Navigating a Hybrid Frontier: Understanding AI Adoption in Liberata's Cardiff Branch, an Automation Specialist, and Its Role in Shaping Industry 5.0

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Abstract

Artificial Intelligence (AI) is transforming public service delivery, enhancing efficiency while raising concerns about job security and organisational change. This qualitative case study investigates AI adoption and acceptance within Liberata's Cardiff branch, an automation-driven workplace delivering public-sector contracts. Using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), the study examines key factors influencing AI adoption, including performance expectancy, effort expectancy, social influence, and facilitating conditions.

Findings reveal that experience level significantly affects AI adoption, with senior employees adapting quickly, while mid-level and newer employees require training and peer support. AI acceptance was strongest when framed as a tool for augmenting work rather than replacing jobs. Robust governance, transparency, and structured training were critical for successful integration. This study highlights the importance of human-centred AI adoption in hybrid public-private organisations, contributing to both practical implementation strategies and academic discourse on pre-adoption perceptions.

1. Introduction

The integration of Artificial Intelligence (AI) into public services is transforming service delivery, balancing efficiency, trust, compliance, and workforce stability (Al Haddad & Kotnour, 2015). AI is expected to streamline workflows and reduce errors, yet its adoption raises concerns around job security, organisational change, and public accountability (Frey & Osborne, 2017; Jarrahi, 2018). In automation-driven workplaces, particularly in private firms delivering public services, AI adoption success depends on both technological efficiency and human-centred integration (Makowski & Kajikawa, 2021; Bergek et al., 2013).

This study investigates AI adoption and acceptance within Liberata, focusing on its Cardiff branch, which specialises in automation processes. Using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012), the research assesses key factors influencing AI adoption, including performance expectancy, effort expectancy, social influence, and facilitating conditions. AI adoption refers to its implementation, while acceptance reflects employees' willingness to engage with and integrate AI into their workflows. Since employee perceptions and organisational readiness are critical in shaping AI outcomes, it is essential to explore how workers conceptualise AI's role before full implementation (Armenakis et al., 1993; Vakola et al., 2004; Maheshwari & Vohra, 2015).

Most research on AI adoption examines post-integration effects, but fewer studies explore pre-adoption perceptions, despite evidence that organisational learning environments influence AI acceptance (Bligh et al., 2018; Stouten et al., 2018; Harden et al., 2020). This study addresses that gap by examining employee attitudes before full AI integration, providing insights into organisational readiness and trust factors. Leadership also plays a crucial role in managing AI adoption, particularly in hybrid organisations that must balance private-sector efficiency with public-sector accountability (Karp & Helg, 2008). Findings contribute to both academic discussions and practical AI adoption strategies, ensuring efficient and socially sustainable AI integration in hybrid public-private organisations (De Vries et al., 2015).

2. Methodology

This qualitative case study explores employee perceptions of AI adoption at Liberata's Cardiff branch, where automation plays a central role. A case study approach was selected due to its ability to capture complex organisational dynamics (Yin, 2018). By focusing on pre-implementation perspectives, the study assesses concerns, expectations, and organisational factors shaping AI integration. Aligning with UTAUT2 (Venkatesh et al., 2012), the study examines how employees perceive AI's potential impact before workplace restructuring occurs.

Using purposive sampling (Palinkas et al., 2015), participants were selected based on direct experience with automation. Employees from various hierarchical levels were included, with particular focus on those experienced in automation but new to AI integration. A total of 20 employees (n=20) participated (Table 1). Interviews were conducted in person or via Microsoft Teams between 28/06/2023 and 03/07/2023, lasting 20 to 60 minutes depending on depth of discussion.

3. Data Collection and Analysis

Semi-structured interviews provided a structured yet flexible approach to exploring attitudes, concerns, and expectations regarding AI adoption (Brinkmann, 2014). Questions were aligned with UTAUT2 (Table 2), ensuring systematic analysis of performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2012). Data were transcribed verbatim and analysed using thematic analysis (Braun & Clarke, 2006). The process involved familiarisation, coding, categorisation, and refinement of key themes. Participants were assigned experience levels based on self-reported exposure and technical understanding (Table 3), ranging from Beginner (Level 2) to Advanced (Level 5). Categorising experience levels provided a nuanced exploration of how familiarity influences AI adoption (Bligh et al., 2018; Stouten et al., 2018; Harden et al., 2020). To ensure reliability, coding was conducted independently, and all data were anonymised. Themes were systematically mapped onto UTAUT2 constructs, ensuring a structured interpretation of AI adoption and acceptance.

4. Results

Interviewees demonstrated varying levels of automation and AI experience (Figure 1). Most (n=10, Level 3) used automation in operational tasks but had limited technical involvement. Six participants (n=6, Level 4) actively developed automation solutions, while one expert (Level 5, T8) displayed strategic leadership and deep technical knowledge. A smaller group (n=3, Level 2) had basic experience, requiring guidance.

Performance Expectancy

Participants at all levels agreed AI improves job performance. Experienced employees (T8, U9) highlighted efficiency gains, with T8 noting, *"It used to be a manual check… now it's five minutes."* U9 described a shift from execution to management roles, overseeing AI-driven processes. Mid-level employees (N4, Y1, S5) initially hesitated but later saw value, with N4 stating, *"Some struggle to see the benefits… but when they see how much time it saves, they become more accepting."* Less experienced employees (T2, P7, H7) quickly recognised productivity improvements, such as learning new automation skills, with T2 noting, *"I've learned how to write rules—skills I didn't have before."*

Effort Expectancy

Familiarity influenced perceptions of AI's ease of use. Experienced employees (T8, P8) found AI straightforward, while mid-level users (N4, Y1, S5) faced an initial learning curve before adapting. P8 explained, *"You become the person that manages that system."* Less experienced employees (T2, P7, H7) struggled initially but gained confidence with training, with T2 admitting, *"It's taken a while to trust the bots… but now I see the time it saves."*

Social Influence

Managerial and peer support were key in shaping AI acceptance. Senior employees (T8, P8) reassured teams that AI shifts focus to higher-value tasks, with T8 stating, *"AI is freeing people for more complex work."* Mid-level employees (N4, S5, Y1) noted that AI success stories encouraged adoption, while less experienced employees (T2, P7, H7) relied on peer endorsements. T2 commented, *"Now I appreciate the time it saves."*

Facilitating Conditions

Robust infrastructure, governance, and training were essential for AI adoption. Experienced employees (T8, P8) warned, *"If companies don't adopt AI, they risk falling behind… but rushing in without controls risks security issues."* Mid-level employees (N4, S5, Y1) valued structured training and escalation paths, while lower-experience users (T2, P7, H7) depended on clear guidelines and mentorship. T2 remarked, *"You need guidance at first."*

Hedonic Motivation

While AI wasn't described as "fun," participants appreciated how it eliminated mundane tasks. T8 noted, *"It's about giving people tools, not replacing them."* Mid-level employees (N4, S5, Y1) enjoyed AI more once its benefits became evident, and a lower-experience participant (T2) expressed relief, saying, *"It's taken a while… but now I see the time it saves."*

Price Value

AI was widely accepted when it demonstrated clear efficiency gains. T8 cautioned, *"Rushing AI adoption without ensuring returns risks security and reputational damage."* Mid-level employees (N4, S5, Y1) linked AI's value to time savings, while lower-experience employees (T2, P7, H7) saw learning AI as worthwhile if it improved efficiency.

Habit

AI adoption followed a pattern of initial resistance, followed by reinforcement. Experienced employees (T8, P8) noted that longstanding manual routines slowed adoption, with P8 explaining, *"If someone's been doing the same role for 10 to 15 years, change can feel* *intimidating."* However, mid-level and lower-experience employees (N4, S5, Y1, T2, P7, H7) found repeated exposure built confidence, with T2 stating, *"It took a while to trust AI… but now I see the time it saves."* Over time, AI became an ingrained part of workflows, reinforcing its role in Industry 5.0 adoption.

5. Discussion

Findings align with UTAUT2 and Industry 5.0, showing that AI shifts roles from repetitive tasks to strategic, exception-based work (Makowski & Kajikawa, 2021; Bergek et al., 2013; Khanagha et al., 2018). AI was most accepted when framed as a tool for efficiency rather than a job displacement mechanism, reinforcing previous research that highlights AI's impact on employment paradigms and workforce restructuring (Frey & Osborne, 2017; Jarrahi, 2018; Dwivedi et al., 2021). Experience level influenced adaptation speed, senior employees were prepared to integrate AI faster, while mid-level and newer employees displayed a want for more training and peer support, aligning with studies that emphasise learning-oriented environments in AI adoption (Bligh et al., 2018; Stouten et al., 2018; Harden et al., 2020). The potential for AI adoption relied heavily on governance frameworks, social validation, and clear implementation strategies, reflecting the critical role of leadership in balancing AI-driven efficiency with ethical considerations (Karp & Helg, 2008; Masawi et al., 2025).

A key takeaway is that AI must be positioned as a collaborative tool rather than a replacement for human roles, particularly in public-sector environments where transparency and accountability are critical (De Vries et al., 2015). Compliance concerns around GDPR and ethical AI deployment highlight the need for strong oversight and governance, reinforcing calls for ethical AI frameworks and transparency in decision-making (Borenstein & Howard, 2020; Feuerriegel et al., 2020; Hagendorff, 2020). Hybrid organisations, which balance automation with human oversight, provide an ideal testing ground for AI adoption. Piloting AI in controlled environments allows organisations to refine best practices while mitigating risks, supporting arguments that hybrid organisations offer valuable insights into AI implementation in government services (Raisch & Krakowski, 2021). Ultimately, AI's success depends on technical efficiency, governance, and cultural acceptance, ensuring a human-centred, Industry 5.0-aligned workplace transformation.

6. Conclusion

AI's impact on efficiency and job roles depends on employee experience, leadership messaging, and organisational readiness. AI was widely accepted when framed as augmenting rather than replacing human work, shifting tasks toward more analytical and customer-facing roles. Trust in AI hinged on transparency and explainability, particularly in public-sector contexts, reinforcing the need for strong governance and ethical oversight. Future research should examine post-integration adaptation, focusing on skill development, habit formation, and long-term benefits. Exploring demographic factors such as age and gender could enhance equitable and human-centred AI implementation strategies.

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Table 1. Employee roles from the organisation involved in automation services interviewed during this study

Job title	Number of participants interviewed
IT Systems Developer	4
IT Systems Solutions Support	3
Senior Specialist	3
Business Analyst	1
Finance Specialist	7
Finance Officer	2
Director of Middle Office and Automation Services	1
Delivery Manager	1

Table 2. Interview stages, overarching research questions, and corresponding interview questions designed to explore employee perceptions of automated services and AI adoption within the organisation.

Stage	Overarching Research Question	Interview Question
1	Questions designed to gain an understanding of employees' general understanding and perception of automated services within the organisation.	Tell me about your role and whether automated systems have an impact on your role? Before this role, have you had any previous experience with working with automated systems? Can you explain further/tell me about how automated systems impact the way you conduct your role
2	Exploring organisation members' perspectives on the needs/conditions for successful acceptance, adoption, and implementation of artificial intelligence based technology	What is your perspective on AI technologies? What are the advantages and opportunities of using AI innovations with automated services? What are the barriers and/or risks in using AI technology with automated services? What would the successful adoption of AI technology in automated services look like? What would make it successful? (i.e. what were the factors that would make the acceptance/adoption successful) What would the unsuccessful adoption of AI innovation in automated services look like? What would make it unsuccessful? (i.e. what were the factors that would make the acceptance/adoption unsuccessful)

Table 3. *Framework for assessing participant experience levels with automation and AI, including justifications for classification.*

Level	Label	Description	General Justifications
1	No Experience (Beginner)	No prior knowledge or hands-on experience with automation or AI.	New to the field, learning from scratch. Requires extensive training and supervision. Limited understanding of automation concepts.
2	Basic Experience	Some exposure to automation concepts but minimal hands-on experience.	Familiar with the theory of automation but lacks practical application. May have used basic automation tools but not in-depth. Requires guidance to implement automation solutions.
3	Intermediate Experience	Regularly interacts with automation but does not specialize in it.	Uses automation tools in daily work but doesn't develop them. Understands automation workflows and can troubleshoot minor issues. May require support for more complex automation tasks.
4	Advanced Experience	Strong technical expertise in automation and AI systems.	Develops and implements automation solutions. Can work independently on complex automation projects. Experienced with multiple automation tools and AI models. Can provide training and support to others.
5	Expert (Specialist/Leader)	Highly specialized in automation and AI, leads development.	Drives innovation and strategy in automation. Designs and architects automation frameworks. Recognized as an authority in automation and AI integration. Leads automation teams or projects on an organisational level.

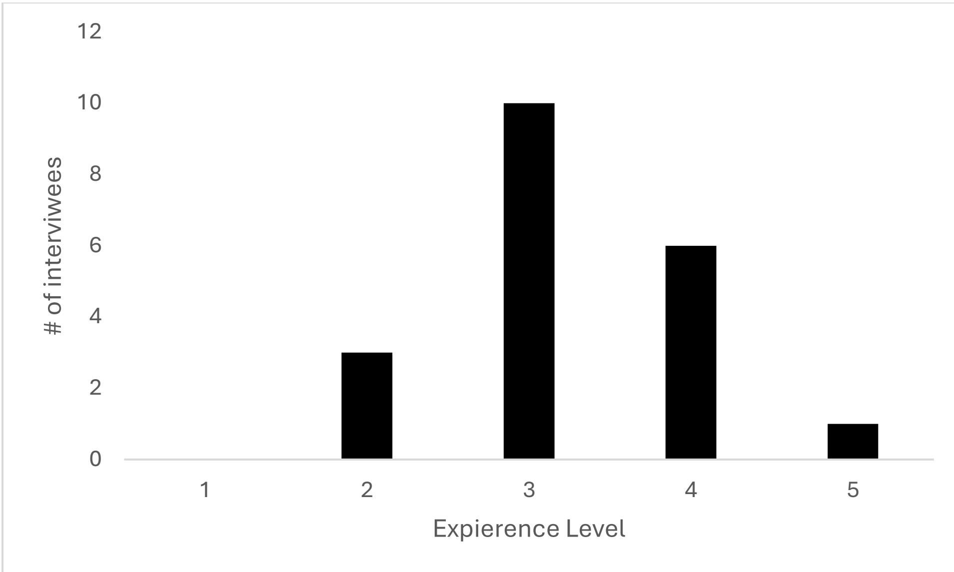

Figure 1. *Distribution of participants' experience levels with automation and AI, classified from Level 1 (No Experience) to Level 5 (Expert).*