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Challenges in AI Adoption Reported by Employees on LinkedIn (1392 words)

Introduction

Generative AI tools such as ChatGPT, Claude, and Gemini are rapidly transforming professional work by assisting with tasks like writing, analysis, and decision-making. While these tools offer efficiency and creativity gains, working professionals also face significant challenges around bias, misinformation, transparency, and responsible use (Dwivedi et al., 2023). LinkedIn, the most widely used professional networking platform, provides a unique space where employees openly discuss their experiences with AI, making it a valuable source for understanding how challenges are perceived and articulated in practice. Identifying these issues is crucial, as it not only highlights barriers to adoption but also helps organizations design training, policies, and support structures that encourage more effective and ethical use.

Despite growing research on AI in the workplace, little attention has been paid to how employees themselves describe their difficulties with AI in unstructured, real-world contexts. Prior studies emphasize concerns about data security, trust, and job impacts (Raisch & Krakowski, 2021; Dwivedi et al., 2023), but these often rely on surveys or expert interviews rather than user-generated reflections. This study addresses that gap by applying content analysis to recent LinkedIn posts from professionals, categorizing the types of challenges they report. Content analysis is particularly suited here, as it allows for systematic identification of both the frequency and framing of issues, thereby providing actionable insights for practitioners, tool designers, and policymakers.

Research Question

How do professionals on LinkedIn report challenges in understanding and utilizing AI tools effectively, and what kinds of challenges are most prevalent in their posts?

Method

The analysis was conducted using qualitative content analysis with a deductive coding framework adapted from the AI Adoption Challenges Framework (Stack AI, 2023). The framework provided predefined categories for coding LinkedIn posts, while also allowing flexibility for emergent categories. Each LinkedIn post served as the unit of analysis, since posts are the primary means by which professionals articulate their challenges. Posts that contained multiple challenges were coded into multiple categories through a multi-labeling approach.

Data

The dataset for this study consists of LinkedIn posts authored by working professionals. To identify relevant content, a pilot search of LinkedIn posts was first conducted to explore how professionals described difficulties with AI. From this exploratory step, a set of keywords was developed to capture recurring terms used in discussions of AI adoption and limitations. The final search included: “AI challenges” (11 posts), “AI tools problems” (9 posts), “AI mistakes” (14 posts), “AI limitations” (3 posts), “AI pitfalls” (5 posts), “AI errors” (4 posts), and “AI adoption” (5 posts). All searches were case-insensitive to maximize the inclusivity of results. Only textual posts were included, while polls, videos, advertisements, promotional content (e.g., paper launches), and comments were excluded. Posts authored by professional content writers were also excluded, as the focus of this study is on authentic experiences reported by practitioners rather than marketing-oriented materials.

The timeframe of the dataset is the most relevant posts which were one-month period from the date of collection, ensuring the analysis reflects current concerns in the adoption of AI tools. A total of 51 unique posts were collected initially; however, because many posts contained multiple challenges, multi-label coding was applied. Posts that contained more than one challenge were duplicated into separate rows for each challenge type, resulting in a final dataset of 80 coded entries.

Where available, additional metadata such as the author’s professional role and the date of posting were recorded to provide context about which types of professionals were most actively reporting challenges. This dataset is appropriate for the research question because LinkedIn is the most widely used professional networking platform, and it provides direct access to how working professionals themselves articulate the issues they encounter with AI tools.

Analysis

To ensure consistent coding, a codebook was developed with category names, working definitions, and examples drawn from the data. Closely related categories were explicitly distinguished through coding rules. Table 1 summarizes the categories used in this study.

Table 1: Coding Framework for LinkedIn AI Challenge Posts

Category	Definition	Example

Data Quality & Bias	AI outputs are inaccurate, unreliable, or biased due to poor or insufficient training data.	“Well-maintained, correct, usable docs become even more critical in our AI world.”
Insufficient Data	Fragmented or limited in-house datasets hinder effective AI training.	“Many AIs learn from the internet, but often struggle to access high-quality, real-world data.”
AI Talent Shortage	Lack of skilled developers or data scientists to build or maintain AI systems.	“Because you didn’t just lose coders - you lost the people who can tell AI when it’s wrong.”
Unclear ROI & Business Case	Difficulty demonstrating measurable value from AI initiatives.	“I’ve seen businesses waste money trying to automate things that work better without AI.”
Privacy, Security & Compliance	Concerns around data confidentiality, privacy laws, or misuse of sensitive data.	“They mistake AI as a trend, neglecting crucial aspects like data quality and regulatory compliance.”
Integration with Legacy Systems	Outdated or incompatible organizational systems block smooth AI adoption.	“It must be the latest AI update: great at helping others but not so great at communicating its own needs.”
Organizational Resistance	Cultural pushback, mistrust, lack of training, or fear of change in adopting AI.	“78% of employees worry about job security”
High Costs & Resource Intensity	Financial and resource burdens of adopting and maintaining AI systems.	“Hidden costs of ungoverned AI adoption across business units”

After coding, frequencies of each category were calculated, and descriptive statistics were generated in Python. Visualization was done using bar plots and stacked bar charts to explore category distributions overall and across professional roles.

4. Results

The content analysis of 51 LinkedIn posts revealed distinct patterns in the types of challenges reported by professionals regarding AI tool adoption.

Distribution of Challenges: The distribution of challenges revealed that Data Quality & Bias (31.25%) was the most frequently cited issue, followed by Organizational Resistance (23.75%), indicating that concerns about unreliable AI outputs often coexist with cultural barriers to adoption. Other notable challenges included Privacy, Security & Compliance (12.5%), Unclear ROI & Business Case (11.25%), and the AI Talent Shortage (10%), reflecting both regulatory and workforce pressures. Less frequently reported, though still relevant, were High Costs & Resource Intensity (3.75%), Insufficient Data (3.75%), and Integration with Legacy Systems (3.75%), which highlight the resource and infrastructure constraints that persist in practice. Overall, the findings show that while technical concerns such as data quality dominate professional discourse, organizational and strategic barriers remain critical obstacles to effective AI adoption.

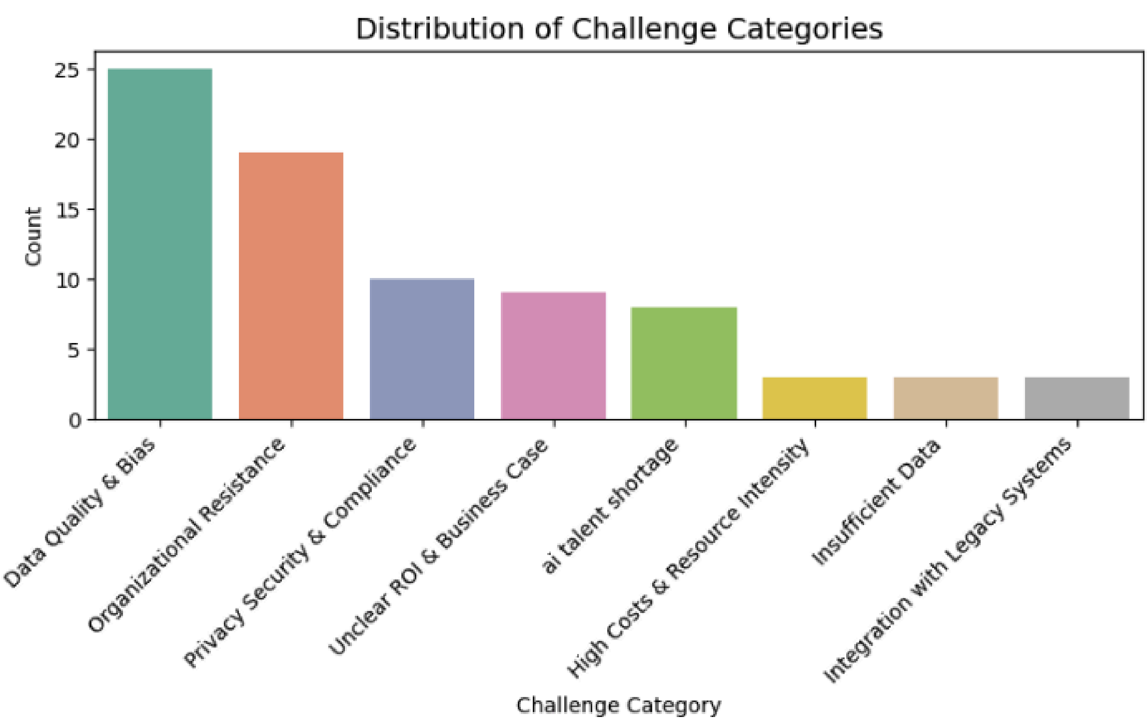


Fig.1 Distribution of Challenge Categories

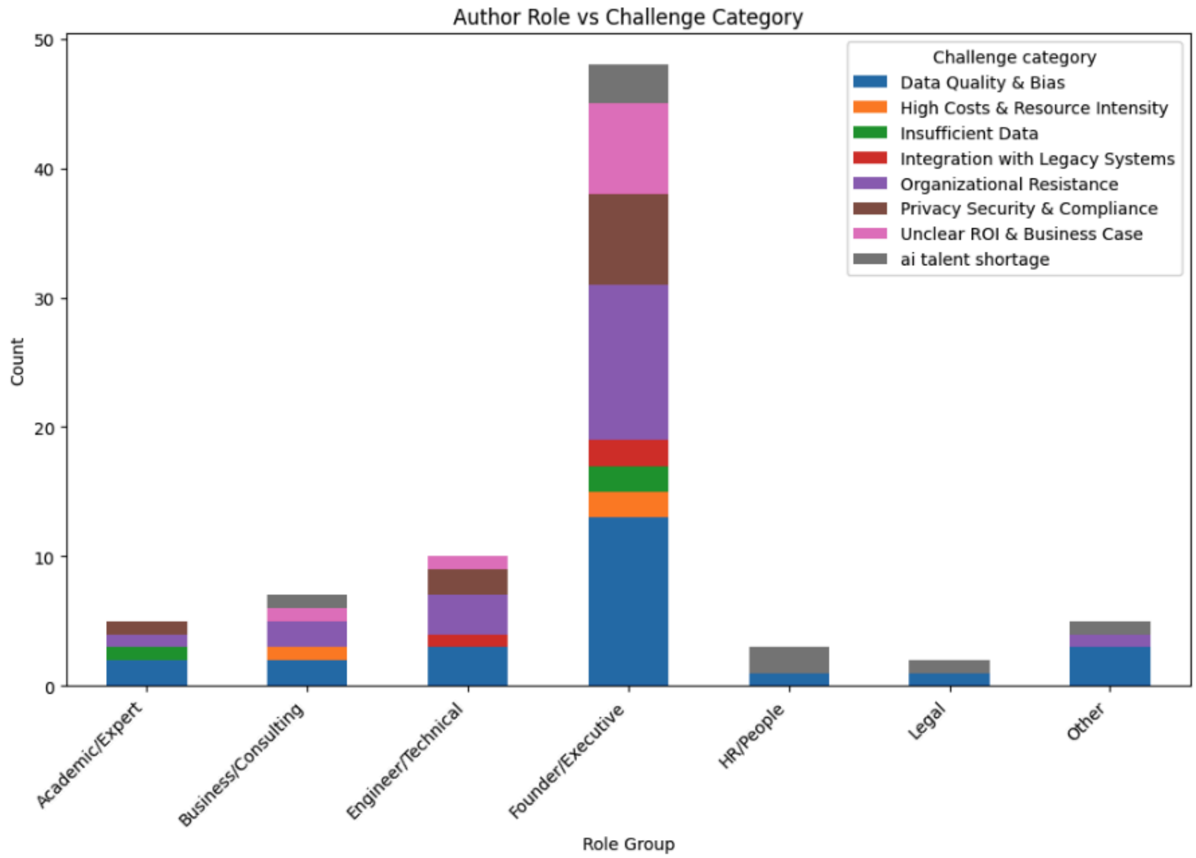


Fig.2 Author Role vs Challenge Categories

Variation Across Professional Roles.

To examine how challenges vary across different professional backgrounds, author roles were mapped into broader categories (e.g., Academic/Expert, Business/Consulting, Engineer/Technical, Founder/Executive, HR/People, Legal, and Other). The distribution shows that Founders and Executives reported the widest range and highest volume of challenges, particularly concentrated in Data Quality & Bias and Organizational Resistance, alongside concerns about Privacy, Security & Compliance and Unclear ROI. In contrast, Engineer/Technical professionals mentioned technical challenges such as data issues and integration problems but to a lesser extent. Academics/Experts highlighted challenges related to insufficient data and technical barriers, whereas Business/Consulting roles focused on strategic concerns such as unclear ROI and compliance. HR and Legal roles were least represented, primarily raising issues tied to AI talent shortages and regulatory risks. Overall, this variation suggests that while technical and data-related challenges are widespread, the prominence of organizational and strategic issues reflects executives' central role in AI adoption decisions.

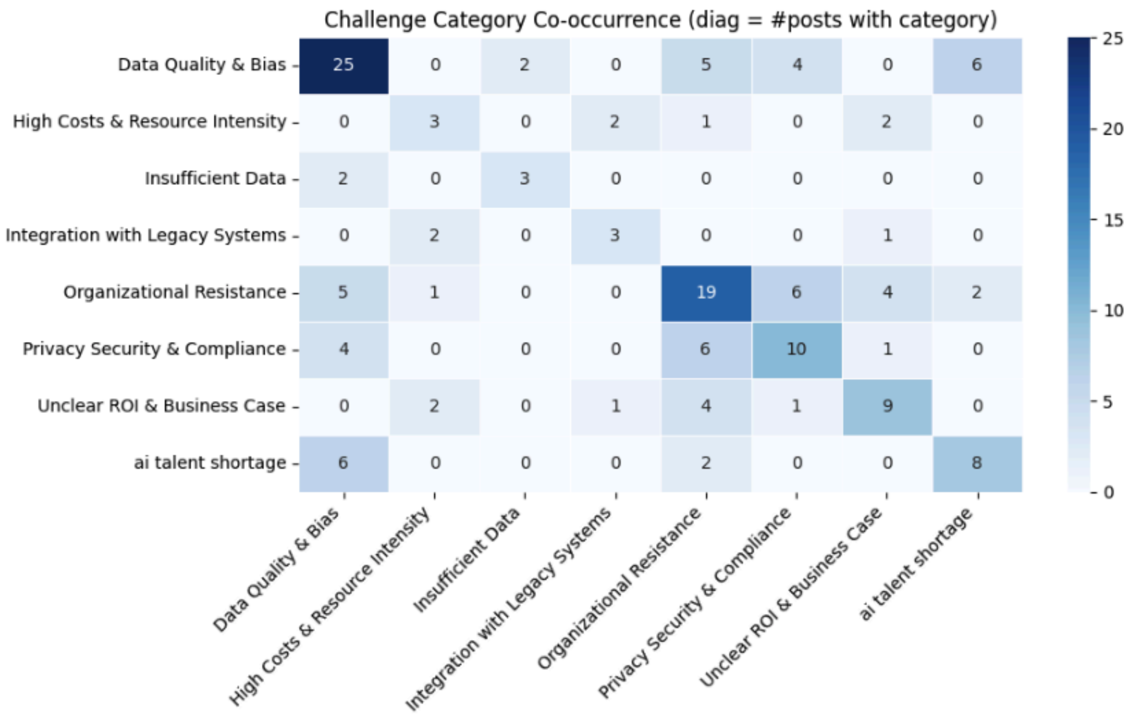


Fig.3 Challenge Category Co-occurence

Co-occurrence of Challenges

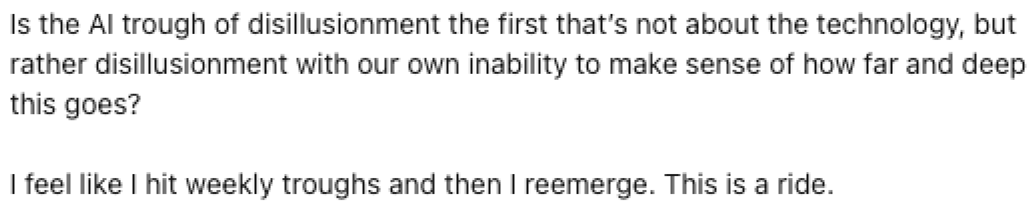
The co-occurrence analysis shows that AI adoption challenges often appear together in professionals' discussions. Organizational Resistance frequently overlapped with Privacy/Security & Compliance and Unclear ROI & Business Case, highlighting how hesitation is tied to regulatory concerns or unclear returns on investment. Data Quality & Bias also co-occurred with Organizational Resistance and AI Talent Shortage, suggesting that technical flaws are compounded by lack of oversight and workforce gaps. Overall, challenges clustered around two central themes: organizational and governance barriers (resistance, compliance, ROI) and technical/data-related issues (data quality, bias, and talent shortages).

In content analysis terms, this reflects a pattern of co-occurrence coding (Saldaña, 2016), where multiple categories appear together in a single unit of analysis. Such overlaps reveal that for many professionals, challenges with AI tools are not discrete problems but interdependent factors, for example, unreliable data not only undermines trust in outputs but also discourages employee adoption.

5. Conclusion and Limitations

This study set out to answer how professionals on LinkedIn report challenges in understanding and utilizing AI tools, and which challenges are most prevalent. The analysis revealed that Data

Quality & Bias and Organizational Resistance were the most frequently cited obstacles, followed by Privacy/Security & Compliance and Unclear ROI & Business Case. Challenges often co-occurred, particularly organizational concerns with data-related issues, suggesting that professionals experience AI adoption barriers as interconnected rather than isolated. These findings highlight the sociotechnical nature of AI challenges, where technical shortcomings such as data bias are reinforced by organizational hesitation and governance concerns.


Is the AI trough of disillusionment the first that’s not about the technology, but rather disillusionment with our own inability to make sense of how far and deep this goes?

I feel like I hit weekly troughs and then I reemerge. This is a ride.

Fig.4 Ambiguous LinkedIn post

Despite these contributions, the study has limitations. The dataset was relatively small (80 coded posts) and limited to one month of LinkedIn activity, which constrains generalizability. Sampling bias is possible since LinkedIn users may not represent all professionals, and trending topics could have skewed results toward certain issues. Additionally, interpretation depended on coder judgment, and some posts were ambiguous, relying heavily on context or author tone (see placeholder example). Finally, the dataset did not account for whether posts were AI-generated, which may influence how challenges are framed. Future research should address these limitations by expanding the dataset, using multiple coders, and applying methods to differentiate between human-authored and AI-generated content.

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