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# Resistance to Change as a Diagnostic Insight: An Interdisciplinary Examination of Stakeholder Opposition to AI in Primary Care

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## Abstract

As artificial intelligence (AI) systems become more integrated into healthcare, understanding the roots of resistance is essential, particularly in complex, value-driven settings like primary care. This interdisciplinary study explores stakeholder resistance to AI through interviews with global experts in organizational transformation and resistance to change (RtC). It identifies three interconnected forms of resistance—logical, sociological, and psychological—each linked to specific concerns around ethics, professional identity, and systemic fit. Unlike prior work, this study centers RtC experts' insights on AI resistance in primary care, a setting often excluded from co-design. Using a qualitative abductive approach, the research highlights resistance as a form of critical feedback and a mechanism for building trust. These findings inform more inclusive, reflexive, and context-sensitive strategies for embedding AI ethically within health systems.

## Introduction

Despite substantial investment, artificial intelligence (AI) adoption in UK primary care remains limited, threatening the National Health Service (NHS) ”digital-first” strategy (NHS England 2025). Dominant models such as the Technology Acceptance Model (TAM) (Davis 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003) tend to interpret resistance as a failure of users to accept or adapt. However, these technology acceptance models prioritize behavioral predictors like perceived usefulness while neglecting the professional, ethical, and sociopolitical forces that shape resistance in healthcare settings (Holden and Karsh 2010; Greenhalgh et al. 2017). This framing obscures resistance as a complex, value-driven response grounded in clinical identity, ethical duty, and patient care norms. This research argues that resistance is not mere friction, but a meaningful signal illuminating misalignments between AI systems and professional values. Reinterpreting resistance in this way provides a more nuanced and ethically grounded lens for guiding AI implementation.

## Problem Statement

Despite its prominence in NHS digital policy (NHS England 2025), AI adoption in primary care remains limited (Sides, Farrell, and Kbaier 2023). Explanations often focus on infrastructure or training deficits, yet this overlooks stakeholder resistance, a complex, value-laden response frequently dismissed as inertia. Prevailing models like the TAM (Davis 1989) and the UTAUT (Venkatesh et al. 2003) describe non-adoption mainly as user-level non-acceptance, neglecting the ethical, professional, and relational dimensions to healthcare resistance (Holden and Karsh 2010; Greenhalgh et al. 2017). Studies show that sidelining resistance leads to mistrust, disengagement, and implementation failure (Essex et al. 2023; Shrivastava, Tapasya, and Joshi 2024; Talwar et al. 2023; Morrison 2021), especially when primary care stakeholders are excluded from design (Kueper et al. 2020; Morrison 2021). Rather than mere friction, the “digitally resistant frontline” signals deep tensions between innovation and professional norms. This study addresses this gap by reframing resistance as a diagnostic resource, revealing misalignments between AI systems and the lived realities of care, and asks: **How can forms of resistance to AI in healthcare serve as constructive insights, rather than simply oppositional responses?**

## Methodology

This study used a qualitative, abductive design to explore how resistance to AI is conceptualized by RtC experts. Abduction enabled iterative theorization, moving between empirical data and conceptual frameworks to generate new insights (Barrett and Younas 2024). Six RtC experts were purposively sampled based on peer-reviewed publications on organizational or healthcare transformation within the past ten years (all within the past five), ensuring academic credibility and topical relevance. Of twenty invited, six consented to participate. Semi-structured interviews (56-77 mins), were conducted via Microsoft Teams between June and August 2024, covering conceptual, ethical, and strategic aspects of resistance. Interviews were transcribed using a denaturalized approach to preserve meaning while omitting filler speech (Oliver, Serovich, and Mason 2005). Thematic analysis followed Braun and Clarke's six-phase model (Braun and Clarke 2014), using abductive reasoning to iterate between empirical insights and existing theoretical frameworks (Barrett and Younas 2024). First-cycle coding (In Vivo, descriptive, values) identified key tensions, while second-cycle coding refined these into coherent themes (Saldaña 2013). Resistance was described as both an ethical and strategic response to systemic misalignment. Saturation was reached by the fifth interview, with no new themes emerging thereafter (Malterud, Siersma, and Guassora 2016; Constantinou, Georgiou, and Perdikogianni 2017; Sebele-Mpofu 2020; Saunders et al. 2018). A collaboratively developed codebook supported rigor and ensured analytical transparency.

## Findings

Resistance manifested in three interconnected forms—logical, sociological, and psychological—each revealing distinct but overlapping concerns about systemic misfit, marginalization and professional autonomy (Kuzhda 2016). **Logical resistance** centered on perceived misalignment between AI tools and professional needs. Experts described how poorly targetted implementations created disillusionment: "Sometimes the technologies are picked just to be picked, without dealing with any pain points." This reflected unmet expectations about relevance, signalling failures in user-needs alignment. **Sociological resistance** reflected power imbalances, cultural inertia, and lack of participation: "One source, usually from a top-down position, is trying to introduce [a new system] and there's another group... not adopting the behaviors or even the thought processes required to enable that implementation." Here resistance is not inertia, but protest against imposed change. Experts stressed that when marginalized stakeholders, such as community practitioners or under-resourced clinics, resist, it often reflects concerns about exacerbating inequality: "They have a real right to resist... So, who gets to draw the line there?" **Psychological resistance** involved emotional and existential responses, fear of deskilling, loss of autonomy and professional devaluation. As one interviewee put it: "People feel things are being automated... making them feel devalued." This form of resistance was not only about individual discomfort but deeper anxieties around loss of purpose and relational care, especially when AI was framed as efficiency-first. These psychological responses were often intensified by broader systemic dynamics, such as the inverse care law (Hart 1971), where digital tools risked widening rather than narrowing access gaps.

Across all forms, resistance functioned as a diagnostic signal, revealing where AI systems failed to resonate with values, workflows, or equity goals. Echoing Sujan et al. and Aquino et al., early engagement with resistance can support more ethical, inclusive and sustainable AI implementation (Aquino et al. 2023; Sujan et al. 2022).

## Steps to Address Resistance

Drawing on interview insights, principles were identified to address this resistance, not as generic best practices, but as strategic responses to specific resistance dynamics outlined above. **Engage early (responding to logical resistance).** Experts consistently argue that resistance surfaces when technologies fail to address the "pain points" of end users. Involving frontline stakeholders at the design stage mitigates misalignment: "People who are going to be using the technology need a substantive stake in the decision-making." However, some cautioned that early engagement must be substantive, not tokenistic, or it may deepen cynicism. **Design inclusively (addressing sociological resistance).** Where AI systems were seen as imposed, resistance intensified. Co-production was viewed as a mechanism to restore agency and legitimacy: "If people feel invested... it's much more apt to unfold with less resistance." Yet interviewees diverged on the feasibility of full co-production in time-pressured health systems, pointing to a need for scalable participatory models. **Communicate clearly (mitigating psychological resistance).** Unrealistic promises or ambiguous language often fuelled anxiety and mistrust. Experts stressed the need for transparent framing of both capabilities and limitations: "People might want the moon, but we can't do that... what's really important from a safeguarding perspective." Together, these principles reflect a model of anticipatory resistance engagement, transforming resistance from a reactive problem into a proactive diagnostic resource.

## Significance and Interdisciplinary Impact

This study makes three distinct contributions: **Conceptually**, it reframes resistance as a generative, ethically significant response rather than a failure of acceptance. **Methodologically**, it foregrounds RtC expert perspectives to offer cross-sectoral insight into organization resistance. **Interdisciplinarily**, it integrates RtC theory, AI ethics, and NHS primary care data to propose resistance as an ethical signal, surfacing misalignments before harm occurs (Shrivastava, Tapasya, and Joshi 2024; Inuwa-Dutse 2023). This has wider relevance for ethically grounded AI implementation across high-stakes public systems.

## Conclusion

This study makes a two-fold contribution.**Empirically**, it centers RtC experts perspectives to show how logical, sociological, and psychological resistance function as diagnostic tools for uncovering misalignments between AI systems and frontline realities. **Conceptually,** it integrates RtC theory with AI ethics and primary care practice to recast resistance as an ethical signal rather than an implementation barrier. To translate this into practice, designers should embed anticipatory resistance mapping into early development; policymakers should establish governance structures that legitimize constructive dissent; and clinical leaders should promote training that frames resistance as a professional responsibility. However, this reframing carries risks. Resistance could be co-opted to stall innovation or dismissed when inconvenient. Judging what constitutes "constructive" dissent raises questions of power and equity in already unequal systems. Future research should explore how to institutionalise this diagnostic approach without undermining its critical intent. Resistance when recognised as signal rather than noise, can guide the development of more ethically aligned and socially legitimate AI systems.

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