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

FIELD	DETAILS
Team Name	G-13
Team Members	Nipun Patlori| Ranvendra | Samarth | Keshav | Ashutosh | Aditya
Institute	Rishihood University
Faculty / Program	Aayushi Vashishth
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1. Executive Summary

This report examines whether increasing AI adoption in the workplace improves long-term organizational sustainability, or whether it introduces hidden risks—skill atrophy, burnout escalation, and workforce fragility. Analyzing 5,600 employee records across 15 variables and six engineered KPIs, the findings reveal a nuanced picture: AI delivers genuine productivity benefits, but only within a balanced adoption range.

Key Finding:

Medium AI users (5–12 hrs/week) consistently outperform extreme groups in long-term sustainability metrics. High AI usage (>12 hrs/week) produces higher error rates (~2.4%) and elevated burnout without proportional productivity gains.

Key Recommendation:

Organizations should govern AI usage through defined bands, protect focused work time, and embed sustainability metrics into performance reviews—not just short-term output.

2. Sector & Business Context

Sector Overview

Organizations across industries are integrating AI tools into daily workflows to accelerate task completion, automate repetitive processes, and augment decision-making. AI is now embedded in writing, data analysis, project management, and communication—functions spanning every role in this study.

While efficiency gains are real and measurable, growing AI dependence introduces structural challenges that most organizations have not yet instrumented: skill erosion, reduced deep thinking time, and chronic burnout accumulation.

Current Challenges

- Over-dependence on AI risks reducing employees' independent problem-solving ability over time, as critical tasks are delegated to automated systems without human verification.
- Rising structural stress: even where AI increases output, heavy meeting loads, constant collaboration demands, and continuous learning requirements create psychological pressure and sustainability deficits.
- Measurement gap: most organizations track productivity volume but not productivity quality, sustainability, or long-term workforce health.

Why This Problem Was Chosen

AI adoption is accelerating in every workplace, yet most performance frameworks remain rooted in short-term output metrics. This project investigates whether the efficiency gains from AI are being purchased at the cost of employee capability, stability, and long-term organizational resilience.

3. Problem Statement & Objectives

Formal Problem Definition

To examine whether increasing AI utilization improves productivity while simultaneously reducing employee skills, deep thinking capacity, and long-term workforce stability. In short: are organizations becoming more efficient today but more fragile tomorrow?

Project Scope

This project analyzes how AI usage intensity affects employee productivity, stress levels, deep work balance, learning sustainability, and overall workforce viability. The analysis is confined to the provided 5,600-employee dataset and uses KPIs, pivot tables, and visual dashboards developed in Google Sheets. It does not capture real-time behavioral data or longitudinal trends, but provides a structured cross-sectional evaluation of current AI adoption impact.

Success Criteria

The project succeeds if it produces data-backed evidence on how AI usage levels affect productivity, error rates, burnout, and long-term sustainability—and if it delivers actionable recommendations that allow organizations to balance efficiency with sustainable workforce management.

4. Data Description

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

Data Structure

The dataset contains 5,600 employee records with 15 raw operational columns covering AI usage, productivity, workload, stress, and learning behavior. Each row represents one employee. Six additional KPI columns were engineered during the analysis phase to enable deeper sustainability assessment.

Column Overview

Raw operational columns include: AI Tool Usage Hours Per Week, Tasks Automated Percent, Manual Work Hours Per Week, Learning Time Hours Per Week, Meeting Hours Per Week, Collaboration Hours Per Week, Error Rate Percent, Task Complexity Score, Focus Hours Per Day, Work-Life Balance Score, Burnout Risk Score, Role, and Experience Years.

Engineered KPI columns include: Efficiency Leverage, Deep Work Balance, Learning Zone, Sustainability Rating, AI Leverage Classification, and Employee Persona.

Data Limitations

- The dataset is a single-period snapshot; longitudinal trends cannot be directly observed.
- Burnout Risk Score and Work-Life Balance Score are modelled or self-reported estimates and have not been externally validated against clinical benchmarks.
- The dataset is publicly available on Kaggle and is synthetic or anonymized in nature. Direct extrapolation to specific organizational contexts requires caution.

5. Data Cleaning & Preparation

Missing Values

Several columns contained blank or missing entries, particularly in numeric fields such as AI usage hours, task automation percentage, burnout risk score, and work-life balance score. Missing numeric values were imputed using column medians to preserve distribution shape without introducing bias. Missing categorical entries were replaced with a standardized placeholder to ensure consistent grouping in pivot analysis.

Outlier Treatment

Extreme values were reviewed using statistical sorting and range checks. No impossible or clearly invalid values were identified. Given that the dataset captures genuinely varied employee behavior, extreme values were retained unless demonstrably erroneous, as they may represent real high- or low-performance cases.

Standardization

Text columns with inconsistent casing (e.g., HIGH, high, HiGh) were standardized using TRIM() and PROPER() functions. Numeric fields were validated and converted to proper number format to prevent calculation errors during KPI derivation and pivot analysis.

Feature Engineering

Six KPI columns were engineered to enable analysis beyond raw data: Efficiency Leverage, Deep Work Balance, Learning Zone, Employee Persona, AI Leverage Classification, and Sustainability Rating. These derived fields allow simultaneous evaluation of short-term productivity and long-term workforce stability.

Assumptions

Median imputation was assumed to preserve realistic distribution without materially distorting patterns. Derived KPIs represent analytical approximations and are not externally validated psychological or organizational scales.

6. KPI & Metric Framework

Six KPIs were developed to evaluate both short-term performance and long-term workforce sustainability. Each KPI maps directly to a project objective.

KPI	Definition / Formula	Business Purpose	Mapped Objective
Efficiency Leverage	Output per AI usage hour=IF(D2=0,0,E2/D2)	Measures how effectively AI converts usage hours into productive output.	Measure AI-driven productivity
Deep Work Balance	Remaining focus hrs after meetings & collaboration=(M2*5)-(I2+J2)	Indicates whether employees retain sufficient uninterrupted time for critical thinking.	Protect deep thinking capacity
Learning Zone	Categorizes learning intensity: Risk (<2 hrs), Stable (≤5), Growth (≤9), Overload (>9)	Identifies employees under-learning, balanced, growing, or overloaded.	Ensure sustainable skill growth
Sustainability Rating	Composite score penalising burnout=IF(O2=0,0,(E2*(10-K2))/(O2^2))	Evaluates long-term workforce viability, not just output volume.	Monitor burnout & long-term stability
AI Leverage	Groups employees by AI usage: Low (<5 hrs), Medium (≤12), High (>12)	Enables structured performance and stress comparison across adoption levels.	Compare AI intensity impact
Employee Persona	Rule-based classification: Star Performer, Toxic High Performer, Struggler, Steady Worker	Identifies high-performing but high-risk employees for strategic planning.	Identify workforce risk segments
Future Risk	=(0.4 * Efficiency_Score) + (0.3 * (10 - Burnout_Score)) + (0.3 * Work_Life_Balance_Score)	Predict about burnout Escalation Risk	

7. Exploratory Data Analysis

AI Usage vs. Productivity

Cross-role analysis reveals a non-linear relationship between AI usage and output. From low to medium AI adoption (up to 12 hours per week), output rises meaningfully. Beyond 12 hours per week, productivity gains plateau and error rates escalate. This inflection point is visible across multiple role types, signalling diminishing returns from intensive AI use.

Dataset averages: Average AI usage is 10.7 hours per week, and average task automation is 28.8%. Developers and Writers record the highest AI usage hours (approximately 15 and 14 hours per week respectively), while Managers and Designers remain in the 6–7 hour range.

Role-Level AI Adoption & Workload

Developers and Writers record the highest absolute AI usage hours. Managers and Marketers show competitive automation rates relative to their AI usage, suggesting efficient leverage. Notably, high AI usage does not eliminate manual workloads—Managers retain significant manual effort despite lower AI adoption, indicating AI is being used to augment rather than replace.

Workforce Composition

The 5,600-employee dataset is distributed across six roles after standardizing casing inconsistencies: Developers (23.2%), Analysts (18.9%), Designers (16.3%), Marketers (15.1%), Managers (14.9%), and Writers (11.5%). No 'Others' category exists in the underlying data. Resource consumption, estimated as the combined weight of AI usage hours and meeting hours, is led by Developers (27.0%), followed by Analysts (17.3%) and Managers (16.8%).

Error Rate by AI Leverage

Error rate analysis by AI adoption group reveals a clear upward trend with increasing AI intensity. Low AI users (<5 hrs/week) average a 1.90% error rate; Medium AI users (5–12 hrs/week) average 2.07%; and High AI users (>12 hrs/week) record the highest rate at 2.42%. This counterintuitive finding suggests that over-automation without adequate human verification reduces task accuracy.

Meeting Load & Deep Work Deficit

Managers face the most severe structural compression in the dataset. They average 13.8 meeting hours per week—more than double any other role—while maintaining only 3.3 focus hours per day, the lowest across all roles. Every other role averages approximately 4.8–4.9 focus hours per day and 6–7 meeting hours per week. This compression is a direct structural driver of Managers' elevated burnout scores (8.24 out of 10).

Burnout Risk by Role

Average burnout risk scores (on a 0–10 scale) vary meaningfully by role: Developers (8.01), Managers (8.24), Analysts (7.83), Marketers (7.67), Writers (7.50), and Designers (7.46). Burnout risk is high across all roles, indicating a dataset-wide structural concern rather than an isolated segment issue.

Error Rate by Experience Band

Error rate follows a declining trend with experience. The 0–4 year band records the highest average error rate (2.40%), followed by 4–8 years (2.37%), 8–12 years (2.19%), 12–16 years (2.02%), and 16–20 years (1.92%). This pattern suggests that experience reduces error rates progressively, rather than the non-monotonic peak at 8–12 years referenced in earlier analyses.

8. Advanced Analysis

Segmentation Analysis

Employees were segmented across three dimensions: AI Leverage Classification (Low, Medium, High), Learning Zone (Risk, Stable, Growth, Overload), and Employee Persona (Star Performer, Toxic High Performer, Struggler, Steady Worker). Medium AI users consistently showed stronger sustainability profiles compared to extreme groups, indicating that balanced adoption produces more stable long-term outcomes.

Workforce Risk: The Toxic High Performer

A critical risk segment was identified within the Employee Persona framework: Toxic High Performers. These employees exhibit high productivity output but operate at burnout scores above 8 out of 10. They represent a hidden organizational liability—their departure would remove both their high output and the undocumented AI workflows that generate it.

- Profile: High AI usage (>15 hrs/week), strong productivity output, critically elevated burnout, and low collaboration.
- Business Risk: This group tends to automate work using private AI workflows. If they exit—which burnout data suggests is likely—the organization loses productivity speed without retaining transferable skills or documented processes.
- Estimated exposure: If Toxic High Performers represent even 15% of total output, their attrition creates disproportionate organizational fragility.

Sustainability Rating Framework

The Sustainability Rating composite score penalises high burnout, ensuring that strong output alone does not mask long-term instability. This formula structure deliberately favours employees who produce good results with controlled burnout—the Steady Worker profile—over those whose output is unsustainable. Pattern analysis confirms that Deep Work deficit and learning overload are primary drivers of low Sustainability Ratings.

9. Dashboard Design

Dashboard Objective

The three-view dashboard translates raw employee data into decision-ready visual intelligence. It enables HR managers, department heads, and organisational leaders to simultaneously monitor AI adoption efficiency, performance versus health risk trade-offs, and long-term sustainability patterns. Interactive slicers support both executive summary viewing and role-by-role or persona-level drilldown.

View Structure

View	Title	Charts Included	Primary Audience
View 1	Summary / Hero Dashboard	4 KPI scorecards: Total Employees, Avg AI Usage, Avg Tasks Automated, Avg Burnout Risk Score	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 presents four KPI scorecards: Total Employees (5,600), Average AI Usage (10.7 hrs/week), Average Tasks Automated (28.8%), and Average Burnout Risk Score (7.79 out of 10). These tiles provide an immediate high-level snapshot anchoring all subsequent analysis on a measurable organizational scale.

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

The upper section contains three charts: an AI Adoption & Automation Efficiency by Role grouped bar chart; an AI Usage vs. Manual Workload comparison; and an AI Leverage vs. Error Rate bar chart showing that High AI users record the highest average error rate (2.42%) versus Medium (2.07%) and Low (1.90%) users.

The lower section features a Performance vs. Health Scatter plotting Efficiency Leverage against Burnout Risk Score by Employee Persona, and a Burnout Risk by Role bar chart confirming Managers (8.24) and Developers (8.01) as the highest-risk segments.

View 3 — Sustainability & Long-Term Risk

This section surfaces structural risk patterns: Error Rate by Experience Level (declining trend from 2.40% at 0–4 years to 1.92% at 16–20 years); Meetings vs. Focus vs. Learning by Role (Managers averaging 13.8 meeting hours crowding out 3.3 focus hours); Workforce Composition (Developers 23.2%, Analysts 18.9%); and Resource Consumption (Developers 27.0%, Analysts 17.3%, Managers 16.8%).

Filters & Drilldowns

Each dashboard section includes interactive slicers: Role (Analyst, Designer, Developer, Manager, Marketer, Writer), Employee Persona, AI Leverage (Low, Medium, High), 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 5,600-employee dataset.

10. Key Insights

#	Insight	Organizational Implication
1	AI Has a Productivity Ceiling	Medium AI usage (5–12 hrs/week) maximises output. Beyond this threshold, productivity gains plateau while burnout and error rates rise. Chasing higher AI adoption without guardrails yields diminishing returns.
2	High AI Usage Increases Error Rates	High AI users record a 2.42% average error rate vs. 2.07% for Medium and 1.90% for Low users. Automation intensity without adequate human review introduces quality risk that offsets efficiency gains.
3	Toxic High Performers Are a Hidden Liability	Employees with strong output but burnout scores above 8/10 are at high attrition risk. Their departure removes both their productivity and the undocumented AI workflows they operate.
4	Managers Face Severe Workload Compression	With 13.8 meeting hours per week and only 3.3 focus hours per day, Managers experience the most acute Deep Work deficit. This structural compression directly drives their elevated burnout score of 8.24.
5	Deep Work Time Is a Sustainability Input	Roles with more protected focus time consistently show stronger Sustainability Ratings. Focus hours are a structural input into long-term performance stability, not a discretionary luxury.
6	Developers Combine High AI Use with Reasonable Sustainability	Despite the highest AI usage hours, Developers maintain relatively healthy sustainability profiles, suggesting role-function fit where AI genuinely augments structured technical tasks.
7	Learning Overload Undermines Sustainability	Employees in the Overload zone (>9 hrs/week of learning) show lower sustainability ratings despite higher short-term output. Aggressive upskilling without recovery time is counterproductive.
8	Experience Progressively Reduces Error Rate	Error rates decline with experience: from 2.40% at 0–4 years to 1.92% at 16–20 years. Senior employees are better positioned to verify and correct AI-generated output.

#	Insight	Organizational Implication
9	Burnout Is Role-Structural, Not Just AI-Driven	Managers and Developers carry the highest burnout scores. For Managers, meeting load and collaboration demands are primary drivers; for Developers, AI usage volume plays a greater role.
10	Resource Concentration Creates Dependency Risk	Developers and Analysts together account for over 45% of organizational resource consumption. Talent attrition in these two groups would create disproportionate operational disruption.
11	Steady Workers Achieve the Most Stable Outcomes	Employees with moderate AI usage, stable learning intensity, and controlled burnout show the most consistent sustainability ratings—even if they do not lead short-term productivity rankings.
12	Risk Is Concentrated Despite Broad Headcount Distribution	While headcount spans six roles, performance instability concentrates in Managers (burnout-driven) and Developers (volume-driven). Interventions should prioritize these two segments.

11. Recommendations

#	Recommendation	Action	Mapped Insights	Impact	Feasibility
R1	Implement AI Usage Governance Policy	Define a recommended AI usage band of 5–12 hrs/week. Introduce quarterly AI audits tracking both output and error rates simultaneously. Flag roles exceeding the threshold without proportional quality improvement.	1 & 2	High	Medium
R2	Embed Sustainability KPIs in Performance Reviews	Augment performance review frameworks with Sustainability Rating, burnout trajectory, and error trend metrics. Evaluate employees on how consistently and healthily they produce output—not volume alone.	3 & 11	High	High
R3	Protect Deep Work Time Across All Roles	Mandate a minimum of 3 uninterrupted focus hours per day. Cap weekly recurring meetings at 8 hours organisation-wide. Implement no-meeting blocks on at least two mornings per week, particularly for Managers.	4 & 5	High	Medium
R4	Redesign Learning Programmes to Prevent Overload	Target 3–5 hrs/week of structured, spaced learning. Replace high-volume sprint training with modular self-paced tracks. Measure effectiveness through skill application, not hours logged.	7	Medium	High

#	Recommendation	Action	Mapped Insights	Impact	Feasibility
R5	Create Prompt Transparency and Knowledge Documentation	Require that productivity gains achieved via AI be documented as organisational assets. Establish a shared company prompt library to prevent knowledge silos created by Toxic High Performers.	3	High	Medium
R6	Reduce Structural Burnout Drivers for Managers	Conduct a meeting audit for Managers targeting a 20–30% reduction in weekly meeting load. Delegate routine decision gates to Steady Worker profiles to redistribute cognitive load. Monitor burnout scores quarterly.	4, 9 & 12	High	Medium

12. Impact Estimation

Category	Lever	Estimated Impact
Cost Savings	Reducing Toxic High Performer attrition	Replacing a skilled employee costs 50–200% of annual salary. If sustainability KPI frameworks prevent 5% of burnout-driven exits across 5,600 employees (at an assumed median replacement cost of 75% of $60,000 salary), the organization avoids approximately $12.6M in annual replacement costs.
Quality Improvement	Optimising AI usage toward the Medium band	If High AI users (>12 hrs/week) reduce usage to the Medium band, error rates are projected to drop from approximately 2.42% to 2.07%—a 15% quality improvement. In high-volume environments, this directly reduces rework cycles and time-to-completion.
Performance Improvement	Protecting Deep Work time for Managers	Increasing Manager focus hours by 1–2 hours per day through meeting reduction is estimated to improve decision quality and strategic output quality by 15–25%, based on established research on cognitive flow states.
Risk Reduction	Implementing prompt transparency and AI documentation	Establishing a shared company prompt library reduces organizational dependency on individual employees' undocumented AI workflows, directly reducing continuity risk from Toxic High Performer attrition.
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. Spaced learning has been shown to improve retention by 40–60% over intensive sprint formats.

13. Limitations

Data Issues

The dataset is a single-period snapshot and does not capture longitudinal change. All trend analysis is cross-sectional, reflecting correlations within a point-in-time population rather than causal trajectories over time. Individual employee trajectories—whether improving, stable, or declining—cannot be determined from this data.

Burnout Risk Score and Work-Life Balance Score are self-reported or model-generated estimates and may carry calibration bias. They have not been validated against external clinical or organizational psychology benchmarks. The dataset source is publicly available on Kaggle and is synthetic or anonymized; direct extrapolation to specific organizational contexts requires caution.

Assumption Risks

Missing values were imputed using column medians. While this preserves distribution shape, it reduces variance in imputed columns and may understate extremity in performance and burnout distributions. KPIs including Sustainability Rating and Deep Work Balance are analytical approximations constructed by the project team—different formula designs would produce different ratings, introducing model sensitivity risk.

What Cannot Be Concluded

Causality cannot be established from this data. While high meeting hours correlate with lower Deep Work Balance, it cannot be concluded that meetings cause lower productivity or burnout—confounding factors such as role seniority, project type, and organizational culture are not captured. Future sustainability trajectories cannot be predicted from a single-period dataset. A low Sustainability Rating reflects a structural snapshot, not a directional forecast.

14. Future Scope

Additional Analysis with Current Data

Regression analysis could quantify the relative contribution of each variable—AI usage, meeting hours, learning intensity, task complexity—to the Sustainability Rating, producing a weighted predictor model with statistical significance scores per driver.

Clustering algorithms such as K-Means could replace rule-based Employee Persona classification to identify naturally occurring behavioral groups, potentially revealing sub-segments within each persona that carry distinct risk profiles.

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, enabling prediction of burnout trajectory, skill degradation curves, and the threshold at which AI dependence begins to impair independent capability.

Organizational hierarchy and team-level data would enable differentiation between role-driven and management-driven burnout—a critical distinction for targeted intervention design. External benchmarking data from industry surveys would allow findings to be contextualized against sector norms.

15. 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 15 variables, supported by six purpose-built KPIs and an interactive three-view dashboard, delivers a clear, 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 data does not support the assumption that more AI always means better performance.

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

The value this project delivers is threefold: it reframes productivity measurement by making sustainability a KPI rather than an afterthought; it identifies the specific organizational levers—meeting reduction, AI governance, learning redesign—most likely to improve long-term workforce health; and it provides a replicable analytical framework that can be adapted to any organization's own data.

> ***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.***

16. Appendix

A. Data Dictionary

Column Name	Data Type	Description
Role	Categorical	Employee job function: Analyst, Designer, Developer, Manager, Marketer, Writer
Experience Years	Numeric	Years of professional experience
AI Tool Usage Hours Per Week	Numeric	Hours per week the employee uses AI tools
Tasks Automated Percent	Numeric (%)	Percentage of tasks automated through AI
Manual Work Hours Per Week	Numeric	Hours per week spent on non-automated tasks

Column Name	Data Type	Description
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 Score	Score	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
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: =(M2*5)-(I2+J2)
Learning Zone	Derived (Categorical)	Risk (<2 hrs), Stable (≤5), Growth (≤9), Overload (>9)
Sustainability Rating	Derived (Numeric)	Composite score penalising burnout: =IF(O2=0,0,(E2*(10-K2))/(O2^2))
AI Leverage	Derived (Categorical)	Low (<5 hrs), Medium (≤12 hrs), High (>12 hrs)
Employee Persona	Derived (Categorical)	Star Performer, Toxic High Performer, Struggler, Steady Worker
Experience Range	Derived (Categorical)	Experience band: 0–4, 4–8, 8–12, 12–16, 16–20 years

B. Data Verification Notes

The following corrections were made to figures in earlier drafts of this report based on direct analysis of the raw dataset:

- Role composition: The dataset contains six roles (no 'Others' category in raw data). Corrected percentages: Developer 23.2%, Analyst 18.9%, Designer 16.3%, Marketer 15.1%, Manager 14.9%, Writer 11.5%.
- Avg AI Usage: 10.7 hrs/week (not 1,053—that figure corresponds to the Analyst headcount).
- Avg Tasks Automated: 28.8% (not an output 'units/hr' metric).
- Avg Burnout Risk Score: 7.79 out of 10 (not '1,294 aggregate'—that figure corresponds to the Developer headcount).
- Error rate by experience: Pattern is monotonically declining from 2.40% (0–4 yrs) to 1.92% (16–20 yrs), not a non-monotonic peak at 8–12 years.

- Error rate by AI leverage: Low AI 1.90%, Medium AI 2.07%, High AI 2.42% (confirmed from raw data).
- Manager meeting hours: 13.82 hrs/week (confirmed); Manager focus hours: 3.34 hrs/day (confirmed).

17. Contribution Matrix

Team Member	Dataset & Sourcing	Data Cleaning	KPI & Analysis	Dashboard	Report Writing	Presentation	Overall Role
Samarth Chaudhary					✓	✓	Lead Analyst
Aditya Raj	✓				✓		Report Writer
Ashutosh Singh			✓	✓			Dashboard Developer
Nipun Patlori	✓	✓		✓			Data Engineer
Keshav		✓	✓				KPI Designer
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: ____