

Realizing value from AI/ML

Increasing velocity and consistency through MLOps

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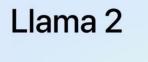
Al is becoming a part of our everyday lives



Chat GPT



watsonx Code Assistant















Every business has a use for AI/ML



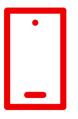
Healthcare

- Increased clinical efficiency
- Faster/better diagnosis
- Improved outcomes



Financial services

- More personalized services
- Improved risk analysis
- Reduced fraud
- Better predictions



Telcos

- Better customer insights/experiences
- Optimized network performance & operations
- Improved threat detection



Insurance

- Automated claims processing and handling
- Usage-based insurance services



Automotive

- Autonomous driving
- Predictive maintenance
- Improved supply chains

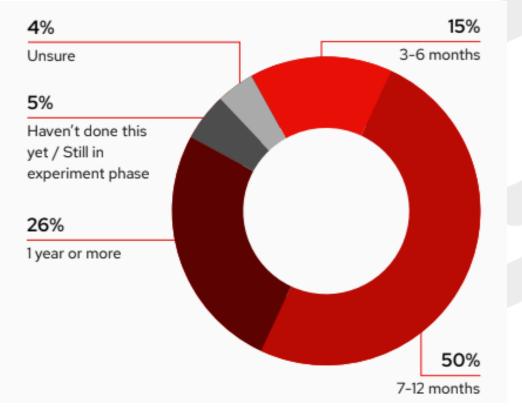




Operationalizing AI is still a challenging process

Half of respondents (50%) say their average AI/ML timeline from idea to operationalizing the model is 7-12 months.

What is the average AI/ML timeline from idea to operationalizing the model?





The reality of enterprise IT environments

Infrastructure	Applications	Processes and people
50% of apps being run by enterprises are on hybrid cloud. 41%	Al/ML Analytics Serverless	Developer tools
claim that IT Agility is one of main		C/D
reasons to run apps on hybrid cloud ¹ ::	Cloud-native services and microservices	Methods and practices
Bare metal Virtualization Private Edge Public cloud cloud	Java™ .Net ISV	2-8 Culture and policy





The reality of enterprise IT environments

Infrastructure	Applications	Processes and people
of apps being run by enterprises are on hybrid cloud.¹ 41% claim that IT Agility is one of main reasons to run apps on hybrid cloud¹	Al/ML Analytics Serverless Cloud-native services and microservices	Developer tools CO Methods and practices
Bare metal Virtualization Private Edge Public cloud cloud	Java™ .Net ISV	Culture and policy





Complexities of operationalizing models

build models

"a consistent application

platform for the management of existing, modernized, and cloudnative applications that runs on any cloud."

machine data monitoring resource verification management data collection configuration serving larger system infrastructure analysis tools feature extraction process management frameworks to

(Adapted from Sculley et al., "Hidden Technical Debt in Machine Learning Systems." NIPS 2015

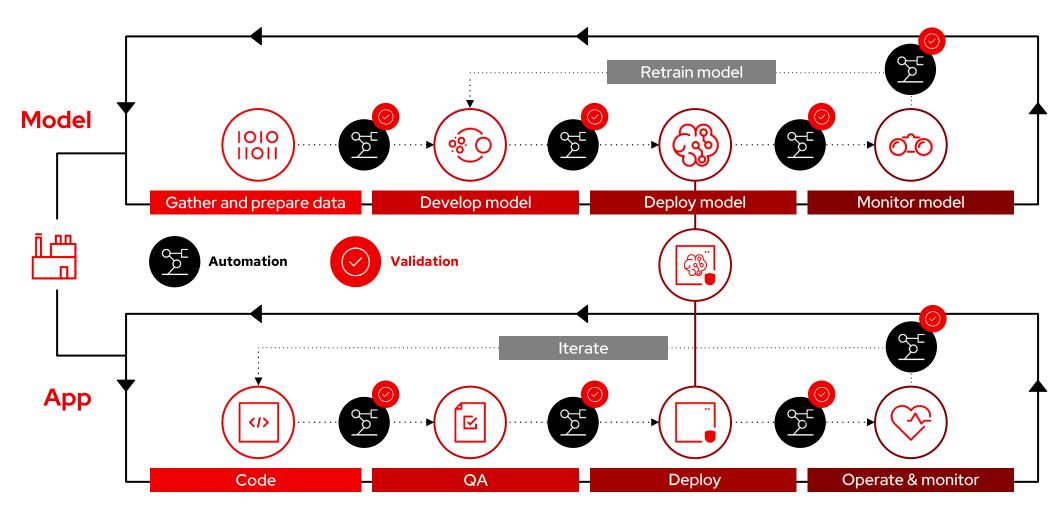
"a common abstraction layer across any infrastructure to

give both developers and operations teams commonality in how applications are packaged, deployed, and managed."





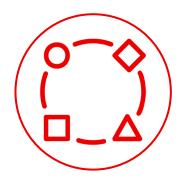
Lifecycle for operationalizing models





Workload management

Training jobs require variable compute resource requirements with access to accelerators. Serving requires the ability to scale on demand based on inference requests





Orchestration

Consistency in repeatable and secure pipelines for data ingestion and processing through to model build and staging. Deployment across multiple platforms often leads to varying methodologies.



Training, Serving & Monitoring



Platform and vendor complexity

Machine learning models typically optimized for specific hardware platforms which vary based on each model and use case. Adopting emerging technologies introduces risk.



Fleet management

Insights into model performance and quality are inconsistent and varied across the enterprise. Lack of model transparency increases risk within deployments.









Rollout coordination

Friction in handoffs between data science, application developer, and devops teams leads to high quality experiments never making it into production.



Challenges

Model Lifecycle



Software supply chain

Multiple orchestration platforms and bespoke build processes introduce risk into the software supply chain through lack of auditability, traceability, and transparency.



Agility

The ability to maximize value out of Al/ML is driven by more and more experiment iterations. Manual process and interventions reduce overall volume of runs.



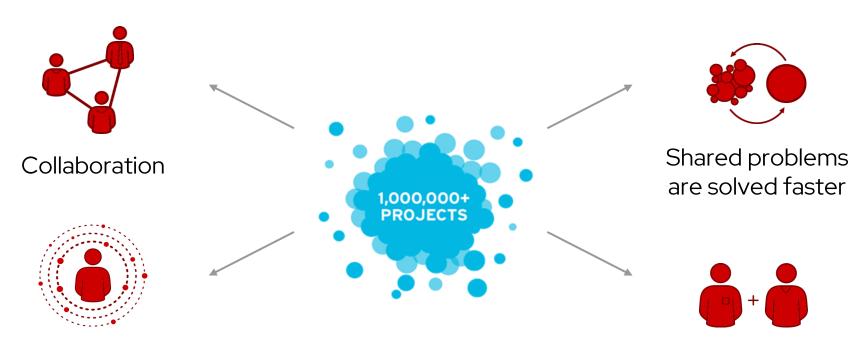
Loss of confidence

Repeated failures in model rollout leads to lack of confidence in AI/ML which limits the overall potential of the business.





AI/ML innovation driven by open source



Transparency/Security (both access and the ability to act)

Working together creates standardization





- Secure, composable, and compliant platform with a consistent administration experience across platforms
- Support for core AI/ML libraries, hardware, and accelerators



- Simplified deployment, scaling, and management of AI/ML training and serving
- Cloud-hosted or self-managed options across data center, public cloud, and edge
- Extend DevOps to the entire ML lifecycle, and enable collaboration across teams

Red Hat Ansible Automation Platform

- Build, provision, and manage applications and infrastructure across platforms
- Automate application deployments, installations, upgrades, and day-to-day management repeatable and reliable







Red Hat OpenShift Al provides an integrated platform for building, training, tuning, deploying and monitoring Alenabled applications, predictive and foundation models securely and at scale across hybrid-cloud environments.

Built on top of Red Hat OpenShift delivers a consistent, streamlined and automated experience to help organizations rapidly innovate and deliver Al-enabled apps into production.





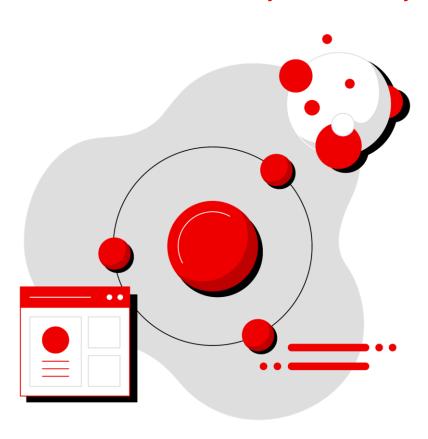






Use the power of enterprise-ready open source

Set yourself and your teams up for success with a solid foundation



The AI/ML ecosystem is complex

- Technologies are rapidly evolving
- Vendor landscape is constantly changing
- No single vendor can provide everything you need
- Organizations need a supported, secure enterprise version of open source tools and technologies for AI/ML
- Success with AI/ML starts with having a solid foundation to build upon

