DATA VISUALIZATION & ANALYTICS

AI at Work: Are We Gaining Efficiency but Losing Stability?

An Analysis of AI Adoption, Productivity, Burnout & Long-Term Workforce Sustainability

SECTOR: Artificial Intelligence & Human Capital Management

FINAL PROJECT REPORT

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Submission Date	February 2026

1. Problem Statement:

Artificial Intelligence is increasingly being adopted by organizations to enhance productivity and reduce employee burnout. However, excessive dependence on AI may unintentionally weaken human skills, critical thinking, and decision-making abilities. This raises a critical concern:

Approach:

We started with the raw employee dataset that included AI usage, work output, stress, learning hours, and Burnout. First, we cleaned the data in Google Sheets by fixing errors and checking for missing values.

After cleaning, we reviewed basic statistics to understand overall patterns in AI usage, productivity, and stress. This helped us see how employees were performing.Then, we created important KPIs like Efficiency Leverage, Deep Work Balance, Learning Zone, and Sustainability Rating to measure both performance and long-term stability.

Finally, we used pivot tables and charts to compare different AI usage levels and find clear, meaningful insights from the data.

Key Insights:

Using AI helps employees complete more work in less time. But using too much AI does not always increase results and can sometimes increase stress.

The most stable employees are those who use AI in balance, keep enough focused work time, and do not overload themselves with too much learning.

Key Recommendations:

Companies should use AI as a support tool, not something employees completely depend on. Success should be measured not just by output, but also by how healthy and stable employees are in the long run.

Organizations should protect focused work time and limit unnecessary meetings. Learning should be steady and manageable so employees can grow without feeling stressed or overloaded.

3. Sector & Business Context

Sector Overview

Today, many companies are using Artificial Intelligence (AI) in daily work to complete tasks faster and improve efficiency. AI tools are helping in writing, analysis, automation, and decision-making.

The main aim is to increase productivity and reduce workload. However, as AI use grows, companies must also think about its effect on employee skills, stress, and long-term stability.

Current challenges:

As AI becomes common in workplaces, one major challenge is over-dependence. Employees may start relying too much on AI, which can reduce independent thinking and problem-solving skills over time.

Another challenge is rising stress and reduced focus. Even if AI increases output, heavy meetings, constant communication, and continuous learning demands can create mental pressure and affect long-term employee stability.

Why this problem was chosen:

This problem was chosen because AI is growing very fast in every workplace, and most companies focus only on productivity gains. Very few studies look at whether this growth is affecting employee skills, stress, and long-term stability.

We wanted to understand if AI is truly building stronger organizations, or if it is creating hidden risks that may impact performance and sustainability in the future.

4. Problem Statement & Objectives

Formal problem definition:

To examine whether increasing AI use improves productivity while slowly reducing employee skills, deep thinking ability, and long-term stability.

In simple terms, are companies becoming more efficient today but weaker in the future?

Project Scope:

This project focuses on analyzing how AI usage affects employee productivity, stress levels, deep work balance, learning intensity, and overall sustainability. The study is limited to the given dataset and evaluates patterns using KPIs, pivot tables, and visual analysis in Google Sheets.

It does not measure real-time behavior or long-term historical trends, but provides a structured evaluation of current AI usage impact within the available data.

Success criteria

The project will be successful if it clearly shows how AI usage affects productivity, stress, and long-term employee stability using data-based evidence.

It should provide practical insights and realistic recommendations that help organizations balance efficiency with sustainable workforce growth.

5. Data Description

Dataset Source Link-
https://www.kaggle.com/datasets/ashyou09/ai-productivity-tools-and-feature-impact-dataset

Data Structure

The dataset contains **5,600 employee records** with **24 columns** covering AI usage, productivity, workload, stress, learning behavior, and calculated KPIs.

Each row represents one employee, and each column represents either a performance variable (like AI usage hours or burnout score) or a derived metric (like Efficiency Leverage or Sustainability Rating).

The dataset includes both raw operational data and engineered KPIs to allow deeper sustainability analysis.

Columns Explanation:

The dataset includes important operational columns such as:
AI Tool Usage Hours Per Week, Tasks Automated Percent, Manual Work Hours, Learning Time, Meeting Hours, Collaboration Hours, Error Rate, Task Complexity, Focus Hours, Work-Life Balance Score, and Burnout Risk Score.

It also includes calculated KPI columns like Efficiency Leverage, Deep Work Balance, Learning Zone, Employee Persona, Sustainability Rating, AI Leverage, and Experience Range. These KPIs help measure not just performance, but long-term workforce stability and risk.

Data Size:

The dataset contains **5,600 employee records**, which provides a strong sample size for comparison and segmentation analysis.

With 24 structured variables, the dataset allows detailed analysis across productivity, stress, automation level, and sustainability dimensions.

Data Limitations:

The dataset represents a single-time snapshot and does not track changes over time. Therefore, long-term trends cannot be directly observed.

Some indicators such as burnout risk and work-life balance are behavioral scores and may include subjective interpretation. Additionally, sustainability metrics are calculated models and not externally validated organizational measures.

6. Data Cleaning & Preparation

Missing Values Handling:

Several columns contained blank or missing values, especially in numeric fields such as AI usage hours, task automation percentage, burnout risk score, and work-life balance score.

To maintain data distribution and avoid bias, missing numerical values were replaced using the median of the respective column. For categorical fields, blank entries were replaced with “Others” to ensure consistent grouping during analysis.

Outlier Treatment:

Extreme values were reviewed using basic statistical checks and column sorting. No unrealistic or impossible values were found in key numerical fields.

Since the dataset represents varied employee behavior, extreme values were retained unless clearly invalid, as they may represent real high or low performance cases.

Transformations

Text columns with inconsistent casing (e.g., HIGH, high, HiGh) were standardized using `TRIM()` and `PROPER()` functions to ensure uniform formatting.

Numeric fields were validated and converted into proper number format to avoid calculation errors during KPI creation and pivot analysis.

Feature Engineering

Several new columns (KPIs) were created to enable deeper analysis beyond raw data.

These included Efficiency Leverage (output per AI hour), Deep Work Balance (remaining focus time), Learning Zone (learning intensity category), Employee Persona (behavior classification), AI Leverage grouping, and Sustainability Rating.

These engineered features allowed evaluation of both short-term productivity and long-term workforce stability.

Assumptions:

It was assumed that median replacement would preserve realistic distribution without significantly altering patterns.

Derived KPIs such as Sustainability Rating are model-based indicators and represent analytical approximations rather than externally validated psychological scales.

7. KPI & Metric Framework

KPI definitions

To evaluate the impact of AI usage on productivity and long-term workforce stability, a structured KPI framework was developed. These KPIs measure efficiency, focus quality, learning sustainability, and burnout risk.

Why each KPI matters

KPI	Definition	Formula	Business Purpose

Efficiency Leverage	Output generated per AI usage hour	=IF(D2=0,0,E2/D2)	Measures how effectively AI is being used. Higher values indicate stronger productivity per AI hour.
Deep Work Balance	Remaining focused work hours after meetings & collaboration	=(M2*5)-(I2+J2)	Evaluates whether employees have sufficient uninterrupted work time for critical thinking and skill development.
Learning Zone	Categorizes learning intensity	`=IFS(G2<2,"Risk", G2<=5,"Stable", G2<=9,"Growth", G2>9,"Overload")`	Identifies whether employees are under-learning, balanced, growing, or overloaded.
Sustainability Rating	Composite score combining productivity, error rate & burnout	=IF(O2=0,0,(E2*(10-K2))/(O2^2))	Penalizes high burnout to evaluate long-term workforce stability rather than short-term output.
AI Leverage Classification	Groups employees by AI usage intensity	=IF(D2<5,"Low AI", IF(D2<=12,"Medium AI","High AI"))	Enables comparison of performance and stress across different AI usage levels.
Employee Persona	Behavioral performance classification	=IF(AND(E2>35,OR(O2>8,K2>3)),"Toxic High Performer", IF(E2>35,"Star Performer", IF(OR(O2>8,K2>3),"Struggler","Steady Worker")))	Identifies high-performing but high-risk employees for strategic workforce planning.

Mapping KPIs to objectives

The KPIs were directly aligned with the core objective of evaluating whether AI improves productivity while maintaining long-term workforce sustainability.

Project Objective	Supporting KPI	How It Supports
Measure AI-driven productivity	Efficiency Leverage	Shows output generated per AI hour
Protect deep thinking ability	Deep Work Balance	Measures remaining focused work time
Ensure continuous skill growth	Learning Zone	Identifies balanced vs overloaded learning behavior
Monitor burnout & stability	Sustainability Rating	Penalizes high burnout risk to assess long-term viability
Compare AI intensity impact	AI Leverage Classification	Enables structured comparison across AI usage levels
Identify workforce risk segments	Employee Persona	Highlights high-performing but high-risk employees

8. Exploratory Data Analysis (EDA)

Trend Analysis — AI Usage vs. Productivity Output

Plotting average productivity output against AI usage hours per week reveals a clear non-linear trend. From zero to approximately 12 hours per week (Medium AI band), output rises proportionally with AI adoption. Beyond 12 hours (High AI), productivity gains flatten and in several role segments begin to decline marginally. This inflection point, visible across Analyst, Designer, and Writer cohorts, signals diminishing returns from intensive AI use. The average productivity across the full dataset stands at 908 units per hour, while the average AI usage totals 1,053 hours, suggesting that not all AI usage time translates into proportional output.

Comparison Analysis — AI Adoption & Automation Efficiency by Role

The grouped bar chart (Dashboard View 2 — AI Adoption & Productivity section) compares average AI Tool Usage Hours Per Week and average Tasks Automated Percent across seven role types. Key observations include:

- Developers and Writers record the highest absolute AI usage hours, averaging approximately 35–38 hours per week.
- Managers and Marketers record high automation percentages relative to their AI usage hours, indicating efficient AI leverage.
- Analysts use comparatively fewer AI hours but maintain competitive automation rates, suggesting manual process depth.

The AI Usage vs. Manual Workload Analysis chart confirms that roles with the highest AI usage do not uniformly reduce manual work hours — Managers retain notably high manual workloads despite elevated AI adoption, pointing to AI being used for augmentation rather than replacement.

Distribution Analysis — Employee Personas & Workforce Composition

The Workforce Composition donut chart (Dashboard View 3) reveals a broadly distributed workforce across six roles. Developers form the largest segment at 23.1%, followed by Others (16.2%), Managers (15.0%), Analysts (14.8%), Designers (16.5%), and Writers (11.5%). The Resource Consumption pie chart mirrors a similar distribution, with Managers consuming 19.5% of organizational resources and Developers 18.7%, reflecting their high AI tool and meeting hour usage.

Employee Persona distribution across the scatter chart (Performance vs. Health view) shows a clear bifurcation: Star Performers cluster at high Efficiency Leverage (~8.2) with moderate burnout (~4.8), while Toxic High Performers show slightly lower efficiency (~6.2) but dramatically elevated burnout (~8.2). Strugglers present low efficiency and moderate burnout. Steady Workers occupy a stable mid-range — lower output but sustainable health profiles.

Correlation Analysis — Key Relationships

Cross-variable pivot analysis identified the following directional relationships:

- AI Usage & Output: Positive correlation up to the Medium AI band. High AI usage does not produce proportional output gains; the relationship weakens beyond 12 hrs/week.
- AI Usage & Burnout Risk: Moderate positive correlation. High AI users average burnout scores that are 18–22% higher than Medium AI users, despite comparable or lower productivity outputs.

- AI Leverage vs. Error Rate: The AI Leverage vs. Error Rate bar chart (Dashboard View 2) reveals that High AI users exhibit the highest average error rate (~2.1%), compared to Medium AI (~1.6%) and Low AI (~1.9%). This counterintuitive finding suggests that excessive AI reliance may reduce task accuracy through over-automation or reduced human verification.
- Meeting Hours & Deep Work Balance: The Meetings vs. Focus vs. Learning chart (Dashboard View 3) confirms that Manager roles endure the highest weekly meeting load (~13.8 hrs) while simultaneously maintaining the lowest focus hours (~2.68 hrs/day), creating the most acute Deep Work deficit across all roles.
- Error Rate & Experience Level: The Error Rate by Experience Level line chart shows a non-monotonic pattern — error rates dip at the 12–16 year experience band (1.91%) before rising again at the 8–12 and 16–20 year bands. The 8–12 year cohort records the highest error rate at 2.19%, potentially reflecting senior employees being assigned the highest task complexity and AI workloads.
- Learning Hours & Burnout: Employees in the Learning Overload zone (>9 hrs/week) show elevated burnout and lower sustainability ratings, confirming that aggressive upskilling mandates without recovery time are counterproductive.

9. Advanced Analysis

Although the dataset represents a single-time snapshot, advanced analytical techniques were applied to understand deeper behavioral patterns and workforce risk structures.

Segmentation Analysis

Employees were segmented using:

- **AI Leverage Classification** (Low, Medium, High AI usage)
- **Learning Zone** (Risk, Stable, Growth, Overload)
- **Employee Persona** (Star Performer, Toxic High Performer, Struggler, Steady Worker)

This segmentation enabled structured comparison across productivity, burnout risk, and sustainability scores.

Key observation:
Medium AI users consistently showed stronger sustainability scores compared to extreme low or high AI usage groups, indicating that balanced AI adoption may produce more stable performance outcomes.

Correlation & Relationship Analysis

Exploratory correlation analysis was conducted using pivot comparisons and trend evaluation between:

- AI Usage vs Output
- AI Usage vs Burnout Risk
- Meeting Hours vs Deep Work Balance
- Learning Hours vs Stress Indicators

Findings indicate that:

- AI usage positively correlates with output up to a moderate level.
- Excessive AI usage does not proportionally increase productivity and may increase burnout risk.
- Higher meeting and collaboration hours significantly reduce deep work balance.
- Extremely high learning hours are associated with overload risk.

This suggests diminishing returns beyond moderate AI and workload levels.

Workforce Risk Modeling

A composite **Sustainability Rating** was developed to measure long-term employee viability.

The formula heavily penalizes burnout risk, ensuring that high output alone does not inflate sustainability.

Additionally, Persona classification identified a critical segment:

Toxic High Performers — employees with high output but elevated burnout or error levels.

This group represents a hidden organizational risk, as short-term performance may mask long-term instability.

Workforce Risk Modeling

Pattern analysis suggests that reduced deep work balance and excessive workload intensity are primary drivers of lower sustainability ratings.

High AI usage combined with:

- High meeting hours
- High learning overload
- Elevated burnout scores

creates performance instability despite strong output.

This indicates that structural work design, not AI alone, influences long-term workforce health.

Since the dataset represents a single-period snapshot, time-series forecasting and scenario simulations were not conducted. The analysis is therefore based on cross-sectional comparison, segmentation, and relationship assessment within the available data.

10. Dashboard Design

Dashboard Objective

The dashboard was designed to translate raw employee data into clear, decision-ready visual intelligence. Its primary purpose is to allow HR managers, department heads, and organizational leaders to monitor three interconnected dimensions simultaneously: AI adoption efficiency, performance versus health risk trade-offs, and long-term sustainability trends. The dashboard enables both summary-level executive viewing and detailed role-by-role or persona-by-persona drilldown through interactive filters.

View Structure

The dashboard is organized across three logical view sections within Google Sheets:

View	Title	Charts Included	Primary Audience
View 1	Summary / Hero Dashboard	KPI Tiles: Total Employees (5,600), Avg AI Usage (1,053 hrs), Avg Productivity (908), Avg Burnout Risk (1,294)	C-Suite / Executives
View 2	AI Adoption & Productivity | Performance vs Health Risk	5 interactive charts with Role and Persona slicers	HR Managers / Team Leads
View 3	Sustainability & Long-Term Risk	4 charts: error trend, meetings vs focus, workforce composition, resource consumption	Operations / Strategy

View 1— Summary / Hero Dashboard

The hero view opens with the project title 'AI at Work: Are We Gaining Efficiency but Losing Stability?' accompanied by four KPI scorecards: Total Employees (5,600), Average AI Usage Hours (1,053), Average Productivity (908 units/hr), and Average Burnout Risk Score (1,294 aggregate). These tiles provide an immediate high-level snapshot that anchors all subsequent analysis on a measurable organizational scale. Visual imagery reinforces the human-AI duality theme of the study.

View 2 — AI Adoption & Productivity / Performance vs Health Risk

This view is divided into two thematic sections. The upper section — AI Adoption & Productivity — contains three charts:

- AI Adoption & Automation Efficiency by Role: A grouped bar chart showing average AI Tool Usage Hours and average Tasks Automated Percent by role, filterable by Role slicer. Developers and Writers show peak AI usage; Managers and Marketers show high automation efficiency.
- AI Usage vs Manual Workload Analysis: A grouped bar chart comparing AI usage hours against manual work hours per role, revealing that high AI usage does not eliminate manual effort, particularly for Managers.
- AI Leverage vs Error Rate: A bar chart segmented by AI Leverage classification (Low, Medium, High). High AI users record the highest average error rate (~2.1%), challenging the assumption that more AI always means better quality.

The lower section — Performance vs Health Risk — contains two charts:

- Performance vs Health Scatter: Plots Efficiency Leverage (y-axis) against Burnout Risk Score for each Employee Persona. Star Performers show high efficiency with moderate burnout; Toxic High Performers reveal the dangerous high-output, high-burnout profile. Filterable by Employee Persona slicer.
- Burnout Risk by Role: A bar chart comparing average Burnout Risk Score across all six roles. Managers (~7.5) and Marketers (~7.3) carry the highest risk, while Others (~4.5) record the lowest. Filterable by Burnout Risk by Role slicer.

View 3 — Sustainability & Long-Term Risk

This section surfaces structural and longitudinal risk patterns:

- Error Rate by Experience Level: A line chart revealing error fluctuation across five experience bands (0–4, 4–8, 8–12, 12–16, 16–20 years). The 8–12 year band peaks at 2.19%, while 12–16 years dips to 1.91%. Filterable by Experience Range slicer.
- Meetings vs Focus vs Learning (Role Comparison): A stacked/grouped bar chart comparing average Learning Time, Focus Hours per Day, and Meeting Hours per Week across all roles. Managers face the most acute compression — 13.8 meeting hours crowding out 2.68 focus hours.
- Workforce Composition Donut: Displays percentage share of each role within the 5,600-employee dataset. Developers lead at 23.1%.
- Resource Consumption Pie: Shows proportional resource usage by role. Managers (19.5%) and Developers (18.7%) consume the largest share. Filterable by Role slicer.

Filters & Drilldowns

Each chart section includes an interactive slicer that dynamically filters the connected charts. The available filters are: Role (Analyst, Designer, Developer, Manager, Marketer, Others, Writer), Employee Persona (Star Performer, Steady Worker, Struggler, Toxic High Performer), AI Leverage (Low AI, Medium AI, High AI), Burnout Risk by Role, and Experience Range (0–4, 4–8, 8–12, 12–16, 16–20 years). Setting any slicer to 'All' reverts the view to the full dataset.

11. Insights Summary

#	Insight Title	What It Means for the Organization
1	**AI Has a Productivity Ceiling**	Medium AI usage (5–12 hrs/week) maximizes output. Beyond this threshold, productivity gains plateau while burnout risk continues to climb. Organizations chasing higher AI adoption without guardrails are investing in diminishing returns.
2	**High AI Usage Does Not Mean Higher Quality**	High AI users record the highest average error rate (≈2.1%) compared to Medium (1.6%) and Low (1.9%) AI users. Automation intensity without adequate human review introduces quality risk that offsets efficiency gains.
3	**Toxic High Performers Are a Hidden Liability**	A segment of employees delivers strong output but operates at burnout levels above 8/10. These individuals are at high attrition risk. Losing them represents a disproportionate organizational cost given their output contribution.
4	**Managers Face the Most Severe Workload Compression**	With ≈13.8 meeting hours per week and only ≈2.68 focus hours per day, Managers experience the most acute Deep Work deficit of any role. This structural compression is a direct driver of their elevated burnout scores.
5	**Deep Work Balance Is a Leading Indicator of Sustainability**	Roles with higher protected focus time consistently show stronger Sustainability Ratings. Focus hours are not a luxury — they are a structural input into long-term performance stability.
6	**Developers Have the Strongest Sustainability Profile**	Despite the highest AI usage hours, Developers maintain relatively healthy sustainability scores, suggesting a role-function fit where AI genuinely augments structured technical tasks without replacing critical thinking.
7	**Learning Overload Reduces Sustainability**	Employees in the Overload learning zone (>9 hrs/week) show lower sustainability ratings despite higher short-term productivity. Excessive learning demands without recovery time are counterproductive to long-term growth.
8	**Mid-Career Employees (8–12 Years) Carry the Highest Error Risk**	Error rates peak at 2.19% for the 8–12 year experience band. This may reflect senior employees being assigned the highest complexity AI-augmented tasks without proportional support or error-checking processes.
9	**Burnout Risk Varies Significantly by Role — Not Just AI Usage**	Managers and Marketers carry the highest burnout scores despite not always having the highest AI usage. Structural factors — meeting load, collaboration demands, multi-stakeholder pressure — are independently driving burnout beyond AI usage alone.

10	**Resource Consumption Concentration Increases Organizational Fragility**	Managers and Developers together consume over 38% of organizational resources. Over-concentration in two role segments creates dependency risk if key talent in these groups disengages or exits.
11	**Balanced AI Users Achieve the Most Stable Long-Term Outcomes**	Employees classified as Steady Workers — moderate AI usage, stable learning, controlled burnout — show the most consistent sustainability ratings over time, even if they do not top short-term productivity leagues.
12	**Workforce Composition Is Broadly Distributed but Risk Is Concentrated**	While headcount is spread across six roles (11.5%–23.1%), performance instability is concentrated in two segments: Managers (burnout) and Developers (volume). Any talent intervention should prioritize these groups first.

12. Recommendations

R1: Implement an AI Usage Governance Policy	
Mapped Insight	Insights 1 & 2 — Productivity ceiling and rising error rates at high AI usage
Recommended Action	Define a recommended AI usage band of 5–12 hours per week per employee. Introduce quarterly AI usage audits that track both output and error rate trends simultaneously. Roles exceeding the threshold without proportional quality improvement should be flagged for review.
Business Impact	Medium–High
Feasibility	Medium
R2: Introduce Sustainability KPIs in Performance Reviews	
Mapped Insight	Insights 3 & 11 — Toxic High Performers and Steady Worker advantage
Recommended Action	Augment existing performance review frameworks with Sustainability Rating, burnout trajectory, and error trend metrics. Employees should be evaluated not only on output volume but on how healthily and consistently they produce that output over time.
Business Impact	High
Feasibility	High
R3: Protect Deep Work Time Across All Roles	
Mapped Insight	Insights 4 & 5 — Manager compression and Deep Work Balance as a sustainability driver
Recommended Action	Mandate a minimum of 3 uninterrupted focus hours per day across all roles. Cap weekly recurring meetings at 8 hours organization-wide. Introduce

	'no-meeting' blocks of at least two mornings per week, particularly for Managers and Marketers.
Business Impact	High
Feasibility	Medium
R4: Redesign Learning Programmes to Prevent Overload	
Mapped Insight	Insight 7 — Learning Overload reduces sustainability
Recommended Action	Redesign mandatory learning programmes to target 3–5 hours per week of structured, spaced learning. Replace high-volume sprint training with modular, self-paced tracks. Measure learning effectiveness through skill application, not hours logged.
Business Impact	Medium
Feasibility	High
R5: Create Error Rate Monitoring for Senior AI Users	
Mapped Insight	Insight 8 — Mid-career employees carry the highest error rate
Recommended Action	Implement role-based quality review triggers for employees in the 8–12 year experience bracket who are classified as High AI users. Pair these employees with structured peer review cycles and provide access to AI output verification training.
Business Impact	Medium
Feasibility	High
R6: Reduce Structural Burnout Drivers for Managers and Marketers	
Mapped Insight	Insights 4, 9 & 10 — Role-specific burnout and resource concentration risk
Recommended Action	Conduct a meeting audit for Manager and Marketer roles with a target of reducing weekly meeting load by 20–30%. Delegate routine decision gates to Steady Worker profiles to redistribute cognitive load. Monitor burnout scores quarterly for these two segments specifically.
Business Impact	High
Feasibility	Medium

13. Impact Estimation

Category	Lever	Estimated Impact & Logic
Cost Savings	Reducing Toxic High Performer attrition	Replacing a skilled employee costs 50–200% of annual salary. If sustainable KPI frameworks prevent even 5% of burnout-driven exits across a workforce of 5,600, and assuming average replacement cost of 75% of salary at a median of $60,000, the organization avoids approximately $12.6M in replacement costs annually.
Efficiency Gain	Optimizing AI usage to the Medium AI band	If the 20–25% of employees currently in the High AI bracket reduce usage to the Medium band, error rates are projected to drop from 2.1% to approximately 1.6% — a 24% quality improvement. For high-volume task environments, this translates directly into fewer rework cycles and faster time-to-completion.
Service Improvement	Protecting Deep Work time for key roles	Increasing focus hours for Managers and Writers by 1–2 hours per day through meeting reduction is estimated to improve decision quality and creative output by 15–25%, based on established productivity research on cognitive flow states. Downstream client-facing output quality improves proportionally.
Risk Reduction	Monitoring mid-career error rates	Implementing peer review cycles for the 8–12 year experience cohort — which currently records the highest error rate (2.19%) — reduces the probability of high-stakes output errors. In knowledge-work environments, a 20% reduction in error rate for senior employees can prevent significant reputational and compliance risk.
Sustainability	Redesigning learning programmes	Shifting employees from Learning Overload (>9 hrs/week) to the Stable or Growth zone (3–7 hrs/week) reduces stress-driven absenteeism and improves knowledge retention. Industry data suggests that spaced learning improves retention by 40–60% over intensive sprint formats, yielding better skill ROI per training hour invested.

14. Limitations

Data Issues

The dataset represents a single-time snapshot and does not capture longitudinal change. As a result, trend analysis is cross-sectional rather than time-series based, meaning it reflects correlations within a point-in-time population rather than causal trajectories over time. It is not possible to determine from this data whether individual employees are improving, declining, or stable in their performance or burnout metrics.

Several key behavioral variables — including Burnout Risk Score and Work-Life Balance Score — are self-reported or model-generated estimates and may carry inherent subjectivity or calibration bias. They have not been externally validated against clinical or organizational psychology benchmarks.

The dataset source is publicly available on Kaggle and while it contains plausible employee patterns, it is synthetic or anonymized in nature. Direct extrapolation to specific real-world organizational contexts requires caution.

Assumption Risks

Missing values were imputed using column medians. While this preserves distribution shape, it artificially reduces variance in imputed columns and may slightly understate the extremity of performance and burnout distributions. The degree of impact depends on the proportion and distribution of missing values, which could not be fully verified.

KPIs such as Sustainability Rating and Deep Work Balance are derived metrics constructed by the project team. They are analytical approximations and have not been validated against external organizational performance data. Different formula designs would produce different ratings, introducing model sensitivity risk.

The Employee Persona classification is a rule-based segmentation. Real employee behavior is more nuanced and continuous; discrete persona labels may oversimplify complex behavioral patterns.

What Cannot Be Concluded

Causality cannot be established from this dataset. For example, while high meeting hours correlate with lower Deep Work Balance, it cannot be concluded from this data alone that meetings cause lower productivity or higher burnout — confounding variables such as role seniority, project type, and organizational culture are not captured.

Future sustainability trajectories cannot be predicted from a single-period dataset. An employee with a low Sustainability Rating today may not be at imminent exit risk; the rating reflects a structural snapshot, not a directional forecast.

Organizational or industry-level differences cannot be controlled for, as the dataset does not include company type, size, or sector. Findings should not be applied uniformly across all organizational contexts without further segmentation.

15. Future Scope

Additional Analysis Possible with Current Data

Regression analysis could be applied to quantify the relative contribution of each variable — AI usage, meeting hours, learning intensity, and task complexity — to the Sustainability Rating. This would produce a weighted predictor model that assigns statistical significance to each driver, enabling more targeted interventions.

Clustering algorithms such as K-Means could replace the rule-based Employee Persona classification to identify naturally occurring employee behaviour groups from the data itself, rather than from pre-defined thresholds. This would likely reveal sub-segments within each persona that carry different risk profiles.

Network analysis of collaboration patterns, if collaboration partner data were available, could reveal structural dependencies and single-point-of-failure risks within teams — employees whose departure would disproportionately disrupt workflow.

New Data Required for Deeper Analysis

Time-series employee data collected over 6–12 months would transform the analysis from static description to dynamic forecasting. Longitudinal data would allow prediction of burnout risk trajectory, skill degradation curves, and the point at which AI dependence begins to impair independent capability.

Organizational hierarchy and team-level data would enable analysis of whether burnout and performance instability are role-driven or management-driven — a critical distinction for targeted intervention.

Training completion records and post-training performance data would allow evaluation of whether current learning programmes are producing measurable capability improvements, or whether learning investment is not translating into operational outcomes.

External benchmarking data from industry surveys or HR analytics platforms would allow the dataset findings to be contextualized against sector norms — determining whether the AI usage and burnout patterns observed are typical, above-average, or anomalous relative to comparable organizations.

16. Conclusion

This project set out to answer a deceptively simple question: as organizations adopt AI at scale, are they building sustainable capability or accumulating hidden fragility? The analysis of 5,600 employee records across 24 variables, supported by six purpose-built KPIs and an interactive three-view dashboard, delivers a clear and evidence-based answer.

AI integration delivers genuine productivity benefits — but only within a balanced adoption range. Medium AI users consistently outperform their counterparts in long-term sustainability metrics, achieving strong output without the burnout burden that shadows high-AI users. The narrative that more AI always means better performance is not supported by this data.

The more significant finding is structural: the employees most at risk are not necessarily those using AI incorrectly, but those working within organizational designs that compress focus time, overload learning schedules, and measure success exclusively through short-term output. Managers and Marketers bear the heaviest structural burden; Toxic High Performers represent the most acute hidden risk.

The value this project delivers is threefold. First, it reframes productivity measurement — sustainability must be a KPI, not an afterthought. Second, it identifies the specific organizational levers — meeting reduction, AI governance, learning redesign — that are most likely to improve long-term workforce health. Third, it provides a replicable analytical framework that organizations can adapt to their own datasets to monitor AI-workforce dynamics on an ongoing basis.

The most efficient organization is not the one that uses AI the most. It is the one that uses AI wisely enough to keep its people capable, engaged, and sustainable over the long term. This study provides the evidence and the roadmap to make that distinction actionable.

17. Appendix

Data Dictionary

The following table documents all columns present in the dataset, including both raw operational fields and derived KPI columns created during feature engineering.

Column Name	Data Type	Description
AI Tool Usage Hours Per Week	Numeric	Number of hours per week the employee uses AI tools
Tasks Automated Percent	Numeric (%)	Percentage of tasks automated through AI tools
Manual Work Hours	Numeric	Hours per week spent on non-automated manual tasks
Learning Time Hours Per Week	Numeric	Hours per week dedicated to learning or upskilling
Meeting Hours Per Week	Numeric	Total weekly hours spent in meetings
Collaboration Hours	Numeric	Hours spent in collaborative work with colleagues
Error Rate Percent	Numeric (%)	Percentage of tasks containing errors or requiring rework
Task Complexity	Categorical / Score	Qualitative or scored measure of assigned task difficulty
Focus Hours Per Day	Numeric	Average daily uninterrupted deep work hours
Work-Life Balance Score	Score (0–10)	Self-reported or model-generated work-life balance indicator
Burnout Risk Score	Score (0–10)	Composite indicator of stress and burnout risk level
Efficiency Leverage	Derived (Numeric)	Output per AI usage hour: =IF(D2=0,0,E2/D2)
Deep Work Balance	Derived (Numeric)	Remaining focus hours after meetings and collaboration: =(M2*5)-(I2+J2)
Learning Zone	Derived (Categorical)	Risk (<2 hrs), Stable (≤5 hrs), Growth (≤9 hrs), Overload (>9 hrs)
Sustainability Rating	Derived (Numeric)	Composite score penalizing burnout: =IF(O2=0,0,(E2*(10-K2))/(O2^2))
AI Leverage	Derived (Categorical)	Low AI (<5 hrs), Medium AI (≤12 hrs), High AI (>12 hrs)
Employee Persona	Derived (Categorical)	Star Performer, Toxic High Performer, Struggler, Steady Worker
Experience Range	Categorical	Years of professional experience band: 0–4, 4–8, 8–12, 12–16, 16–20
Role	Categorical	Employee job function: Analyst, Designer, Developer, Manager, Marketer, Others, Writer

KPI Formulas Reference

All KPI formulas below reference row 2 as the first data row. Replace the row number dynamically when applied across the full dataset.

KPI	Formula	Notes
Efficiency Leverage	=IF(D2=0,0,E2/D2)	D = AI Usage Hours, E = Output
Deep Work Balance	=(M2*5)-(I2+J2)	M = Focus Hrs/Day, I = Meeting Hrs, J = Collab Hrs
Sustainability Rating	=IF(O2=0,0,(E2*(10-K2))/(O2^2))	O = Burnout Score, K = Error Rate
Learning Zone	IF(L2<2,"Risk",IF(L2<=5,"Stable",IF(L2<=9,"Growth","Overload")))	L = Learning Hours/Week
AI Leverage	IF(D2<5,"Low AI",IF(D2<=12,"Medium AI","High AI"))	D = AI Usage Hours/Week

Dataset Source

Dataset Title: AI Productivity Tools and Feature Impact Dataset

Source: Kaggle — https://www.kaggle.com/datasets/ashyou09/ai-productivity-tools-and-feature-impact-dataset

Access: Publicly available. No registration required for download via Kaggle API.

All data cleaning and KPI engineering were performed in Google Sheets as per capstone project requirements.

18. Contribution Matrix

Team Member	Dataset & Sourcing	Cleaning	KPI & Analysis	Dashboard	Report Writing	PPT	Overall Role
Samarth Chaudhary	✓					✓	Lead Analyst
Aditya Raj	✓				✓		Data Engineer
Ashutosh singh	✓	✓					KPI Designer

Patlori Nipun		✓		✓			Dashboard Developer
Keshav		✓	✓				Report Writer
RANVENDRA PRATAP SINGH			✓	✓			Presentation Lead

Declaration:

We confirm that the above contribution details are accurate and verifiable through version history and submitted project artifacts.

Team Signature Block: ____