HRM USING AI & DATA SCIENCE

DIPLOMA WALLAH

CSE

Jharkhand University Of Technology (JUT)

UNIT -3 (Learning and Development)

Topic 3.1 – "Introduction to Learning & Development in HR using AI & Data Science

3.1 Introduction to Learning & Development (L&D) in the context of AI & Data Science

1. Learning & Development (L&D) refers to systematic efforts by an organisation to improve employees' knowledge, skills, and abilities so that they can perform effectively now and in future roles.
2. In engineering/technical organisations (manufacturing, automation, software) the pace of technological change means L&D is **critical** — skills become obsolete faster; employees must up-skill/reskill continuously.
3. Traditional L&D approaches (classroom lectures, one-size-fits-all training) are becoming **less effective** because they don't tailor to individual needs or use data to measure impact.
4. With AI & Data Science, L&D moves from generic to **personalised learning experiences**: training tailored to what each employee needs, when they need it. (AIHR)
5. Data science enables **analysis of employee performance and feedback data** (e.g., KPI metrics, error rates, quiz results) to identify where the learning gaps are.
6. AI algorithms can detect patterns & trends across large employee populations (for example: technicians who skip module X have higher defect rates) and thus refine training decisions. (ScienceDirect)
7. L&D becomes aligned with business outcomes: e.g., reducing machine downtime, improving quality, faster product

development. Training is not just for “finishing a course” but for strategic impact.

8. Using data, organisations can **forecast future skill needs** (in line with evolving technology) and prepare their workforce proactively. (ASU Learning Enterprise)
9. L&D platforms today integrate **adaptive learning**, where systems adjust content, pace, difficulty based on employee responses and progress. (AIHR)
10. Feedback loops become continuous: after training, organisations measure outcomes (performance improvement, retention) and adjust subsequent training accordingly.
11. L&D also becomes **scalable** – via AI/data-driven platforms, many employees across locations/roles can receive tailored training at once, without heavy manual overhead.
12. Implementing AI-driven L&D requires up-skilling HR/L&D teams themselves (data literacy, understanding algorithms) so they can interpret insights. (SHRM)
13. Ethical, privacy and bias concerns arise: data used for L&D must be handled with care; algorithmic recommendations must be transparent and fair.
14. For diploma engineering students (and future engineers/technicians), understanding how L&D is evolving gives you an edge: you will likely face workplaces where your own training path is data-driven.
15. Summary of 3.1: L&D in the AI/data era is about more than training—it’s about **smarter, measured, individualised development tied to business goals**.

3.1.1 Why Engineering/Technical Organisations Must Embrace AI-Driven L&D

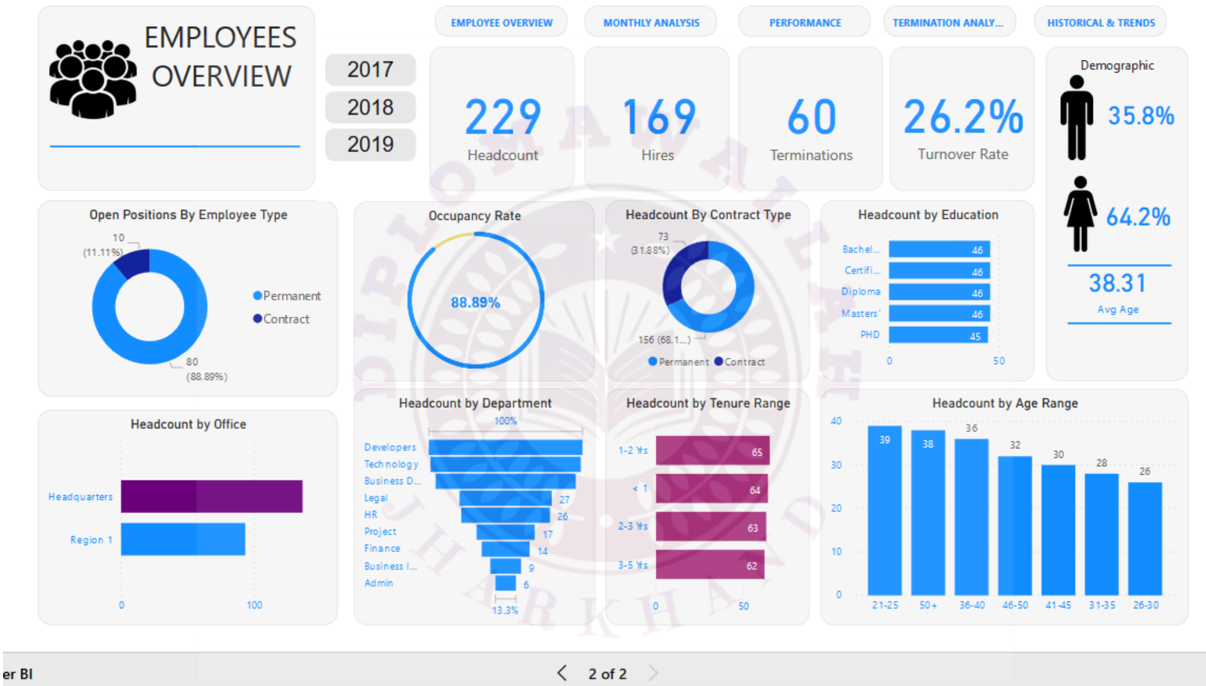
1. **Rapid technology change**: In mechanical/industrial/automation engineering, new machines, software (CNC, PLC, IoT) emerge often. If your workforce training lags, productivity and quality suffer.

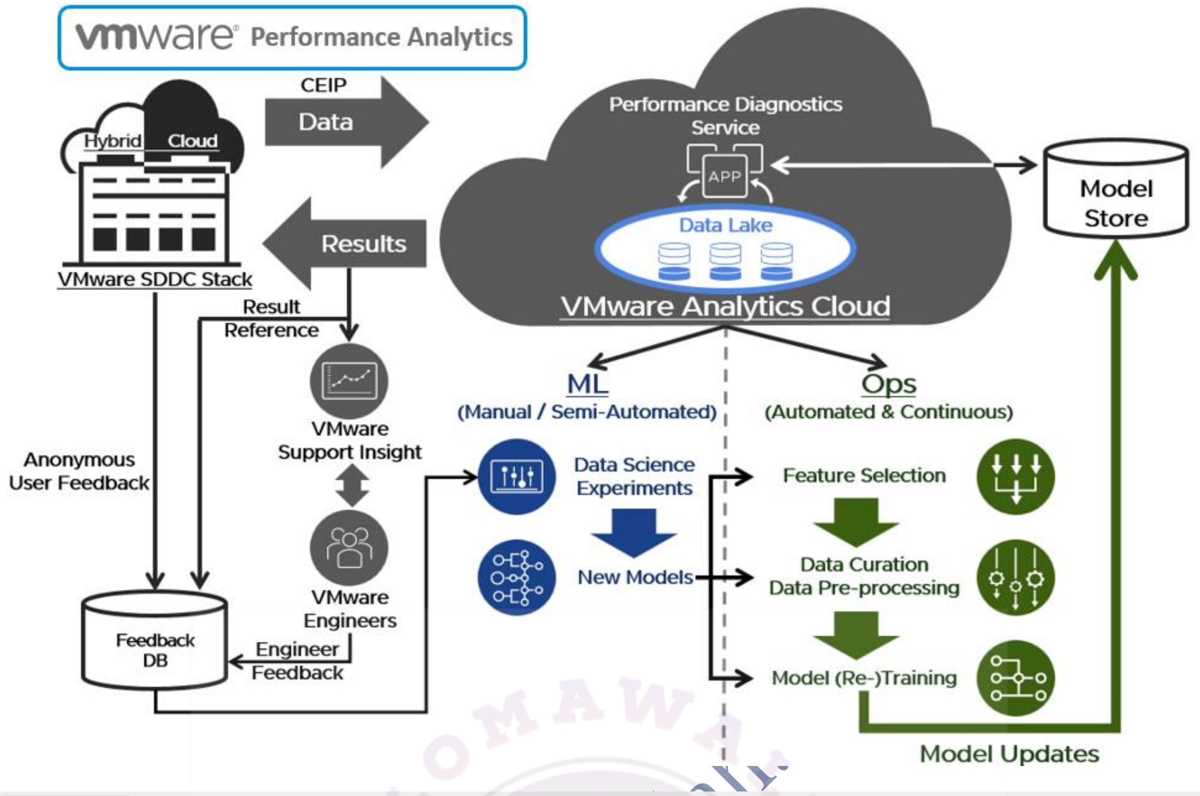
2. **Quantifiable technical KPIs**: For example, error rates on machines, production cycle time, defect percentages—these metrics can be linked to training outcomes and measured.
3. **Skill gap urgency**: A study showed many L&D leaders identify skill gaps plus slow AI adoption as a top challenge. (The Times of India)
4. **Tailored training reduces waste**: If half the team already knows basic PLC programming, giving them all the same training wastes time. AI can personalise who needs what.
5. **Data-driven training decisions**: Using performance & feedback data, organisations can decide which module to offer to whom—thus training becomes strategic, not just procedural.
6. **Adaptive learning in action**: E-learning platform adjusts content for a new engineer who performs poorly on "robot-vision calibration" quiz, offering extra modules automatically.
7. **Better ROI on training investment**: By measuring outcomes (e.g., after training: machine uptime improved by 10%), engineering firms can justify training spend.
8. **Scalability across sites**: A manufacturing firm with plants in multiple cities can deliver consistent training via AI-driven platforms rather than sending trainers to each site.
9. **Future readiness**: As automation, AI, IoT become part of engineering jobs, organisations need workforce ready for next wave of technology—so L&D must prepare them.
10. **Example-real life**: Suppose a company uses CNC machines and introduces "predictive maintenance via IoT". Training reveals many operators lack IoT sensor-data interpretation skills. Data analysis shows these operators have higher breakdown rates. The solution: AI-driven L&D identifies those specific operators, delivers tailored modules on IoT analytics, and monitors post-training outcomes. Result: fewer breakdowns, better productivity.

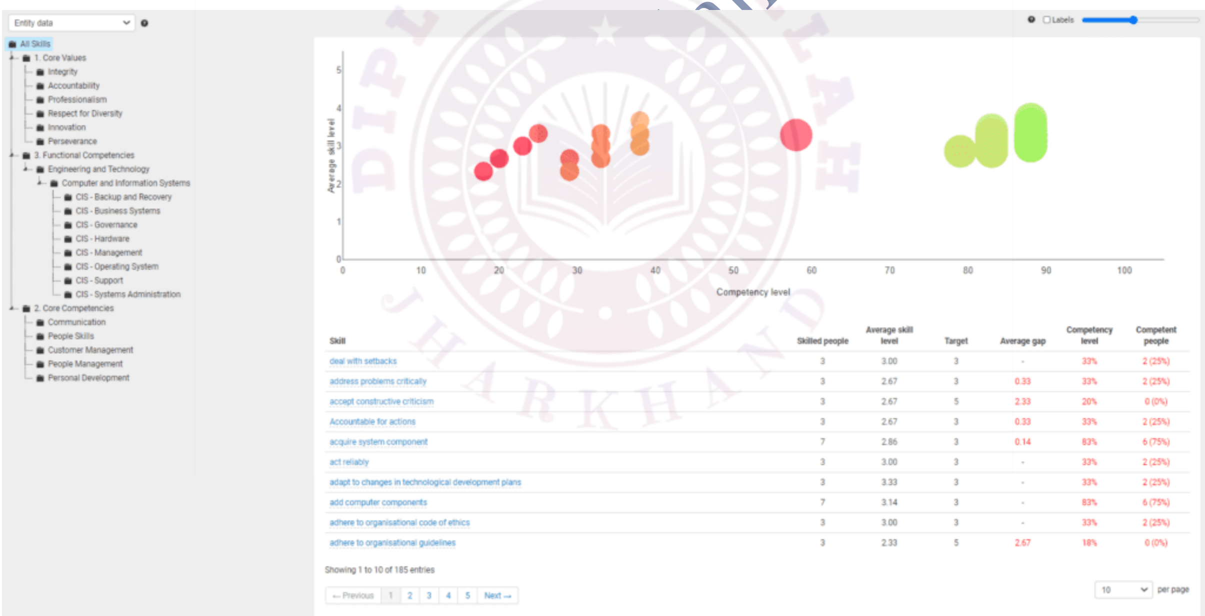
Summary (Hinglish)

"Engineering ya technical organisation mein Learning & Development ka role sirf ek 'training session' tak nahi rukta. Ab AI aur Data Science ki madad se ye **smart, personalised, aur business-aligned** ban gaya hai. Aapko sirf course complete karne ka target nahi, balki woh skill acquire karna hai jo aapki job ko better banaye — machines ko samajhne se lekar IoT data analyse karne tak. Agar organisation apne engineers ko time pe sahi module deti hai, jisme unki khami ho, toh downtime kam hota hai, defect rate girta hai aur productivity badh jati hai. Aise L&D platforms par kaam karna aapko future ke workforce mein competitive banata hai."

3.2 (Analysis of Employee Performance Data & Feedback using Data Science).







3.2.1 What is Performance & Feedback Data? (≈10 detailed points)

1. **Performance metrics**: For engineering or technical roles, this can include cycle-time per part, machine downtime (minutes per shift), defect rate (percentage of faulty products), mean time between failures (MTBF), etc.

2. **Training-related data**: Number of training hours completed, quiz scores, certification passage, time since last training – these feed into performance analysis.
3. **Feedback data**: Includes supervisor evaluations, peer reviews, self-assessments, 360° feedback. For example: "Operator needs improvement in PLC debugging" becomes a qualitative data point.
4. **Behavioural / usage data**: e-learning module completion times, number of support queries raised, number of tool-tips accessed – these generate signals about learning engagement.
5. **Historical data**: Past performance (year-on-year changes), past training history, promotions, role changes – help in trend analysis and forecasting.
6. **Data integration**: Bringing together data from machines (IoT logs), HRIS systems, LMS systems, feedback forms – necessary for holistic view.
7. **Pre-processing**: Cleaning, normalising, anonymising data; dealing with missing values, different formats (CSV logs, Excel sheets, database entries).
8. **Feature engineering**: Creating derived variables like "training hours per defect incident", "time since last certification", "average downtime per shift for operator".
9. **Exploratory data analysis (EDA)**: Using visualisations (histograms, box-plots, scatter plots) to find patterns, outliers, correlations – e.g., operators with >50 training hours had <2% defect rate.
10. **Model building / prediction**: Using regression, classification or clustering to answer questions such as "Which employees are likely to have high downtime next month?" or "Which training module effectively reduces defects?"

3.2.2 Key Points for Data Science Analysis (≈10-15 valid points)

1. **Correlational analysis**: Identify relationships — for instance, does higher frequency of training correlate with fewer faults?

2. **Segmentation & clustering**: Group employees by performance behaviour (e.g., cluster A: high performance + low training; cluster B: medium performance + high training) to tailor interventions.
3. **Predictive analytics**: Build models that forecast upcoming performance issues or identify high-potential employees for advanced roles.
4. **Dashboard & visualisation**: Use analytics tools to display KPIs in real time — such as machine stoppages by operator, training gap by shift, performance drop alerts.
5. **Link training outcomes to performance**: After a learning module, evaluate if participant's defect rate or downtime improved — this closes the loop between L&D and performance.
6. **Root cause analysis**: Data science helps dig deeper: if defect rate increased, is it due to insufficient skill, poor training, machine error or shift scheduling?
7. **Feedback-driven refinement**: Use feedback data (qualitative) combined with quantitative metrics to refine training content – e.g., many employees say "don't understand robot-vision module" → analytics show higher error rates in that area → update module.
8. **Skill-gap heat-maps**: Visual maps showing which employees or teams have which missing skills; for example: "Team B lacks advanced PLC troubleshooting" and "Operators in Shift C have higher downtime due to calibration errors".
9. **ROI measurement**: Use data to show training return-on-investment (ROI) – e.g., after customised training, machine downtime reduced by 20% in 3 months, hence training cost justified.
10. **Continuous improvement loop**: Performance data after each training feeds back into analysis; modules updated, new skill-gaps found, next cycle begins.
11. **Engineering context application**: For a manufacturing line: data may show that operators who didn't complete "robot-arm safety calibration" had 30% more stoppages – training then targeted.

12. **Ethical and data-privacy concerns**: Employee data is sensitive; ensure consent, anonymisation, secure storage, fairness in modelling.

13. **Data quality & integration challenges**: Disparate systems (machine logs vs HR logs) may cause data mismatch; ensuring data lineage is key.

14. **Human interpretation still essential**: Even with models, human experts must interpret insights—just because model predicts high risk doesn't mean human context is irrelevant.

15. **Building analytics culture**: Organisations need to make L&D decisions based on data (not just intuition) – train HR teams, create dashboards, set KPIs aligned to business outcomes.

3.2.3 Real-Life Example (Engineering/Technical Context)

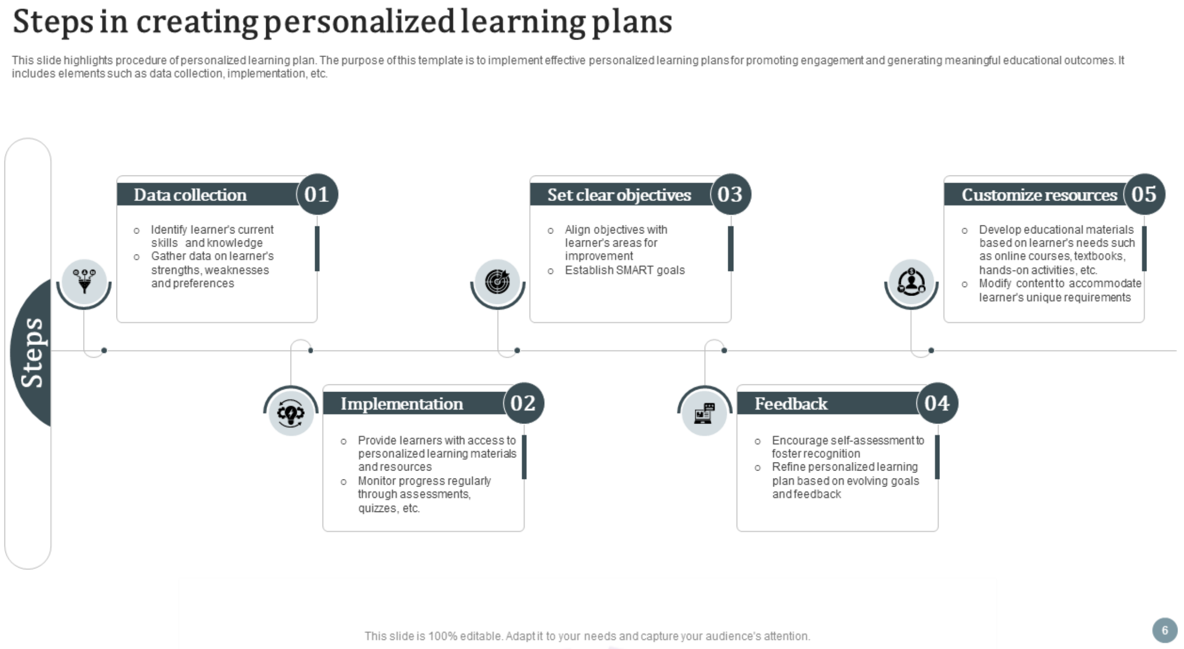
A manufacturing company analysed data from its CNC machine operators. They found:

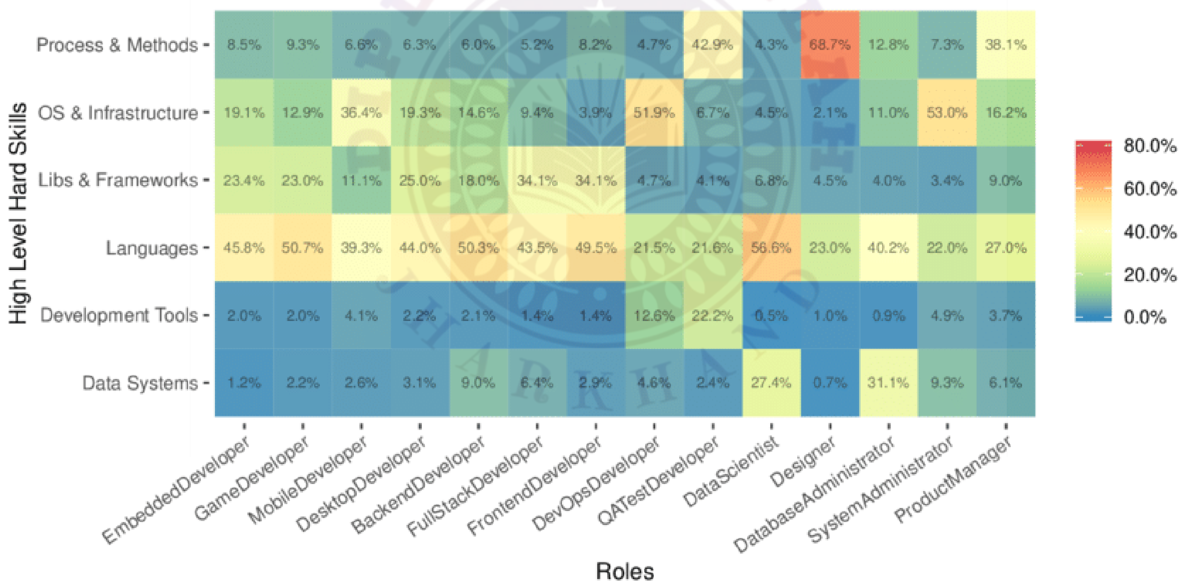
- Operators who had **not** completed the "CNC µ-code advanced" training module had an average of **4.8 downtime hours per week**, while those who completed it had **2.9 hours**.
- Feedback data from operators indicated many felt "less confident in µ-code optimisation".
- Using clustering, they identified a group (Cluster C) of operators with >2 years service but no training in µ-code.
- They built a predictive model which flagged these operators as likely risk of higher downtime in next month.
- They assigned the customised training module to them, tracked progress via dashboard. After 3 months, the average downtime for that group dropped by 18%.
- This case ties performance data + feedback + custom training = improved business metric (downtime)
- Engineering/technical takeaway: Use data + feedback to find real skill-gaps and align training accordingly.

3.2.4 Summary (Hinglish)

"Engineering ya manufacturing organisation mein kaam karte waqt success sirf training lena nahi balki **uske baad dekhna hai ki**

performance sudhaari hai ya nahi. Data science aur feedback analytics ka use karke hum yeh jaan sakte hain ki kaun sa employee ya team kis skill mein weak hai, aur kaun si training sabse zyada beneficial hogi. Phir training ke baad performance data dubara check karte hain — agar machine downtime kam hua, defect rate gira, to training ka impact dikha. Isi process se L&D casual session se business-oriented engine ban jata hai."





3.3 Identification of Skill Gaps & Creating Customized Learning & Development Plans

1. A **skill gap** exists when the skills required for a job (current or future) are higher or different than the skills the employee currently has.
2. Identifying skill gaps is foundational for effective L&D: without knowing what's missing, training may be irrelevant or wasteful.

3. In engineering/technical settings, skill gaps may show up as: outdated machine-programming skills, lack of IoT/data analytics knowledge, safety protocol weaknesses, etc.
4. Skill gap identification uses multiple sources: job descriptions, competency frameworks, performance metrics, feedback, training history.
5. With the help of AI and Data Science, organisations can **automatically map** the skills required (from role/job profiles) with existing employee skill profiles (from data) to locate gaps. (MIT Sloan)
6. Once gaps are identified, a **customised Learning & Development (L&D) plan** means training is tailored for each individual (or group) based on their specific gaps, learning style, pace, and role.
7. Customised L&D plans result in more efficient training, higher engagement, better knowledge retention, and improved alignment with business outcomes. (workramp.com)
8. The process of designing customised plans involves: assessment → gap analysis → content selection → delivery → monitoring & evaluation.
9. AI tools help create **personalised learning paths**: e.g., skip modules the employee already knows, accelerate modules for urgent gaps, suggest more advanced material for high performers. (Docebo)
10. In engineering contexts, tracking progress is measurable: e.g., number of defects per shift, machine downtime, first-time success rate, etc. Training effectiveness can be tied to these KPIs.
11. Data & analytics help evaluate whether learning plans are working: e.g., post-training error rate dropped by X%, time-to-competency reduced by Y%. (University of Phoenix)
12. Organisations must maintain **up-to-date** competency frameworks because technology evolves quickly; a skill gap today may become obsolete tomorrow.
13. Customised L&D plans are scalable: via digital platforms, many employees across roles/locations can be handled. AI assists in scaling without losing personalisation. (workramp.com)

14. Challenges: data quality (accurate employee skill data), change management (employees willing to follow customised plans), content relevance, ensuring human-machine balance.
15. Strategic benefit: When skill gaps are proactively addressed and customised training deployed, organisations become more agile, competitive, and able to adapt to industry changes (especially in automation/engineering).

3.3.1 Detailed Points: How to Identify Skill Gaps & Design Customised L&D Plans (with Engineering Example)

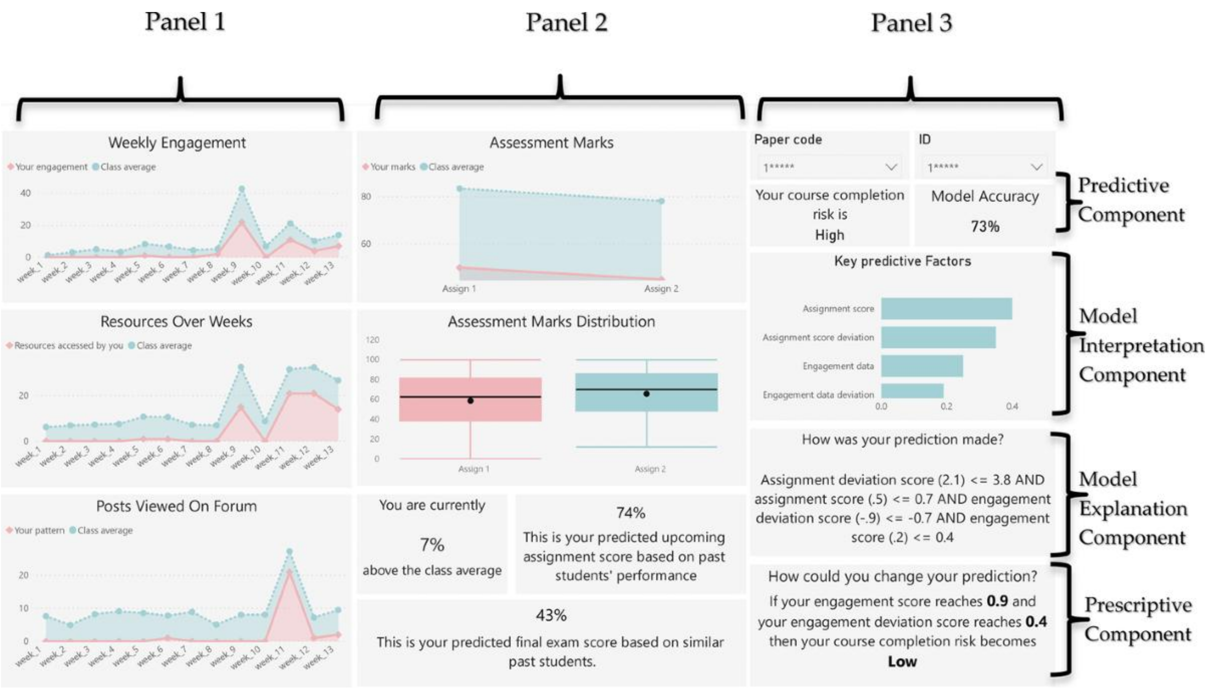
1. **Define required skill profile**: For each role (e.g., CNC Technician, Automation Engineer), list all required skills: e.g., PLC programming, robot calibration, predictive maintenance analytics.
2. **Collect existing employee skill data**: Use past training records, performance data, assessments, certifications, feedback, self-ratings.
3. **Use AI/data-science tools to compare**: Align required skills with existing skills, compute gap metrics (e.g., "Employee A lacks 'robot calibration'", "Employee B lacks 'data analytics for machine performance'"). (MIT Sloan)
4. **Prioritise gaps based on business impact**: Some gaps may be critical (e.g., safety-related, machine downtime) and should be addressed first. (Robert Half)
5. **Design customised learning path**: For each gap, select content (e-modules, workshops, on-job practice), define sequence, timeline. E.g., for a technician lacking data analytics: module1 – "Introduction to sensor data", module2 – "Interpretation of machine analytics", module3 – "Apply analytics to reduce downtime".
6. **Consider learning style & speed**: Some employees prefer video modules, others hands-on labs; customise accordingly. AI can recommend based on past learning behaviour. (workramp.com)
7. **Deploy & monitor**: Use LMS or digital platform to deliver training; track progress, completion, quiz results, on-job performance changes.

8. **Evaluate training effectiveness**: Measure outcomes: e.g., before training machine downtime was 6 hrs/week, after training 4 hrs/week; or defect rate reduced by 20%. Use data to assess ROI.
9. **Feedback & adjust**: If training does not deliver expected results, revise plan: maybe module lacked depth, or employee needed more practical work. Continuous improvement.
10. **Engineering/real-life example**: A manufacturing unit found via analytics that operators lacking "sensor-data interpretation" had higher number of unplanned stoppages. They identified this skill-gap, designed a 3-week digital-plus-lab training plan, and within 2 months downtime reduced. Data science was used to identify gap, design plan, measure result.

Summary (Hinglish)

"Ab training ka matlab sirf classroom session nahi hai. Pehle dekhna zaroori hai ki *kaun-kaun se skills missing hain* — yaani skill gap. Fir un skills ke hisaab se *customised learning plan* banao — jisme har vyakti ko uski need ke according training mile. Engineering ya technical field mein ye bahut important hai, kyunki machines, automation aur data analytics tezi se badal rahi hain. Agar aapne proper identification aur customisation nahi kiya, toh training ka fayda kam hoga. AI aur data science ki madad se ye process efficient, measurable aur business-aligned banta hai."

3.4 Continuous Monitoring, Feedback & Evaluation of Learning Programmes



Panel 1
Panel 2
Panel 3
Weekly Engagement
Your engagement Class average
Resources Over Weeks
Resources accessed by you Class average
Posts Viewed On Forum
Your pattern Class average
Assessment Marks
Your marks Class average
Assign 1
Assign 2
Assessment Marks Distribution
You are currently
7%
above the class average
74%
This is your predicted upcoming assignment score based on past students' performance
43%
This is your predicted final exam score based on similar past students.
Paper code
ID
Your course completion risk is
High
Model Accuracy
73%
Key predictive Factors
Assignment score
Assignment score deviation
Engagement data
Engagement data deviation
How was your prediction made?
Assignment deviation score (2.1) <= 3.8 AND assignment score (.5) <= 0.7 AND engagement deviation score (-.9) <= -0.7 AND engagement score (.2) <= 0.4
How could you change your prediction?
If your engagement score reaches 0.9 and your engagement deviation score reaches 0.4 then your course completion risk becomes Low
Predictive Component
Model Interpretation Component
Model Explanation Component
Prescriptive Component

Brigid.ai
Employee Profile
HOME > EMPLOYEE PROFILE
Back
Employee
Oakleigh Thomas
Email
o.thomas@company.com
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Department
Cork
Office
Office B
Group
Group 3
Level
Team Leader
Step
1
Manager
Xena Williams
Start
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Finish
05.12.2021
Total Days of Learning
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Potential
0,87
Potential
0,90
Learning Agility
29,82
Progress %
Tests
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Zones of Attention
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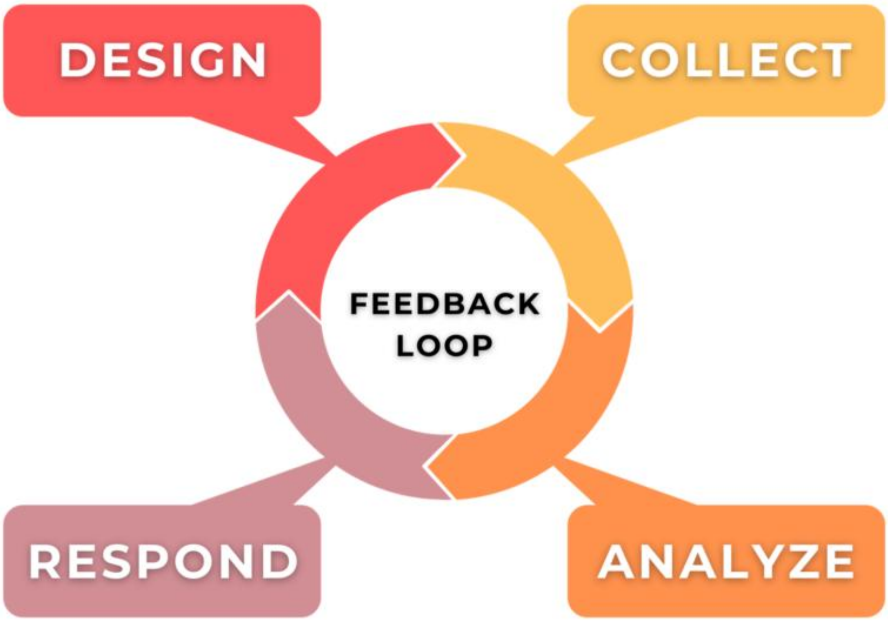
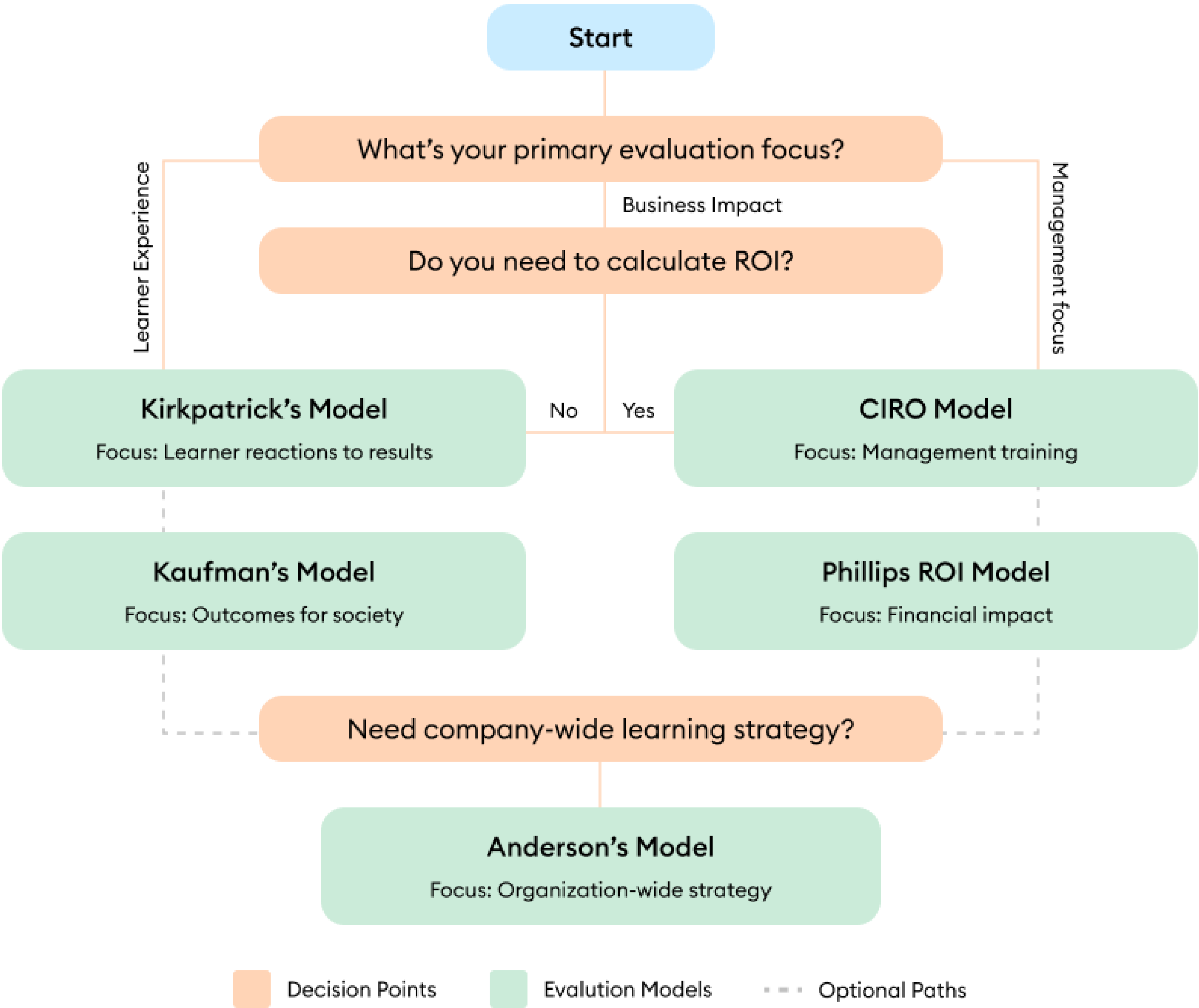
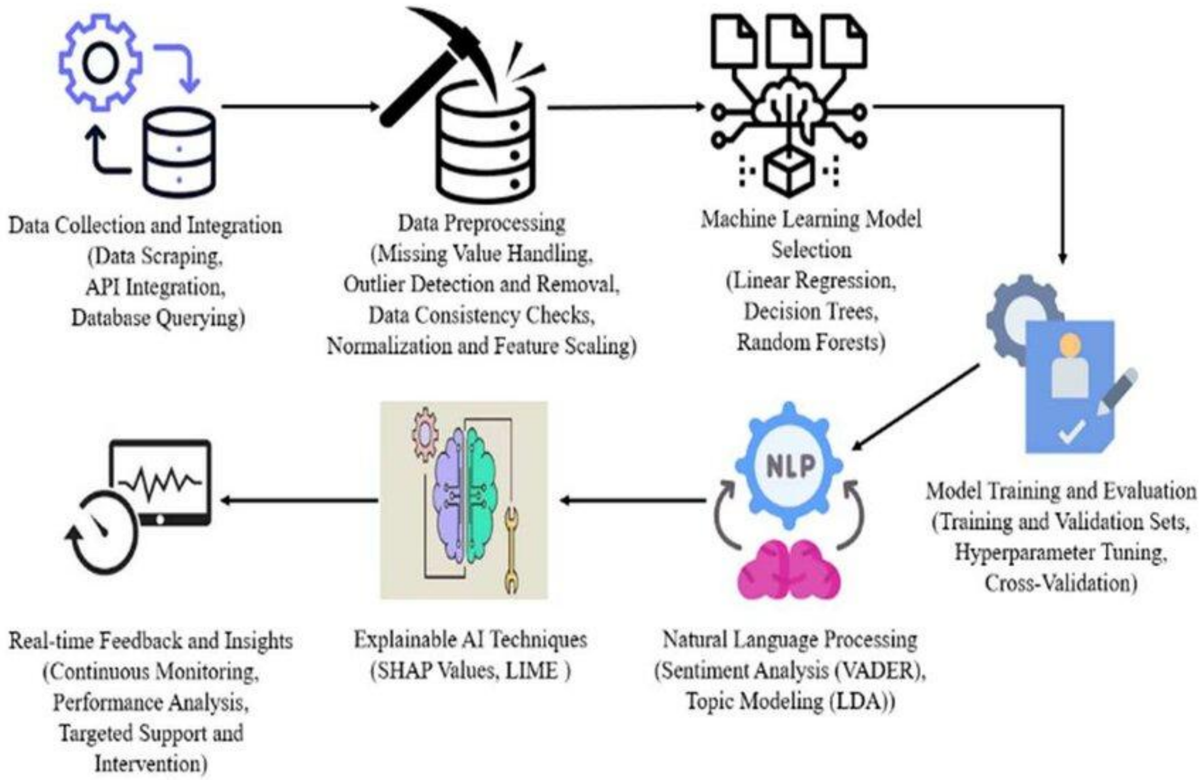
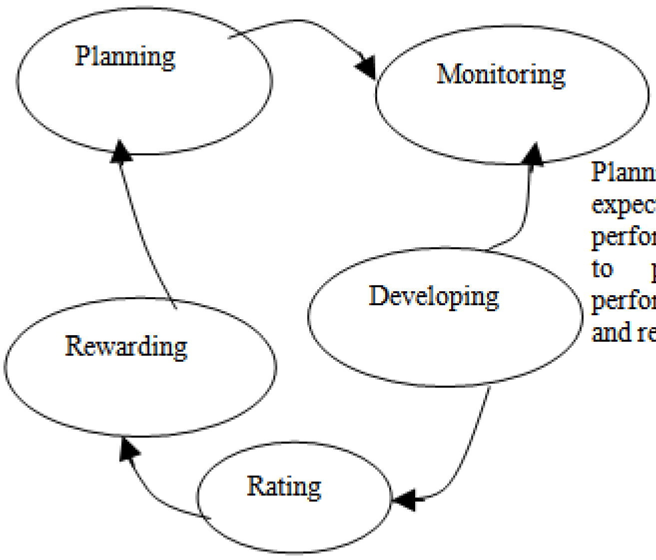


Decision Tree: Choosing the Right Training Evalution Model







Planning work and setting expectation, continually monitoring performance, developing the capacity to perform periodically rating performance in a summary, fashion and rewarding good performance.

Source: *Nitschke (1995) The Revisions made to the federal government performance appraisal and awards regulations support sound management principle. About.com News letter.*

1. Once a customised L&D plan is deployed, the next step is **monitoring** the trainee's progress: module completions, quiz scores, on-job performance changes, engagement with training materials.

2. Feedback collection is essential: after training modules, gather trainee feedback (satisfaction surveys), peer feedback, supervisor observations.
3. Use data science to **evaluate training effectiveness**: compare pre- and post-training performance metrics (e.g., defect rate, machine downtime, cycle time) to measure impact.
4. Analytics layers: descriptive (what happened), diagnostic (why it happened), predictive (what might happen), prescriptive (what should be done) in L&D context. (gsdcouncil.org)
5. Use dashboards to visualise trends: e.g., learning completion vs performance improvement, drop-off rates, time to competency.
6. Identify learners who are lagging and trigger **intervention**: additional modules, mentoring, hands-on practice.
7. Continuously update the learning content based on feedback & performance data: modules may need revision if they don't lead to expected outcomes.
8. Establish **key performance indicators (KPIs)** for L&D such as time to proficiency, improvement in key business metrics, training completion rate, learner satisfaction.
9. Ensure alignment with business outcomes: training must tie back to organisational goals (e.g., reduction in stoppages, improved safety compliance).
10. Maintain a continuous improvement loop: Monitor → Feedback → Evaluate → Adjust → Deploy.
11. In engineering/technical fields, measurement is more direct (machine metrics, production output) so the evaluation phase can be robust and quantitative.
12. Also monitor long-term effects: retention of skills, behaviour change over months, impact on promotions or internal mobility.
13. Use predictive analytics to anticipate when refresher training may be needed (skill decay) or new skill needs will emerge. (Cornerstone OnDemand)
14. Feedback culture matters: employees must feel safe giving honest feedback; transparency builds trust. (SHRM)

15. Ethical considerations: ensure data used in evaluation is secure, anonymity preserved where needed, and the focus is developmental not punitive.

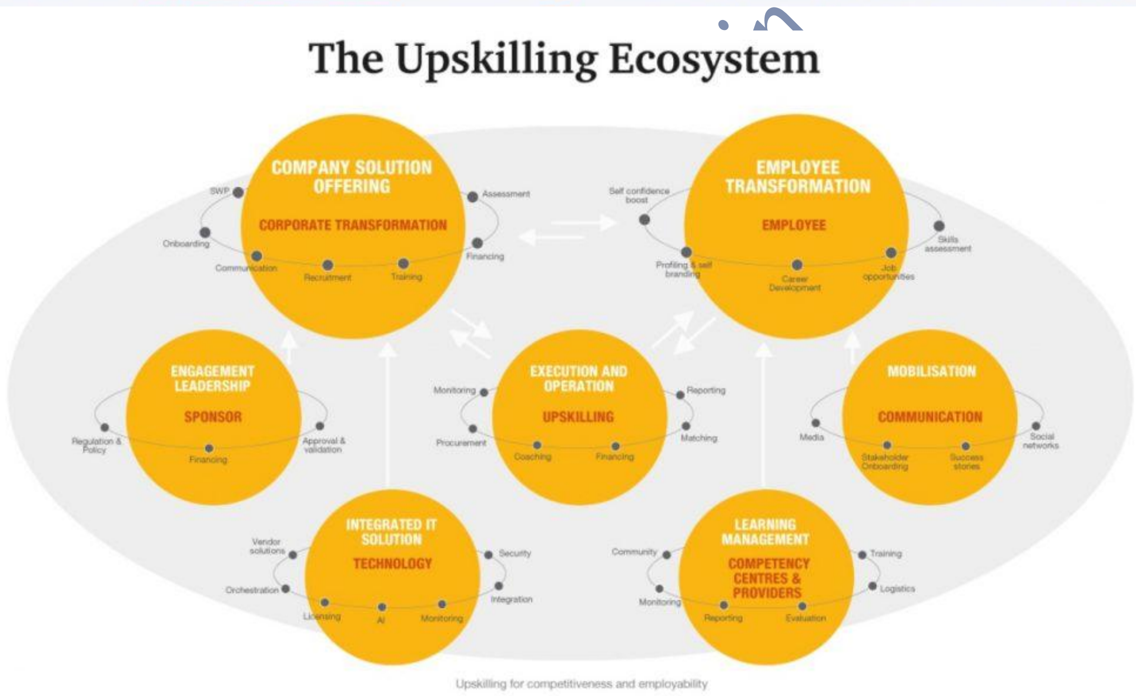
3.4.1 Detailed Points: Implementation of Monitoring & Evaluation in Technical Organisations

1. Define baseline metrics: before training begins, collect current values (e.g., average machine downtime 10 hrs/week, defect rate 5%).
2. Set target outcomes: e.g., after training defect rate to drop to 3%, proficiency in PLC troubleshooting within 8 weeks.
3. Instrument training platform and on-job systems to feed data into central analytics (LMS data + machine logs + HR data).
4. Create dashboards for HR and line managers showing e.g., "Operators with training > 80% completion" vs "Operators with < 80% and higher downtime".
5. Schedule regular feedback points: after module, after 1 month on-job, after 3 months on-job. Collect via surveys and interviews.
6. Use statistical tests (like paired t-tests) or pre-post comparisons to measure if training made significant differences.
7. Identify drop-off patterns: if many trainees stop after module 2, investigate content, platform, engagement.
8. Correlate training metrics with business outcomes: e.g., trainees who completed module "Robot-vision calibration" had 18% fewer stoppages.
9. Use predictive modelling: feed data on trainees' quiz scores, module completion, prior performance to predict who might need extra support.
10. Loop back into content design: if analytics show module 4 is underperforming, revise it or replace with practical lab session.

3.5 Best Practices, Challenges & Future Trends in AI-Driven L&D


Learning and Development in 2025
Microlearning
Delivering bite-sized content for immediate application and knowledge retention.
Skill Agility
Continuous skill development to adapt to technological changes and market demands.
Immersive Learning
Utilizing AR/VR technologies for hands-on, risk-free learning experiences.
AI-Driven Personalization
Tailoring learning paths using AI to enhance engagement and efficiency.
Data-Driven Insights
Leveraging analytics to optimize learning strategies and measure effectiveness.


Learning and Development Trends 2025
Learning Analytics
Tackling FOBO
AI-Powered Personalized Learning Paths
Upskilling and Reskilling
Learning and Development Trends 2025
Microlearning
Immersive Learning with AR and VR
Soft Skills in the AI Era
Learning in the Flow of Work
Continuous Learning Culture



Best Practices:

- Align training goals with business KPIs (not just training completion).
- Ensure learning paths are personalised, adaptive and role-specific.
- Embed learning into the flow of work (just-in-time learning) rather than isolated sessions.

Challenges:

- Data silos and poor data quality hinder analytics.
- Resistance from learners or managers to new digital/AI-driven methods.
- Keeping content updated especially in fast-changing technical fields.
- Privacy, ethics and fairness in AI-driven decisions.

Future Trends:

- Immersive technologies (VR/AR) for hands-on training in technical fields.
- AI content creation and recommendation engines adapting in real time.
- Skills-intelligence platforms that continuously map skills, gaps and jobs. (coassemble.com)

Summary (Hinglish)

"Jab aapne ek tailor-made learning plan bana liya, tab kaam khatam nahi hota — sabse important phase hai usko **monitor aur evaluate** karna. Matlab, training ke baad check karo ki kya asli performance improve hui hai? Data aur analytics se ye kaam hota hai. Agar lagta hai kisi module se result nahi mil raha, to usko revise karo. Plus, technical organisations mein ye cycle-bar-bar chalta rehna chahiye kyunki machines, systems aur skills hamesha badalte hain. Aaj 'training-session' nahi balki **continuous learning engine** ki zaroorat hai."

Diploma Wallah

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