	177	294	60
Underworked	16	4	6

Table 25: Confusion matrix for Random Forest classifier

5.10 Interpretation

Both models perform poorly in detecting the underworked group, possibly due to a short sample size and limited distinguishing features. Furthermore, the distinction between "normal" and "overworked" instances is unclear, leading to frequent misclassifications. Although ensemble models improved accuracy relative to linear regression-based conclusions, their 50% accuracy and confusion matrices indicate that they are not yet suitable for accurate prediction in this context. Future studies should explore alternative class boundaries, feature development, and sample strategies to address class inequality.

6 Discussion and Limitations

This study attempted to explain and predict unpaid work with broad controls over demographic, socioeconomic, and household variables. Although we were able to detect some patterns most noticeably the persistent influence of gender, work, and caregiving behavior the explanatory power of our models collectively was still weak. Even our top-performing linear model, with transformation and winsorization, explained below 20% of variation in unpaid work hours. Models like Random Forest and XGBoost made more than chance classification accuracy predictions.

These findings underscore an even more profound limitation that is conceptual, not statistical. Unpaid work is an internalized, frequently context-dependent practice shaped by norms of culture, family values, personal tastes, perceptions of time, and emotional labor factors not reflected in standard survey data. Regardless of the sophistication of modeling, observable trends cannot capture the full social richness of invisible work. Unlike income or education, unpaid work eludes measurement and abstraction. Just as a poet might only offer us prose, advanced modeling can only deliver data.

Also. Our findings indicate people don't easily fit into sharply demarcated groups or categories of behavior when it comes to unpaid work. Class labels applied in classification (underworked, normal, overworked) were constructed to reflect sense-making of outlier values but instead indicated variation is more continuous and tailored than categorical. This is consistent with wider social science views that unpaid work is influenced by interactional, situational, and even intangible forces.

7 Future Work

Future research can be enhanced with more sensitive data exploring psychological stress, people's experience of time pressure, domestic power, and cultural attitudes toward gender roles. Interview or mixed-methods studies can also be informative where quantitative research is lacking in detail. On the technical side, other methods like multi-level models, structural equation modeling, or time sequence analysis can more effectively illustrate how unpaid work changes over time or across households. In addition, looking at specific subgroups—e.g., two-earner households or single parents—might yield more precise projections in certain instances.

8 Conclusion

This study explored the invisible labor or unpaid work using statistical learning and predictive modeling. After much data manipulation and model tweaking, we discovered that unpaid work is still hard to predict and only partially explained by something observable. Our findings highlight the constraints of modeling behavior that is shaped by society and culture using numbers. They also highlight the need to recognize invisible work and to continue developing our methods of studying it, both quantitatively and in society.

Appendix A: Pooled Coefficient Estimates

A.1 Baseline Model Summary

Table 26: Pooled Coefficient Estimates Sorted by Significance

Variable	Coeff.	SE	t-value	Lower CI	Upper CI	p-value	Signif.
SEXMale	-66.47	5.46	-12.18	-77.17	-55.77	$< .001$	***
HH_CHILDYes	92.13	8.80	10.47	74.89	109.37	$< .001$	***
(Intercept)	204.08	29.34	6.96	146.57	261.59	$< .001$	***
SPOUSEPRESSpouse present	48.24	7.51	6.43	33.53	62.95	$< .001$	***
EMPSTATEmployed - at work	-81.35	19.38	-4.20	-119.33	-43.37	$< .001$	***
EDUCLess than HS diploma	-42.68	14.05	-3.04	-70.21	-15.14	0.003	
RACE4Hispanic/Latino	36.60	13.04	2.81	11.04	62.16	0.006	
FULLPARTPart time	30.72	12.75	2.41	5.73	55.71	0.018	*
EARNWEEK	0.011	0.0046	2.32	0.0016	0.0196	0.023	*
HH_SIZE	-7.01	3.29	-2.13	-13.46	-0.56	0.036	*

A.2 Enhanced Model Summary

Table 27: Pooled Coefficient Estimates from Enhanced Model (Sorted by Significance)

Variable	Coefficient	SE	t-value	Lower CI	Upper CI	Signif.
AGE_SQUARED	-0.118	0.021	-5.730	-0.159	-0.078	***
Male_Unemployed...on.layoff	360.021	88.764	4.056	186.044	534.000	**
(Intercept)	287.862	88.337	3.259	114.720	461.003	**
Female_WithChild	121.811	47.708	2.553	28.303	215.319	*
Unemployed...on.layoff_WithChild	-153.298	60.482	-2.535	-271.842	-34.753	*
FULLPARTPart time	34.125	14.333	2.381	6.033	62.218	*
AGE_GROUP35-44	-56.063	26.723	-2.098	-108.440	-3.686	*
AGE_GROUP45-54	-72.079	35.369	-2.038	-141.402	-2.755	*
Male_White	23.713	11.879	1.996	0.430	46.997	*
...	...	...	...	...	...	

A.3 Log-Transformed Model Summary

Table 28: Pooled Coefficient Estimates from Log-Transformed Model (Sorted by Significance)

Variable	Coeff.	SE	Lower CI	Upper CI	p-value	Signif.
(Intercept)	5.21	0.91	3.42	7.00	$< .001$	***
Male_Unemployed...on.layoff	1.43	0.45	0.54	2.32	$< .001$	***
FULLPARTPart time	0.34	0.13	0.08	0.60	0.01	*
Male_White	0.40	0.19	0.02	0.78	0.04	*
Male_Less.than.HS.diploma	-0.59	0.22	-1.02	-0.16	0.01	*
AGE_SQUARED	-0.00	0.00	-0.0014	-0.0005	0.01	*
Male_HS.diploma	-0.24	0.12	-0.47	-0.01	0.04	*
Male_Some.college	-0.24	0.11	-0.46	-0.02	0.03	*
Male_Employed...at.work	-0.40	0.36	-1.09	0.30	0.26	
Female_WithChild	0.61	0.44	-0.25	1.46	0.17	
LOG_EARN	0.09	0.08	-0.06	0.25	0.23	

A.4 Square Root-Transformed Model Summary

Table 29: Pooled Coefficient Estimates from Square Root-Transformed Model (Sorted by Significance)

Variable	**Coeff.**	**SE**	**Lower CI**	**Upper CI**	***p*-value**	**Signif.**
(Intercept)	15.47	3.37	8.82	22.11	$< .001$	***
Male_Unemployed...on.layoff	10.04	2.33	5.47	14.61	$< .001$	***
Female_WithChild	3.75	1.70	0.42	7.09	0.03	*
FULLPARTPart time	1.41	0.53	0.37	2.45	0.01	*
Male_White	1.18	0.57	0.07	2.29	0.04	*
EMPSTATEmployed - at work	-1.98	1.13	-4.21	0.24	0.08	.
AGE_SQUARED	-0.00	0.00	-0.0061	-0.0029	0.02	*
Male_Less.than.HS.diploma	-1.87	0.73	-3.30	-0.43	0.01	*
AGE_GROUP45-54	-2.71	1.43	-5.52	0.10	0.06	.
Male_HS.diploma	-0.62	0.39	-1.39	0.14	0.11	

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