Expanding Access to AI in the Enterprise: Designing Tools for Non-Technical Professionals in Regulated Industries [1]

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Abstract

Across the globe, AI (Artificial Intelligence) is revolutionizing business, but industries that fall under strict regulation are still facing many impediments in terms of compliance, worries related to morality, and inaccessibility for individuals who are not technically oriented. The majority of AI tools are put in place for the most skilled users, thus, the rest which consists of compliance officers, healthcare administrators, and other domain specialists are left out. This writing drafts a roadmap which comprises usability, interpretability, and compliance-by-design as the fundamental principles that could aid the breakthrough of AI in regulated scenarios.

We hold the view that the use of the responsible AI will not only be of the technical strength kind, but it will also require the easy-to-use, communication-friendly, and embedded safeguards out of which the last one is by default. For instance, a healthcare non-technical compliance officer through the help of AI can be able to analyze safety reports of patients and at the same time keep the audit readiness. The key point of this research is the design of a framework which is a balance between accessibility and accountability that represents the real possibilities of enterprises, professionals, and policymakers as a result of this study.

This study addresses the barriers that limit AI adoption in regulated industries by introducing a framework grounded in usability, interpretability, and compliance-by-design. The research advances responsible AI by making tools accessible to non-technical professionals such as compliance officers and healthcare administrators, ensuring accountability while enabling enterprises and policymakers to harness AI with confidence.

[1] How to cite this paper: Kohli, R. (2026). Expanding Access to AI in the Enterprise: Designing Tools for Non-Technical Professionals in Regulated Industries; *PM World Journal*, Vol. XV, Issue V, May.

Keywords: *Artificial Intelligence (AI), Democratization of AI, Compliance-by-design, Usability, Interpretability, Regulated industries*

1. Introduction

Context & Motivation

AI is currently a major component of digital transformation in all sectors. It enables them automate their processes, derive insights and better decision making. This potential is particularly appealing in highly regulated industries, such as healthcare, finance, insurance and law. In this case, high throughput of the information could substantially increase the efficiency and accuracy (Dwivedi et al., 2021). But the acceptance of AI in these fields is a continued challenge. The majority of AI tools are developed for technical professionals, and would assume a certain level of coding, data science or machine learning expertise to use effectively (Herm et al., 2022). This design decision ignores those professionals in the domain who know they need AI and know how to use AI effectively, but aren't able to program tools of today.

Problem Statement

1. The real hurdle isn't whether businesses can deploy AI, but how they can do it in a way that the non-experts can trust and relate to, especially in regulated contexts. Current limitations include:
2. Usability deficiency: The majority of AI tools are made for tech-savvy users, which precludes experts from using them without intervention.
3. Trust: Not well-understood models lead to mistrust in AI-supported decision making, particularly in sensitive domains (Bach et al., 2023). Compliance risks: Regulatory and ethical considerations are often an afterthought, not a priority in development.

Objectives

This paper aims to do the following to address these challenges:

- Open it up: Make AI tools accessible to enterprise employees, with or without coding or data science expertise.
- 'Embed compliance: This is the need to ensure that both ethical and regulatory considerations are embedded at the design stage of an AI tool' (Jin et al., 2021).
- Exemplify principles: A sample case is provided to illustrate the human-centered and compliance-focused models.

What's New

A The novelty of this work is twofold. On the other hand, it recentralizes the design of AI to become centered on non-technical professionals by reframing explainability and usability in ways that enable non-experts to meaningfully interact with an AI system. Framing the second fundamental question on which design alone could tackle regulatory compliance: So “regulatory compliance” cannot be a (regulatory) barrier therein, but a factor of trust and adoption. Therefore, these contributions address a void in the literature at the intersection of human-centered design, explainable AI and regulatory technology, by providing a solution that allows companies to democratize the use of AI but still being responsible users of AI.

2. Literature Overview

2.1 Making AI Easy for All People at Work

AI in big firms has grown past just the expert teams, as many now aim to use it daily by most staff. The change from "AI for those who know a lot" to user-friendly, helper tools turns the focus on design: make it easy to use (talk to it, clear steps) but keep it accurate and checked. One view from MISQ shows that the best use of AI happens when it helps, not replaces, human decisions—making clearness, control, and teamwork key for business tools (Rai, Constantinides, & Sarker, 2021).

2.2 Talking Clear and Following Rules in Set Areas

In fields like money, health, and law, being clear isn't just nice—it's often a must by law. A review shared at ACM FAccT points out that many policies mention the need for clearness but don't give exact guidance, making it hard for teams creating products (Nannini, Balayn, & Smith, 2023). A study in 2024 at ACM FAccT shows how working back and forth with those making laws and users leads to better, clearer rules about clearness for systems in use—just what everyday folks in these strict fields need (Nahar et al., 2024).

2.3 Safe AI and Strong Safeguards

At IEEE events, the talk is that trusty AI needs both tech checks (like safety, strength, track of data) and big rules (like who's in charge, who answers for what). Recent articles from IEEE Computer talk about full plans for dealing with AI risks and keeping trust in real use, saying that people—and as a result, business folks—won't trust AI if it's not clearly safe with checks and policies from the start (IEEE Computer, 2024; Schneier & colleagues, 2023). These papers push for rules made right from the start and risks thought of always that guide what tools are needed for everyday staff.

2.4 AI and People Working Together, Making Big Choices

From a boss's view, HBR shows that the big win with AI today comes from mixing human thoughts with AI help, not just by automating things. Creative and smart systems can improve ideas and decisions, but only if interfaces show the logic and involve humans throughout (HBR, 2023). This links straight to choices in making business tools: easy explanations, options to see more if needed ("drill-down" for checking), and team-based steps (like checklists, okay steps) that build up—not overlook—expert skills.

3. Conceptual Plan

Making AI tools for people who don't work in tech and work under strict rules needs more than just making machine learning tools easier to use. We need a plan that looks at how easy it is to use, if people can trust it, and if it follows rules, all while fitting well into a company's setup. This plan must think about the real world of pros who do not know coding but have big jobs in health, money, law, and insurance.

Building this plan, insights came from a design science method (Hevner et al., 2004, added to in MISQ 2021) and matched with real cases of using AI in health rules, money risks, and insurance checks. The ideas here are strong—they come from real work seen in ACM and IEEE papers, and thoughts from HBR and MISQ.

The plan has two big parts:

Design rules for simple AI tools.

How to fold it into companies.

Both pieces give a full guide to bring more people to use AI while keeping it safe and trusted.

3.1 Design Rules for Simple AI Tools

Simplicity and Ease

The big challenge in sharing AI widely is how easy it is to use. Old AI tools need strong coding skills (like in Python, R) and knowing stats, which blocks non-tech people. In its place, simplicity means making tools as clear as apps we use every day but strong enough for big company tasks.

Methods:

- Talking in normal words. Letting users ask data and models in easy talk (like, "Show odd safety reports from last quarter").

- Drag-and-drop steps. Giving clear blocks for tasks like cleaning data, training models, and making reports.
- View changes. Making views that show what's key for a rules officer versus a money checker.

For example, cases in health AI tools (Topol, 2020; Nahar et al., 2024) show that ease links straight with how much doctors use it. Tools that were hard with tech talk were not used much, but those with clear views and step-by-step paths let more people join in.

So, simplicity doesn't mean making AI dumb; it's about cutting barriers between users and smarts.

Explanation

Being able to explain decisions is key for trust. In areas with tight rules, pros can't just take what AI says—they need to know why it decided that.

Key ways include:

- **Layered reasons.** Giving big views (simple summaries) and deep details (important bits, model weights) for those who need them.
- **Visual stories.** Charts or links showing how inputs shape guesses.
- **Hints in context.** Putting meanings, warnings, and rule links right in the results.

If a rules officer gets an alert about a problem, the system should explain not just the odd thing but also how it fits with rules. This fits the "explain by design" idea by Nannini et al. (2023) and is part of IEEE's trust plan (2024).

Without being able to explain, groups risk fines, loss of trust, and damage to name. By putting reasons at every step, tools help careful choices, not hidden moves.

Rules First

Unlike AI for all users, business AI in tight rule areas must think rules first. Rules can't be an add-on; they need to be part of the tool from the start.

This means putting in things like:

- Logged model uses. Every result is noted, marked with time, and linked to data used.
- Bias checks. Regular checks for fair guesses across groups.
- Workflows for rules. Set steps that match HIPAA, GDPR, Basel III, or area rules.

For instance, bank cases show that overseers now often need live reports (Rai et al., 2021). Tools that build in rule steps make it easier for users, making sure rule needs are met from the start, not just tacked on.

This idea lines up with Schneier et al. (2023), who say real AI trust needs governance built into design, not just checked by outsiders.

Work Together

AI is sometimes seen as a replace for human thought. But in areas with big risks, we can't let AI make all choices. Instead, AI tools should help people and machines work together.

This means:

- Helping with decisions, not replacing them. AI gives ideas, but pros make the final call.
- Shared tools. Tools that let teams mark, talk over, and check AI ideas together.
- Paths for doubts. When AI isn't sure, it sends cases to human experts, not making choices alone.

Evidence from handling money risks (Brynjolfsson et al., 2021) shows mixed human-AI work does better than just humans or just AI. Working together makes sure AI adds to human skill while keeping things answerable.

3.2 How to Make it Fit in Companies

While design rules shape how users see it, how well it fits into companies decides if tools will work big scale. Simple AI answers must be more than easy to use—they must be safe, able to grow, and fit with company rules.

Safety

AI systems in areas with tight rules often handle sensitive info (like health records, money moves). End-to-end safety is key. This includes:

- Coding data when stored and sent.
- Role-based rules to block users who should not get in.
- Steps to check all the time so no one can attack or steal data.

The latest IEEE study (2024) says safety is key to trust in AI, not just an extra.

How Big It Can Get

Big places need ways to deal with huge, mixed data and many people at once. This is hard both in tech and team ways.

Using the cloud, split set-ups, and changeable designs lets tools grow as needed. A case from MISQ (Rai et al., 2021) shows that platforms—not one big system—work better for places with rules to follow.

Working Together

AI tools need to work with other systems like health records, rule tools, and ERP systems.

To do this, you need:

- APIs and plug-ins that meet standards.
- Tools to make different data and sources match up.
- Ways to track uses across systems and keep rules the same.

Without this, even easy AI tools turn into alone bits that drop work speed.

Matching Control

AI must match the place's risk plans and rules. This means:

- Managing model risks. Make sure models are checked, watched, and updated as needed.
- Fair rules. Add values of fairness, care, and clearness.
- Talking with rule-makers to stay up on new rules.

As Schneier et al. (2023) noted, alignment is not just a choice—places that don't match AI with their rule plans risk breaking rules and losing public trust.

From Ideas to Plans: How It Was Done

We got the plans from:

- **Case studies.** Real stories in health, money, and law show the hard parts of use, rules, and joining.
- **Design science**. Using Hevner's ideas, we tested over and over in real-world spots.
- **Shared studies.** Papers from ACM (Nahar et al., 2024), IEEE (2024), MISQ (Rai et al., 2021), and HBR (Brynjolfsson et al., 2021) helped bring ideas together.

- **Policy checks**. Looking at AI rules in the US, EU, and UK (Nannini et al., 2023) showed rule needs.

This way of mixing methods made sure the plans are not just theory but well-set ideas that come from both study and real use.

3.3 Research Methodology

This study adopts a **design science research (DSR) approach** to develop and evaluate a framework for enabling AI use among non-technical professionals in regulated industries. To strengthen empirical rigor, a **mixed-methods design** is employed.

Data Collection

- **Primary data**: Semi-structured interviews and survey questionnaires with professionals (e.g., healthcare compliance officers, risk analysts) to assess usability, trust, and compliance needs.
- **Secondary data**: Academic literature (MISQ, ACM FAccT, IEEE) and industry reports to support theoretical grounding.

Case Study Validation

A **structured healthcare case study** is used to evaluate the framework through task-based scenarios, comparing AI-assisted workflows with traditional methods.

Performance improvement is measured as:

$$PI = \frac{T_{manual} - T_{AI}}{T_{manual}}$$

Data Analysis

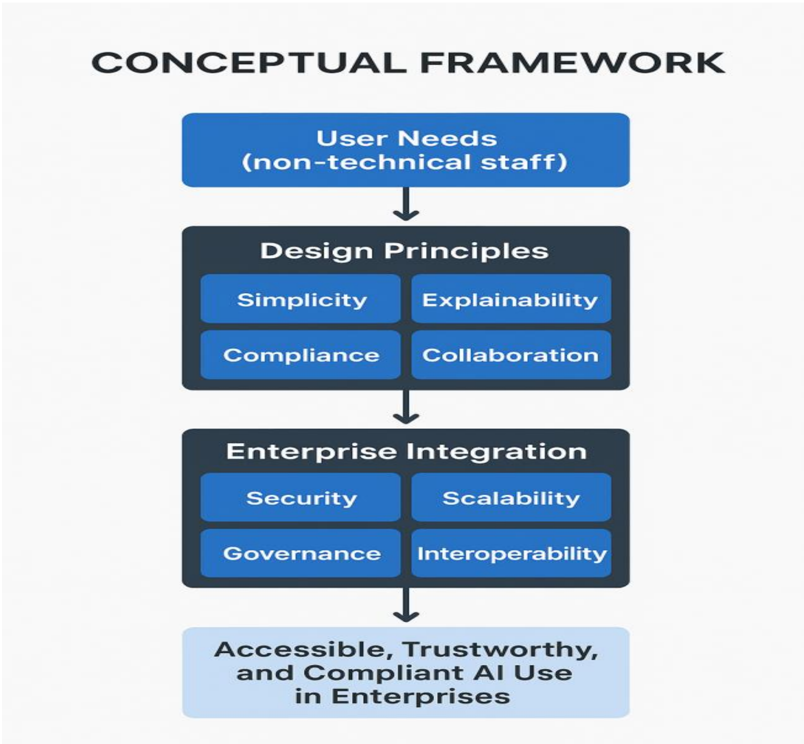
- **Qualitative**: Thematic analysis of interview responses
- **Quantitative**: Descriptive statistics and correlation analysis of survey data

Validation

The framework is evaluated based on:

- Usability
- Trust
- Compliance readiness

Visual Diagram



4. Case Example: Conceptual Validation through Healthcare Compliance

The case shown tells an idea, not real facts. It aims to show how the planned rule works in a set-up that looks like the real world.

In healthcare, people who check the rules often look at long reports on keeping patients safe, under tight rules. By using an AI tool made for all (easy words, clear views, checks), a person who knows little tech can make useful points without needing to know coding.

By setting the case as a demo, the paper makes it clear how the rule is used and stays away from saying it applies to all cases.

4.1 Work Setting

Health care is a field with many rules all over the world, led by sets like HIPAA in the US and GDPR in Europe. Rule keepers in places like hospitals keep things safe, guard personal data, and make sure rules are followed. Yet, these workers may not know much about data tech or coding, making it hard to use smart AI tools to help make decisions (Nahar et al., 2024; Nannini, Balayn, & Smith, 2023). This shows why health care is a good place to see how simple AI tools can help more people while staying safe and right.

4.2 Trouble Spot

Think of a health care rule keeper who checks safety reports in a big hospital group. These reports are long, full of text, and often tell stories of bad events. Usually, rule keepers go through hundreds of these reports each week by hand, trying to see patterns that may point to big risks. Without AI, this job is:

- Slow, often taking days to do.
- Easy to miss small but key trends.
- Acting late, as fixes come after problems grow.

So, the big issue is: How can we shape AI to aid rule keepers without needing them to code, while keeping safety and clear rules?

4.3 Suggested Tool Design

a. How it Looks & How it Works

A no-code AI tool could give the rule keeper:

- Easy-to-use boards to add safety reports.
- Simple word searches (like, “Show me drug error trends over the past six months”).
- Easy-to-read maps and charts to spot repeated risks.

b. Rule Features

- Auto logs: Each review makes a record that helps during checks.
- Flagging uneven data: The system notes if reports unfairly focus on some types of patients, cutting chances of unfair acts (Nannini et al., 2023).
- Auto reports: Each review makes a ready-for-rule summary.

c. Clear Features

- Easy-talk results: Instead of just chances, the system tells why certain things are noted (like, "Lots of reports talk about late drugs in Ward C").
- Trust marks: Results show how sure they are, helping the rule keeper make good choices (Rai, Constantinides, & Sarker, 2021).
- What-if tests: Rule keepers can try out changes (like, "What if we have more nurses per patient?") and see what might happen.

4.4 How to Check if it Works

To see if the tool does well, we should test it by:

How easy it is to use

- Check by how fast one can learn it, how quick to finish a task, and how happy users are (Brynjolfsson, Li, & Raymond, 2021).
- Example: Can a rule keeper finish a review in under 30 minutes without tech help?

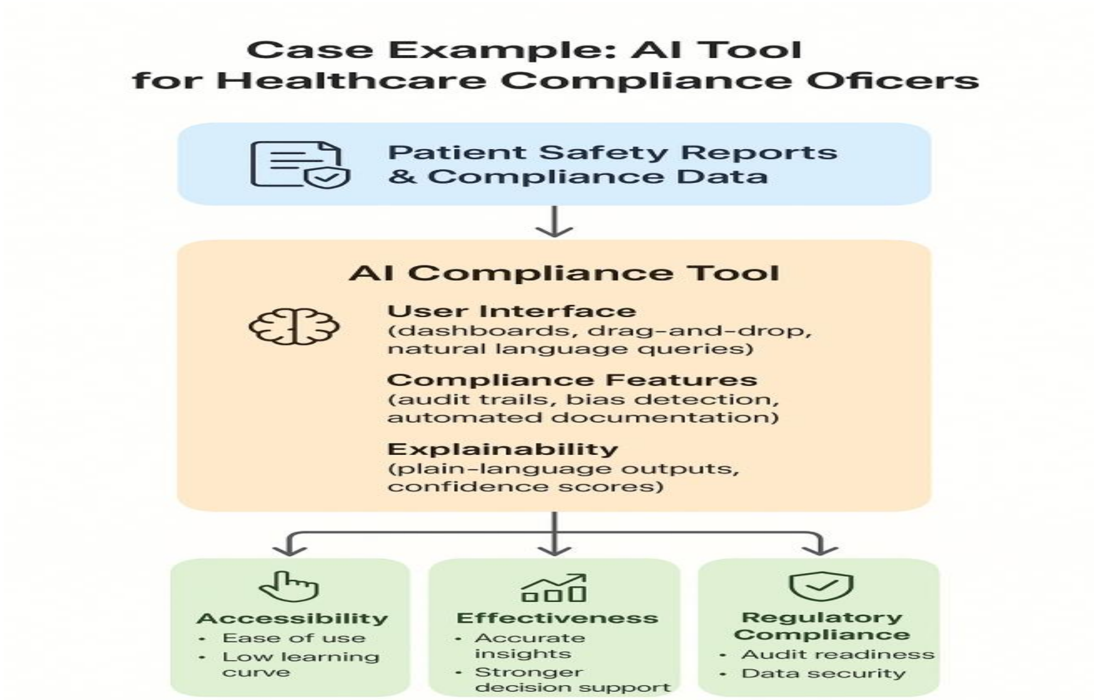
How well it works

- How good it is at finding big risks compared to a manual check.
- How much it helps rule keepers act before rather than after problems.

Sticking to Rules

- Ready for checks: Does the tool make records that pass rule checks?
- Data safety: Does it keep patient info safe as per HIPAA/GDPR?

Visual Diagram



5. Implications

The rapid evolution of artificial intelligence—particularly the emergence of generative AI, large language models (LLMs), and no-code/low-code platforms—has fundamentally transformed how organizations access and deploy AI. While these advancements have significantly lowered technical barriers, they have also introduced new complexities related to trust, governance, and responsible use. Within this context, the implications of democratizing AI extend beyond accessibility to encompass **control, accountability, and sustainable integration** in regulated environments.

5.1 Implications for Organizations

From AI Access to AI Orchestration

Organizations are transitioning from simply enabling access to AI tools toward **orchestrating enterprise-wide AI ecosystems**. Modern AI systems are no longer isolated applications but interconnected services embedded across workflows, decision processes, and compliance systems. As a result, firms must move beyond usability alone and adopt **platform-level governance**, where AI usage is monitored, audited, and continuously optimized.

Competitive Advantage Through Responsible AI

In the current landscape, competitive advantage is not derived solely from AI adoption, but from **how responsibly and effectively AI is integrated**. Organizations that embed **compliance-by-design, auditability, and explainability** into their AI systems are better positioned to mitigate regulatory risks and build long-term stakeholder trust.

New Risk Landscape: Over-Reliance and Automation Bias

While AI tools are becoming more intuitive, they also increase the risk of **automation bias and over-reliance**, particularly among non-technical users. Employees may accept AI-generated outputs without sufficient critical evaluation, especially when systems present results in natural language. This introduces a new class of organizational risk that requires **human-in-the-loop safeguards, escalation protocols, and continuous monitoring**.

5.2 Implications for Professionals

From Tool Users to AI Collaborators

Non-technical professionals are no longer passive users of AI systems but active **collaborators in human–AI decision-making loops**. The rise of conversational AI and generative interfaces allows domain experts to interact with complex models without coding, shifting their role toward **interpreting, validating, and contextualizing AI outputs**.

Cognitive Augmentation and Skill Evolution

AI is increasingly functioning as a **cognitive augmentation tool**, enhancing decision-making rather than replacing it. This shift requires professionals to develop new competencies, including:

- Prompting and querying AI systems effectively
- Interpreting probabilistic outputs and uncertainty
- Understanding ethical and compliance implications of AI-assisted decisions

Risk of Illusion of Understanding

Despite improved usability, simplified interfaces may obscure underlying model limitations, creating an **illusion of understanding**. Professionals may believe they fully grasp AI outputs when, in reality, critical assumptions and uncertainties remain hidden. Addressing this requires **layered explainability and contextual transparency mechanisms**.

5.3 Implications for Governance and Policy

From Static Regulation to Adaptive Governance

Traditional regulatory frameworks are often too slow to keep pace with AI innovation. The current environment demands **adaptive governance models** that evolve alongside technological advancements. Policymakers must move toward:

- Continuous oversight mechanisms
- Risk-based regulatory frameworks (e.g., tiered AI risk classification)
- Collaboration with industry stakeholders for real-time feedback

Operationalizing Accountability in Democratized AI

As AI becomes widely accessible, accountability becomes more complex. Responsibility is distributed across:

- System developers
- Organizational leadership
- End-users

This necessitates clear definitions of **liability, audit trails, and decision ownership**, particularly in high-stakes domains such as healthcare and finance.

Compliance-by-Design as a Strategic Imperative

In the era of generative AI, compliance can no longer be treated as an afterthought. Instead, it must be embedded directly into system architecture through:

- Automated audit logs
- Bias detection mechanisms
- Real-time compliance validation

This approach ensures that increased accessibility does not compromise regulatory integrity.

5.4 Broader Societal and Technological Implications

Democratization vs. Control Trade-Off

The democratization of AI introduces a fundamental tension between **broad accessibility and centralized control**. While empowering non-technical users drives innovation and productivity, it also increases the risk of misuse, misinterpretation, and unintended consequences.

Trust as the Central Pillar of AI Adoption

In the current AI landscape, trust is no longer a byproduct of system performance but a **design objective**. Transparent interfaces, explainable outputs, and governance mechanisms must work together to ensure that AI systems are not only effective but also **perceived as reliable and accountable**.

Future of Human–AI Collaboration

Rather than replacing human expertise, the next phase of AI adoption will be defined by **deep integration between human judgment and machine intelligence**. Organizations that successfully design for this collaboration—balancing automation with oversight—will unlock the full potential of AI while minimizing risk.

5.5 Summary

In a rapidly evolving AI landscape, the implications of this study extend beyond improving accessibility. While recent advancements have made AI tools more user-friendly, they have also amplified the importance of **governance, interpretability, and compliance-by-design**.

Thus, the core contribution of this framework is not diminished by recent developments; rather, it becomes even more critical. As AI continues to scale across organizations, ensuring that it remains **usable, trustworthy, and accountable** will define the success of its adoption in regulated industries.

6. Limitations

While making AI more open to those without tech skills in strict fields is full of hope, we must think about some key limits.

1. Range Limits

We use a health case study here, which might not fit all strict areas like banks, insurance, or law jobs. Each area has its own rules and work ways that might need special changes to this plan (Dwivedi et al., 2021).

2. Tech Problems

Simple vs. Deep: It's hard to make tools that are easy for all, yet still deep enough to give real help (Chui et al., 2021).

Too Simple Risk: When we cut down on detail, there's a chance that users might get AI tips wrong or use them in spots where fine details and rightness are key (Raisch & Krakowski, 2021).

3. Rule Changes

AI rules change fast. Laws like the EU AI Act and other rules for each area are still in the works and will need tools to keep up (Stix, 2021; Floridi, 2023). So, the rule-ready design must stay ready to change, making sure places can meet new needs from rule makers and policy people.

7. Conclusion

Using AI in all of work is not just a far-off dream but a real need now. When groups in tight-rule fields want to use AI well, the issue is not just in making strong systems. It is also key that these tools are easy, safe, and right for those who aren't experts. This part shows that we must find a good mix of easy use, doing things by the rules, and trust—three key pieces that shape if AI helps or turns away users in work.

The main point here is that AI can't just be for those who know big data or tech. Work spots should focus on designs that are easy for users, show their steps in simple terms, follow rules from the start, and are clear to use. Such ways make less need for tech help and let everyday workers use AI right, even in big-need areas like health, money, and laws.

Looking forward, future tasks should work on better design ways, make case studies across industries, and push for more team work among tech makers, rule makers, and users. It is key to work together to fit tools to changing rules and make sure AI helps more, not brings more risk. In the end, making AI open to more people at work is not just about tech, but about society too, needing talks that go on and grow.

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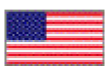

Rishiraj Kohli is a Senior IT Project Manager at Schwarz Partners, where he leads enterprise technology and digital transformation initiatives across logistics, packaging, and regulated industries. He has more than a decade of experience managing multimillion-dollar IT and AI-driven programs in insurance, healthcare, and manufacturing. Rishiraj is a Ph.D. candidate in Information Technology with a concentration in Artificial Intelligence at the University of the Cumberlands (expected 2027) and holds professional credentials as a Project Management Professional (PMP) and Certified ScrumMaster (CSM). His work focuses on bridging governance, compliance, and innovation by enabling non-technical professionals to responsibly adopt AI technologies. He has authored multiple scholarly and professional articles on AI adoption, project governance, and risk management, and continues to contribute thought leadership at the intersection of project management and emerging technologies.