Zwischen individueller KI-Nutzung und organisationaler KI-Adoption:

Eine Analyse individueller Wahrnehmung, Nutzung und organisationaler Verankerung von KI

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Zusammenfassung

Diese kumulative Dissertation untersucht, wie individuelle KI-Nutzung und organisationale KI-Adoption zusammenhängen und unter welchen Bedingungen KI nachhaltig in Organisationen verankert werden kann. Ausgangspunkt ist die Beobachtung, dass KI im privaten Alltag zunehmend niedrigschwellig und experimentell genutzt wird, während KI-Nutzung im Arbeitskontext häufig situativ bleibt und organisationale KI-Adoption trotz technischer Reife oft nicht über Pilotphasen hinauskommt. Die Arbeit argumentiert, dass diese Unterschiede nicht mit einer einheitlichen Adoptionslogik erklärt werden können. Stattdessen wird nachhaltige KI-Verankerung als Mehrebenenprozess verstanden, in dem subjektive Wahrnehmung, Nutzungspraxis und organisationale Einbettung systematisch zusammenwirken. Die Dissertation unterscheidet drei Analyseebenen: individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption. Diese Ebenen werden in drei empirischen Studien untersucht und in einer vierten Studie zusammenführend ausgewertet. Studie 1 zeigt, dass KI-Aversion wesentlich durch die Fehlkalibrierung zwischen subjektivem und objektivem KI-Wissen geprägt ist. Studie 2 rekonstruiert anhand von zwölf Interviews den Übergang von Erprobung zu routinisierter KI-Nutzung im Arbeitskontext und zeigt, dass dieser Übergang an motivationalen, situativen und organisationalen Schwellen scheitern kann. Studie 3 macht deutlich, dass organisationale KI-Adoption trotz technischer Machbarkeit durch organisationale Rollenkonflikte, Rollenunklarheiten und fehlende bereichsübergreifende Koordination blockiert werden kann. Studie 4 führt diese Befunde zu einem kontextübergreifenden Erklärungsrahmen zusammen. Sie legt nahe, dass private KI-Erfahrungen den Einstieg in KI-Nutzung im Arbeitskontext erleichtern können, aber weder automatisch in stabile Nutzung im Arbeitskontext übergehen noch unmittelbar zu organisationaler KI-Adoption führen. Entscheidend sind Brücken- und Anschlussbedingungen wie Aufgabenwert, freigegebene Tools, Verifikationsroutinen, Rollenklärung und Governance, unter denen sich KI-Nutzung im Arbeitskontext stabilisieren und in tragfähige organisationale Adoptionsprozesse überführen lässt. Der zentrale Beitrag der Dissertation liegt darin, individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption nicht als getrennte Phänomene, sondern als miteinander verbundenen Verankerungsprozess zu verstehen. Nachhaltige KI-Verankerung entsteht demnach durch das Zusammenspiel subjektiver Wahrnehmung, routinisierter Nutzungspraxis und organisationaler Einbettung.

Abstract

This cumulative dissertation examines how individual AI use and organizational AI adoption are related and under which conditions AI can become sustainably embedded in organizations. It starts from the observation that AI is increasingly used in private everyday life in accessible and experimental ways, while AI use in the workplace often remains situational and organizational AI adoption frequently does not progress beyond pilot stages despite technical maturity. The dissertation argues that these differences cannot be explained by a single adoption logic. Instead, sustainable AI embedding is conceptualized as a multilevel process in which individual perception, workplace use practices, and organizational embedding systematically interact. The study distinguishes three analytical levels: individual AI use in everyday life, individual AI use in the workplace, and organizational AI adoption. These levels are examined in three empirical studies and brought together in a fourth study. Study 1 shows that AI aversion is strongly shaped by the miscalibration between subjective and objective AI knowledge. Study 2 reconstructs the transition from experimentation to routinized AI use in the workplace and shows that this transition may fail at motivational, situational, and organizational thresholds. Study 3 demonstrates that organizational AI adoption can be blocked by role conflicts, role ambiguity, and a lack of cross-functional coordination despite technical feasibility. Study 4 brings together these findings into a cross-context explanatory framework and suggests that private AI experiences may facilitate entry into workplace AI use, but do not automatically result in stable use in the workplace or in organizational adoption. Rather, this depends on bridging and connection conditions such as task value, approved tools, verification routines, role clarity, and governance. The dissertation's central contribution lies in conceptualizing AI use and AI adoption not as separate phenomena, but as an interconnected embedding process. Sustainable AI embedding thus emerges from the interplay of subjective perception, routinized use practices, and organizational embedding.

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Abkürzungsverzeichnis

AI – Artificial Intelligence

AIOps – Artificial Intelligence for IT Operations

CRM – Customer Relationship Management

ERP – Enterprise Resource Planning

EU – Europäische Union

HR – Human Resources

HRIS – Human Resource Information System

HRM – Human Resource Management

IT – Information Technology

KI – Künstliche Intelligenz

KPI – Key Performance Indicator

MLOps – Machine Learning Operations

PoC – Proof of Concept

RACI – Responsible, Accountable, Consulted, Informed

RM – Rubicon Model of Action Phases

ROI – Return on Investment

SME – Small and Medium-sized Enterprise

SPSS – Statistical Package for the Social Sciences

STS – Socio-Technical Systems Theory

TAM – Technology Acceptance Model

UTAUT – Unified Theory of Acceptance and Use of Technology

UTAUT2 – Unified Theory of Acceptance and Use of Technology 2

1 Einleitung und Motivation

Künstliche Intelligenz (KI) hat sich in den letzten Jahren von einem spezialisierten Technologiefeld zu einer alltagsnahen Basistechnologie entwickelt (Maslej et al., 2025). Insbesondere durch leicht zugängliche, cloudbasierte KI-Anwendungen und generative Systeme ist KI für viele Menschen zu einem vertrauten Alltagswerkzeug geworden (Microsoft AI Economy Institute, 2026). Gleichzeitig zeigt sich jedoch ein auffälliger Unterschied zwischen privater Nutzung, KI-Nutzung im Arbeitskontext und organisationaler KI-Adoption. Während KI im Alltag häufig niedrigschwellig, experimentell und mit vergleichsweise geringen Risiken eingesetzt wird, ist ihr Einsatz im Arbeitskontext an zusätzliche Anforderungen wie Vertraulichkeit, Nachvollziehbarkeit, Verantwortbarkeit und formale Freigaben gebunden (Brynjolfsson et al., 2025). Noch deutlicher wird diese Differenz auf Ebene der Organisation: Trotz hoher Sichtbarkeit, wachsender Investitionen und technischer Fortschritte verharren viele KI-Initiativen in Pilotphasen und werden nicht in stabile Routinen oder skalierte Wertschöpfung überführt (McKinsey & Company, 2025).

Vor dem Hintergrund dieser Diskrepanz liegt der Fokus der Dissertation auf der Frage, wie individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption miteinander zusammenhängen und welche Bedingungen dazu beitragen können, dass aus einzelnen Nutzungserfahrungen eine dauerhafte Verankerung von KI in Organisationen entsteht. Damit rückt nicht nur die Einführung einzelner Technologien in den Blick, sondern auch das Zusammenspiel von subjektiver Wahrnehmung, konkreter Nutzungspraxis und organisationaler Einbettung.

Ausgangspunkt ist dabei die Annahme, dass private KI-Nutzung, KI-Nutzung im Arbeitskontext und organisationale KI-Adoption zwar miteinander verbunden sein können, aber nicht denselben Bedingungen folgen. Individuelle KI-Nutzung im Alltag folgt häufig einer explorativen und freiwilligen Nutzungslogik. Menschen probieren KI aus, weil sie unmittelbar nützlich erscheint, geringe Zugangshürden aufweist und in vielen Situationen ohne größere Konsequenzen getestet werden kann (Siu & White, 2025). Dabei ist KI-Nutzung jedoch nicht allein durch objektive Systemeigenschaften bestimmt, sondern auch durch subjektive Wahrnehmung, Vertrauen und die Einschätzung des eigenen KI-Wissens (Glikson & Woolley, 2020; Logg et al., 2019). Selbst wenn algorithmische Systeme in bestimmten Auf-

gabenbereichen nachweislich leistungsfähig sind, werden ihre Empfehlungen nicht automatisch akzeptiert (Dietvorst & Bharti, 2020; Dietvorst et al., 2015). In der Forschung wird dieses Phänomen unter anderem als Algorithmus- oder KI-Aversion diskutiert (Dietvorst & Bharti, 2020; Dietvorst et al., 2015). Wenn Menschen ihre eigene KI-Kompetenz überschätzen oder eine verzerrte Sicherheit darüber entwickeln, wie KI funktioniert, kann dies paradoxerweise die Bereitschaft erhöhen, KI-Ratschläge abzulehnen und menschliche Empfehlungen zu bevorzugen (Yeomans et al., 2019). Damit wird bereits auf der Ebene individueller Wahrnehmung deutlich, dass KI-Nutzung nicht nur eine Frage technischer Verfügbarkeit ist.

Erfahrungen aus dem privaten Alltag können den beruflichen Umgang mit KI beeinflussen, im Arbeitskontext treffen sie jedoch auf zusätzliche Anforderungen. KI-Nutzung ist dort stärker in organisationale Strukturen, Rollenerwartungen und produktivitätsbezogene Zielvorgaben eingebettet (Frenkenberg & Hochman, 2025). Sie verläuft daher häufig nicht kontinuierlich, sondern situativ und abhängig von konkreten Aufgaben, Freigaben und Nutzungsspielräumen. Zwar können Mitarbeitende durch KI spürbare Leistungsgewinne erzielen, doch geht anfängliches Interesse nicht automatisch in stabile Nutzung über (Cohen & Zalmanson, 2025; Nguyen et al., 2025). Individuelle KI-Nutzung im Arbeitskontext bleibt häufig auf einzelne Anwendungsfälle begrenzt oder wird bei Unsicherheit, negativen Erfahrungen oder organisationalen Veränderungen wieder seltener genutzt (Cohen & Zalmanson, 2025; Ozturkcan & Bozdağ, 2025). Damit stellt sich die Frage, unter welchen Bedingungen aus erster Offenheit und sporadischer Erprobung routinisierte, legitime und verantwortbare KI-Nutzung im Arbeitskontext entstehen kann.

Mit Blick auf organisationale KI-Adoption erweitert sich diese Perspektive nochmals, da individuelle Nutzung hier in strukturelle Einführungs-, Koordinations- und Skalierungsprozesse eingebettet ist (Romeo & Lacko, 2026). Organisationale KI-Adoption vollzieht sich in großen Organisationen typischerweise nicht innerhalb einer einzelnen Abteilung, sondern an Schnittstellen zwischen Business-Rollen, technischen Rollen und funktionalen Bereichen (Ayinaddis, 2025; Miller, 2022). Gerade weil KI nicht nur ein technisches Artefakt, sondern zugleich ein Eingriff in Prozesse, Governance, Datenzugänge, Sicherheitsanforderungen und organisationale Routinen darstellt, ist ein Zusammenwirken unterschiedlicher organisationaler Rollen häufig erforderlich (Horani et al., 2025; Jöhnk et al., 2021; Miller, 2022). Dabei können widersprüchliche Erwartungen, unklare Zuständigkeiten, nicht eindeutig geregelte Entscheidungsrechte und fehlende Verantwortungszuweisungen entstehen (van

Slooten et al., 2024). Solche rollenbezogenen Spannungen können dazu beitragen, dass technisch funktionsfähige KI-Lösungen nicht skaliert werden und Projekte im Pilotstatus verharren (Tursunbayeva & Gal, 2024).

Die dargestellten Unterschiede legen nahe, KI-Nutzung und KI-Adoption entlang mehrerer Ebenen zu betrachten. In der vorliegenden Arbeit wird diese Unterscheidung über drei Analyseebenen umgesetzt: erstens die individuelle KI-Nutzung im privaten Alltag, zweitens die individuelle KI-Nutzung im Arbeitskontext und drittens die organisationale KI-Adoption. Diese Unterscheidung ist nicht rein taxonomisch, sondern analytisch erforderlich, weil auf jeder Ebene andere Mechanismen dominieren können: beispielsweise im Alltag die subjektive Wahrnehmung und Wissenskalibrierung (Dietvorst et al., 2015; Logg et al., 2019), im Arbeitskontext motivational-volitionale Übergänge und organisationale Legitimation (Gollwitzer, 2012; Prasad Agrawal, 2024), auf organisationaler Ebene sozio-technische Koordination und Rollenklärung (Ayinaddis, 2025; Kahn, 1964; Trist & Emery, 2015). Gleichzeitig ist für die Fragestellung relevant, dass zwischen den Ebenen mögliche Übergänge und Anschlussstellen bestehen. Erfahrungen aus dem Alltag können den Umgang mit KI im Arbeitskontext beeinflussen, während individuelle KI-Nutzung im Arbeitskontext nicht zwangsläufig bereits mit organisationaler Verankerung gleichzusetzen ist.

Gerade die Verbindung dieser Ebenen ist im bestehenden Forschungsstand bislang nur begrenzt geklärt. Forschung zur Nutzung von KI im Alltag konzentriert sich vor allem auf Wahrnehmung, Wissen und Akzeptanz (Glikson & Woolley, 2020; Mahmud et al., 2022); Forschung zur Nutzung von KI im Arbeitskontext untersucht Nutzungsbarrieren, Kompetenzen und Routinisierung (Babashahi et al., 2024; Brynjolfsson et al., 2025); Forschung zur organisationalen KI-Adoption richtet den Blick vor allem auf Einführung, Governance und Skalierung (Dwivedi et al., 2021; Jöhnk et al., 2021). Weniger geklärt ist bislang, wie diese Ebenen zusammenhängen und was durch ihre zusammenführende Betrachtung zusätzlich erklärbar wird.

Aus diesen Überlegungen ergibt sich die leitende Annahme der Dissertation, dass nachhaltige KI-Verankerung in Organisationen weder allein durch technische Leistungsfähigkeit noch allein durch individuelle Akzeptanz hinreichend erklärt werden kann. Vielmehr erscheint sie als Mehrebenenprozess, in dem subjektive Wahrnehmung, konkrete Nutzungs-

praxis und organisationale Einbettung systematisch aufeinander bezogen sind. Die übergreifende Fragestellung der Arbeit lautet daher, inwiefern nachhaltige KI-Verankerung in Organisationen als Mehrebenenprozess verstanden werden kann, in dem individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption systematisch miteinander verbunden sind.

Zur Bearbeitung dieser Fragestellung werden drei empirische Studien durchgeführt, die jeweils eine der drei Ebenen adressieren. Eine vierte Studie verfolgt das Ziel, diese verschiedenen Perspektiven zusammenführend auszuwerten. Damit liegt der wissenschaftliche Mehrwert der Dissertation nicht allein in der Betrachtung der Einzelstudien, sondern in ihrer systematischen Verknüpfung. Die systematische Verknüpfung der Studien soll dazu beitragen, genauer zu untersuchen, wie private KI-Vertrautheit, KI-Nutzung im Arbeitskontext und organisationale KI-Adoption miteinander zusammenhängen. Auf dieser Grundlage zielt die Dissertation darauf ab, einen kontextübergreifenden Erklärungsrahmen zu entwickeln, der die Mechanismen, Übergänge und Friktionen zwischen den Ebenen sichtbar macht und Bedingungen benennt, unter denen private KI-Erfahrungen für legitime, routinisierte und regelkonforme KI-Nutzung im Arbeitskontext sowie für tragfähige organisationale Adoptionsprozesse anschlussfähig werden können.

Der Aufbau der Arbeit folgt der Logik einer kumulativen Dissertation. Kapitel 2 entwickelt den begrifflichen und theoretischen Rahmen entlang der drei Analyseebenen. Kapitel 3 präzisiert die übergreifende Forschungslogik, leitet die Forschungsfragen ab und ordnet die drei Publikationen und die vierte Studie in den Gesamtbeitrag der Arbeit ein. Kapitel 4 diskutiert die zusammengeführten Befunde mit Blick auf ihren theoretischen und praktischen Mehrwert. Kapitel 5 fasst die zentralen Ergebnisse in einem übergreifenden Fazit zusammen.

2 Hintergrund und theoretischer Rahmen

Dieses Kapitel entwickelt den theoretischen Rahmen der Arbeit. Es erfüllt zwei miteinander verbundene Funktionen. Erstens werden die drei Analyseebenen der Dissertation, individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption, begrifflich voneinander abgegrenzt. Zweitens werden die theoretischen Perspektiven herausgearbeitet, die dazu beitragen, verständlich zu machen, wie und warum KI auf diesen Ebenen wahrgenommen, genutzt, routinisiert oder nicht dauerhaft verankert wird. Der Schwerpunkt liegt damit nicht auf einer bloßen Beschreibung von KI-Anwendungsfeldern, sondern auf den Mechanismen, Bedingungen und Spannungen, die KI-Nutzung und KI-Adoption in unterschiedlichen Kontexten prägen.

Der Aufbau des Kapitels folgt dieser Logik. Zunächst werden in Abschnitt 2.1 die drei Analyseebenen begrifflich eingeführt und in ihrem jeweiligen institutionellen Kontext verortet. Abschnitt 2.2 entwickelt den theoretischen Rahmen der individuellen KI-Nutzung im Alltag. Abschnitt 2.3 richtet den Blick auf KI-Nutzung in Organisationen und unterscheidet zwischen individueller KI-Nutzung im Arbeitskontext und organisationaler KI-Adoption. Abschnitt 2.4 verdichtet die zentralen Aspekte der drei Ebenen zu einer übergreifenden theoretischen Perspektive.

2.1 Begriffliche Abgrenzung der drei Analyseebenen

Die vorliegende Arbeit unterscheidet analytisch zwischen individueller KI-Nutzung und organisationaler KI-Adoption. Individuelle KI-Nutzung bezeichnet die tatsächliche Anwendung von KI-Systemen durch einzelne Personen und kann sowohl im privaten Alltag als auch im Arbeitskontext erfolgen. Zu den betrachteten KI-Systemen zählen insbesondere generative KI-Anwendungen wie ChatGPT, Claude oder Gemini, die etwa für das Verfassen von E-Mails, die Informationsrecherche, die Zusammenfassung von Informationen oder die Erstellung von Bildern genutzt werden können (Mozelius & Humble, 2024).

Während individuelle KI-Nutzung im Alltag die selbstinitiierte Verwendung solcher Systeme außerhalb organisationaler Strukturen beschreibt, bezieht sich individuelle KI-Nutzung im Arbeitskontext auf die Nutzung von KI durch Mitarbeitende innerhalb organisationaler

Rahmenbedingungen (Savolainen et al., 2025). Beide Formen sind Ausdruck individuellen Nutzungsverhaltens, unterscheiden sich jedoch in ihrem institutionellen Kontext.

Im Unterschied dazu verweist organisationale KI-Adoption nicht auf einzelne Nutzungsakte, sondern auf die strukturelle Einführung, Einbettung und Skalierung von KI auf Ebene der Organisation. Sie umfasst technische Infrastruktur, Governance-Strukturen, Zuständigkeiten, Prozesse und organisationale Routinen (Jöhnk et al., 2021).

Für die vorliegende Dissertation werden die drei Analyseebenen wie folgt bestimmt:

1. Individuelle KI-Nutzung im Alltag bezeichnet die Verwendung von KI-Tools durch einzelne Personen außerhalb organisationaler Strukturen zur Unterstützung konkreter Aufgaben.
2. Individuelle KI-Nutzung im Arbeitskontext bezeichnet die Verwendung von KI-Tools durch Mitarbeitende innerhalb organisationaler Rahmenbedingungen zur Unterstützung konkreter Arbeitsaufgaben.
3. Organisationale KI-Adoption bezeichnet die strategische Einführung, Einbettung und Skalierung von KI auf Ebene der Organisation einschließlich der dafür notwendigen technischen, strukturellen und governancebezogenen Voraussetzungen.

Die Unterscheidung der drei Analyseebenen dient in der vorliegenden Arbeit als analytische Strukturierung und folgt keiner bereits vollständig etablierten Standardtypologie. Sie ist jedoch anschlussfähig an Literatur, die KI in Organisationen als mehrstufiges Phänomen beschreibt und dabei sowohl individuelle Nutzungserfahrungen als auch organisationale Einbettungs- und Adoptionsprozesse in den Blick nimmt (Bankins et al., 2024; Dwivedi et al., 2021; Savolainen et al., 2025; Uren & Edwards, 2023). Zugleich erscheint es für die vorliegende Arbeit sinnvoll, diese Ebenen nicht vollständig isoliert zu betrachten, da Erfahrungen aus einem Kontext in andere Kontexte hineinwirken können. Diese mögliche Verschränkung bildet einen Ausgangspunkt der theoretischen Argumentation und lenkt den Blick darauf, wie subjektive Wahrnehmung, konkrete Nutzungspraxis und organisationale Einbettung zusammenwirken und inwiefern sie zur nachhaltigen KI-Verankerung beitragen können.

2.1.1 Individuelle KI-Nutzung im Alltag

Individuelle KI-Nutzung im Alltag bezeichnet die weitgehend selbstinitiierte Verwendung von KI-Tools außerhalb formaler organisationaler Rahmenbedingungen (Mozelius &

Humble, 2024). Typische Anwendungen reichen von Schreibunterstützung und Informationsrecherche bis hin zu Lern- und Kreativaufgaben (Kalla et al., 2023). Charakteristisch für diesen Kontext ist, dass KI-Nutzung meist ohne formale Freigaben, organisationale Kontrolle oder ausgeprägte Rechenschaftsanforderungen erfolgt. Dadurch können vergleichsweise risikoarme Erprobungsräume entstehen, die niedrigschwellige Experimente und erste Gewohnheitsbildung begünstigen (Gupta et al., 2024). Gerade diese informelle Nutzung unterscheidet den Alltag von organisational gerahmten Kontexten, in denen zusätzliche Anforderungen an Legitimität, Nachvollziehbarkeit, Datenschutz und Verantwortung relevant werden können (Savolainen et al., 2025). Für die theoretische Argumentation der Dissertation steht daher weniger im Vordergrund, in welchen einzelnen Anwendungsfeldern KI im Alltag genutzt wird, sondern unter welchen Bedingungen sie als hilfreich, zugänglich und psychologisch anschlussfähig erlebt wird.

2.1.2 Individuelle KI-Nutzung im Arbeitskontext

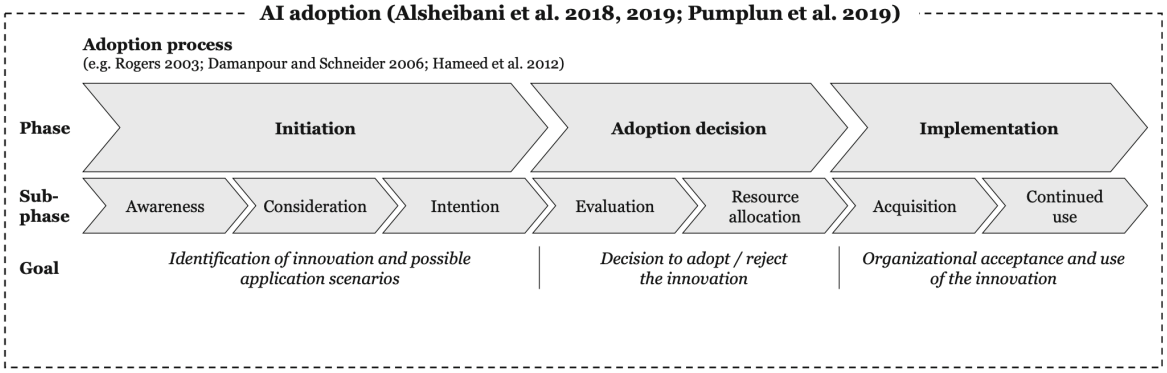
Individuelle KI-Nutzung im Arbeitskontext bezeichnet den Einsatz von KI durch Mitarbeitende innerhalb formaler organisationaler Rahmenbedingungen. Anders als im Alltag ist diese Nutzung stärker durch Leistungserwartungen, Datenschutzvorgaben, Governance-Regeln und rollenspezifische Entscheidungsrechte geprägt (Brynjolfsson et al., 2025). KI wird hier häufig zur Unterstützung wissensintensiver Tätigkeiten eingesetzt, etwa für Recherche, Textproduktion, Analyse oder Entscheidungsvorbereitung (Woodruff et al., 2024; Yun et al., 2025). Für die vorliegende Arbeit steht jedoch weniger im Vordergrund, in welchen konkreten Aufgabenfeldern KI genutzt wird, als vielmehr, unter welchen Bedingungen sich diese Nutzung im Arbeitskontext als legitim, hilfreich, nachvollziehbar und verantwortbar stabilisieren kann. Der Arbeitskontext ist damit als organisational eingebettete Nutzungspraxis zu verstehen, in der individuelle Handlungsspielräume mit institutionellen Anforderungen vermittelt werden.

2.1.3 Organisationale KI-Adoption

Während individuelle KI-Nutzung die konkrete Anwendung von KI-Tools durch einzelne Personen beschreibt, rückt bei organisationaler KI-Adoption die Frage in den Vordergrund, wie KI strukturell eingeführt, koordiniert und dauerhaft in Arbeitsprozesse eingebettet wird.

Organisationen sind durch formalisierte Prozesse, arbeitsteilige Zuständigkeiten, mehrstufige Entscheidungswege und ausgeprägte Governance-Anforderungen geprägt (Prasad et al., 2012). Der Einsatz von KI ist daher nicht ausschließlich als technologische Anwendung zu verstehen, sondern als organisational eingebettete Praxis, deren Einführung, Nutzung und Skalierung durch strukturelle, soziale und institutionelle Rahmenbedingungen mitbestimmt wird (Dwivedi et al., 2021).

Organisationale KI-Adoption (Abbildung 1) bezeichnet damit nicht nur die technische Implementierung einzelner Anwendungen, sondern einen mehrstufigen Prozess organisationaler Einführung, Einbettung und Verstetigung von KI (Jöhnk et al., 2021):



Quelle: Übernommen aus (Jöhnk et al., 2021, p. 8), gekürzter Ausschnitt.

Abbildung 1: Schematische Darstellung der organisationalen KI-Adoption

Für den theoretischen Rahmen der Arbeit steht daher weniger im Vordergrund, welche einzelnen Anwendungsfelder sich empirisch beobachten lassen, sondern welche sozio-technischen Bedingungen relevant werden, damit erste KI-Initiativen in dauerhaftere Formen organisationaler Verankerung übergehen können (Trist & Emery, 2015).

2.2 Theoretischer Rahmen der individuellen KI-Nutzung im Alltag

Dieses Unterkapitel entwickelt den theoretischen Rahmen für die individuelle KI-Nutzung im privaten Alltag. Im Mittelpunkt steht, wie Individuen KI wahrnehmen, bewerten und in alltägliche Nutzungspraktiken integrieren. Dazu werden zunächst Perspektiven der Techno-

logieakzeptanz aufgegriffen, um zentrale Einflussfaktoren individueller Nutzungsbereitschaft zu erläutern. Anschließend wird der Zusammenhang zwischen subjektivem KI-Wissen, Wissenskalibrierung und KI-Aversion betrachtet.

2.2.1 Subjektive Wahrnehmung, Technologieakzeptanz und Nutzungsdynamik

Die Nutzung von KI im Alltag ist nicht allein eine Frage technischer Verfügbarkeit, sondern wird wesentlich durch die Wahrnehmung der Nutzenden geprägt (Mahmud et al., 2022). Durch den vielfältigen Einsatz im Alltag wird KI zunehmend als alltagsnahes Werkzeug wahrgenommen, das situativ unterstützen, entlasten oder inspirieren kann (Kalla et al., 2023). Einerseits kann KI als nützlich, bequem und zeitsparend erlebt werden, insbesondere wenn sie schnelle Antworten liefert, Informationen verdichtet oder alltägliche Aufgaben vereinfacht (Cadario et al., 2021; Fügener et al., 2022). Andererseits ist die Wahrnehmung häufig von Unsicherheiten, ambivalenten Erwartungen und Skepsis geprägt, da viele Nutzende die Leistungsfähigkeit von KI zwar anerkennen, ihre Funktionsweise, Grenzen und potenziellen Fehlerquellen jedoch nur eingeschränkt einschätzen können (Glikson & Woolley, 2020; Mahmud et al., 2022). Die subjektive Wahrnehmung umfasst damit nicht nur Einschätzungen zur technischen Leistung, sondern auch Urteile über Verständlichkeit, Kontrolle, Verlässlichkeit und die Passung zur eigenen Nutzungssituation.

Um zu verstehen, warum Menschen Technologien unterschiedlich akzeptieren, werden häufig Modelle wie das Technology Acceptance Model und die Unified Theory of Acceptance and Use of Technology herangezogen (Davis, 1985; Venkatesh & Davis, 2000). Diese Ansätze erklären Technologiegebrauch vor allem über wahrgenommenen Nutzen, wahrgenommene Benutzerfreundlichkeit, soziale Einflüsse und unterstützende Bedingungen (Gupta et al., 2024). Für die Nutzung von KI behalten diese Modelle ihre Relevanz, greifen jedoch oft zu kurz, um die Spezifika algorithmischer Systeme hinreichend zu erfassen. In der KI-Forschung werden deshalb regelmäßig zusätzliche Konstrukte wie Vertrauen in KI, wahrgenommenes Risiko, Erklärbarkeit, Transparenz und wahrgenommene Fairness berücksichtigt (Fügener et al., 2022; Glikson & Woolley, 2020; Wang et al., 2020). Diese Erweiterungen tragen dem Umstand Rechnung, dass KI häufig als Black-Box-Technologie wahrgenommen wird, deren Entscheidungslogiken für Nutzende schwer nachvollziehbar sind (Goktas, 2024).

Trotz ihrer großen Verbreitung werden klassische Akzeptanzmodelle zunehmend kritisch diskutiert, weil sie Technologieadoption meist als vergleichsweise statischen Zustand konzipieren (Ajibade, 2018). Typischerweise erfassen sie Prädiktoren wie Nutzenwahrnehmung, soziale Einflüsse oder wahrgenommene Bedienbarkeit zu einem bestimmten Zeitpunkt und leiten daraus Nutzungsabsicht oder tatsächliche Nutzung ab. Dadurch erklären sie vor allem Unterschiede zwischen Personen, erfassen jedoch nur unzureichend, wie sich Technologieeinsatz über die Zeit hinweg entwickelt (Ajibade, 2018). Gerade im Kontext von KI ist ein solches Verständnis nur begrenzt ausreichend, da Nutzungserfahrungen, Unsicherheiten, Lernprozesse und situative Rückkopplungen den Umgang mit der Technologie fortlaufend verändern (Mogaji et al., 2024). KI-Nutzung im Alltag erscheint daher weniger als einmalige Akzeptanzentscheidung, sondern vielmehr als ein dynamischer, phasenhafter Prozess, in dem sich Bewertungen, Erwartungen und Nutzungspraktiken im Zeitverlauf verschieben und neu stabilisieren können (Venkatesh et al., 2024).

Um diesen prozesshaften Verlauf theoretisch genauer zu fassen, kann ergänzend das Rubikon-Modell der Handlungsphasen herangezogen werden (Gollwitzer, 2012). Im Unterschied zu klassischen Akzeptanzmodellen beschreibt es Handeln nicht als punktuelle oder statische Entscheidung, sondern als phasenhaften Verlauf, in dem sich Motivation, Handlung und Bewertung über die Zeit verändern können. Das Modell unterscheidet vereinfacht zwischen einer prädezisionalen Phase des Abwägens, einer präaktionalen Phase der Zielbindung und Planung, einer aktionalen Phase der Umsetzung sowie einer postaktionalen Phase der Bewertung (Gollwitzer, 2012). Damit lassen sich nicht nur lineare Übergänge von Nichtnutzung zur Nutzung erfassen, sondern auch nichtlineare Verläufe, in denen sich Intentionen, Verbindlichkeit, Routinisierung und spätere Neubewertungen über die Zeit verändern (Achtziger et al., 2025; Keller et al., 2020). Individuelle KI-Nutzung im Alltag kann vor diesem Hintergrund als heterogen, experimentell und teilweise fragil verstanden werden. Während einige Personen KI zunächst spielerisch ausprobieren und schrittweise in ihre Alltagsroutinen integrieren, bleiben andere zurückhaltend, nutzen KI nur sporadisch oder brechen die Nutzung nach ersten Erfahrungen wieder ab (Hu, 2026).

2.2.2 Wissenskalibrierung und KI-Aversion

Ein zentrales Problemfeld der individuellen KI-Nutzung im Alltag betrifft die Frage, warum algorithmische Empfehlungen trotz nachweislicher Leistungsfähigkeit in bestimmten Aufgabenbereichen nicht automatisch akzeptiert werden. In der Forschung wird dieses Phänomen unter anderem als Algorithmus- oder KI-Aversion diskutiert (Dietvorst, 2016; Mahmud et al., 2022). Positive Erfahrungen mit KI können zwar zu Wiederholung und Gewohnheitsbildung beitragen, wenn die Hürden gering sind und der Nutzen unmittelbar erlebt wird (Hu, 2026). Gleichzeitig können enttäuschende Ergebnisse, wahrgenommene Fehler, fehlende Nachvollziehbarkeit oder ein allgemeines Gefühl des Unbehagens dazu führen, dass KI zwar ausprobiert, aber nicht dauerhaft in Routinen überführt wird (Dietvorst, 2016; Mahmud et al., 2022). Subjektive Bewertungen darüber, ob KI als hilfreiche Unterstützung, als unsicheres System oder als verzichtbare Option erscheint, prägen die Nutzung von KI-Systemen wesentlich (Logg et al., 2019; Yeomans et al., 2019).

Damit rückt die Frage in den Mittelpunkt, wie Personen ihr eigenes Wissen über KI einschätzen und inwieweit diese Selbsteinschätzung mit ihrem tatsächlichen Wissen übereinstimmt. Studien zeigen, dass Nutzende algorithmische Empfehlungen häufig als schwerer nachvollziehbar und komplexer wahrnehmen als menschliche Empfehlungen und die Entstehung von KI-basierten Empfehlungen weniger gut nachvollziehen (Cadario et al., 2021; Yeomans et al., 2019). Weitere Studien weisen darauf hin, dass nicht allein objektives Wissen, sondern gerade die subjektive Einschätzung des eigenen KI-Wissens mitprägt, wie Menschen KI-generierte Ergebnisse bewerten und ob sie KI-Unterstützung annehmen oder zurückweisen (Chiang & Yin, 2021; Fügener et al., 2022).

Aus Perspektive der Wissenskalibrierung reicht es daher nicht aus, lediglich das Ausmaß objektiven KI-Wissens zu betrachten. Relevant ist vielmehr, wie gut die Selbsteinschätzung des eigenen Wissens mit dem tatsächlich vorhandenen Wissen übereinstimmt. Forschung zur Wissenskalibrierung zeigt, dass subjektives und objektives Wissen häufig auseinanderfallen (Alba & Hutchinson, 2000; Koriat et al., 1980; Rozenblit & Keil, 2002). Menschen können ihr Verständnis komplexer Technologien überschätzen, obwohl sie die zugrunde liegenden Mechanismen, Funktionsweisen und Grenzen nur oberflächlich erfassen (Rozenblit & Keil, 2002; Walters et al., 2017). Im KI-Kontext bedeutet dies, dass viele Nutzende zwar

mit Anwendungen und Ergebnissen vertraut sind, nicht jedoch mit den technischen Prozessen, die diesen Ergebnissen zugrunde liegen (Kim et al., 2024). Gerade diese Übereinstimmung oder Diskrepanz zwischen subjektivem und objektivem Wissen ist theoretisch relevant, weil sie erklären kann, warum Menschen KI nicht allein auf Basis tatsächlich vorhandenen Wissens, sondern auch auf Basis ihrer wahrgenommenen Kompetenz bewerten.

Aus empirischer Sicht ist bislang unklar, ob mehr KI-Wissen zu geringerer Skepsis gegenüber KI führt. Einerseits zeigen Studien, dass Personen mit geringerem KI-Wissen algorithmische Entscheidungen eher als unfair wahrnehmen und über verschiedene Kontexte hinweg stärker zu KI-Aversion neigen (Pierson, 2017; Wang et al., 2020; Yeomans et al., 2019). Andererseits finden sich Hinweise darauf, dass Interventionen zur Erhöhung von KI-Wissen nicht in jedem Fall zu geringerer KI-Aversion führen und mitunter sogar Skepsis gegenüber KI verstärken können (Chiang & Yin, 2021). Hinzu kommt, dass in einzelnen Anwendungsfeldern Personen mit geringerem KI-Wissen KI-Empfehlungen sogar häufiger übernehmen, was auf ein heterogenes und kontextabhängiges Wirkungsbild hindeutet (Jacobs et al., 2021). Die Forschungslücke betrifft daher weniger die allgemeine Bedeutung von Wissen, sondern die genauere Erklärung, wie subjektives und objektives Wissen zusammenwirken und unter welchen Bedingungen Fehlkalibrierung Akzeptanz oder Ablehnung von KI begünstigen kann.

2.3 Theoretischer Rahmen von KI-Nutzung im Arbeitskontext und organisationaler KI-Adoption

Dieses Unterkapitel entwickelt den theoretischen Rahmen für KI-Nutzung im Arbeitskontext und organisationale KI-Adoption. Im Mittelpunkt steht die Unterscheidung zwischen individueller Nutzung innerhalb organisationaler Rahmenbedingungen und der strukturellen Verankerung von KI auf Organisationsebene. Dafür werden zunächst Perspektiven auf KI-Nutzung im Arbeitskontext betrachtet. Anschließend wird organisationale KI-Adoption aus einer sozio-technischen Perspektive eingeordnet.

2.3.1 Individuelle KI-Nutzung im Arbeitskontext: Organisational eingebettete Nutzungspraxis

Die individuelle Nutzung von KI im Arbeitskontext unterscheidet sich von rein privater Nutzung vor allem dadurch, dass sie in organisationale Strukturen, Arbeitsprozesse und Verantwortlichkeiten eingebettet ist (Prasad Agrawal, 2024; Romeo & Lacko, 2026; Soulami et al., 2024). Damit KI produktiv eingesetzt werden kann, erscheinen spezifische Kompetenzen und organisatorische Rahmenbedingungen erforderlich. Mitarbeitende benötigen die Fähigkeit, KI-generierte Ergebnisse kritisch zu prüfen und die Ergebnisse in den eigenen Arbeitskontext einzuordnen. Da KI-Tools teilweise unvollständige, fehlerhafte oder irreführende Ergebnisse erzeugen können, ist eine Plausibilitätsprüfung der erzeugten Inhalte zentral (Brynjolfsson et al., 2025). Mitarbeitende sollten daher in der Lage sein, KI-Ergebnisse mit ihrem eigenen Fachwissen zu kombinieren, Informationen zu verifizieren und zu beurteilen, ob generierte Vorschläge für die jeweilige Arbeitssituation geeignet sind (Babashahi et al., 2024).

Neben diesen individuellen Kompetenzen spielt auch die technische und organisatorische Einbettung eine wichtige Rolle. KI-Anwendungen entfalten ihren Nutzen insbesondere dann, wenn sie mit bestehenden Werkzeugen kompatibel sind und sich sinnvoll in bestehende Arbeitsabläufe integrieren lassen (Pinski & Benlian, 2023). Gleichzeitig hängt die tatsächliche Nutzung auch davon ab, ob der Einsatz von KI im organisationalen Umfeld als zulässig, legitim und anschlussfähig wahrgenommen wird (Soulami et al., 2024). Mitarbeitende orientieren sich dabei nicht nur an der technischen Verfügbarkeit von KI-Tools, sondern auch an organisationalen Erwartungen, informellen Normen und wahrgenommenen Nutzungsspielräumen (Tursunbayeva & Gal, 2024).

Im Arbeitskontext zeigen sich zudem verschiedene Barrieren individueller KI-Nutzung. Viele Mitarbeitende verfügen nur über ein begrenztes Verständnis davon, wie KI-Systeme funktionieren, unter welchen Bedingungen sie eingesetzt werden dürfen oder wie KI-generierte Ergebnisse zu bewerten sind (Lin et al., 2026). Diese Unsicherheit kann dazu führen, dass KI entweder gar nicht genutzt wird oder dass KI-generierte Ergebnisse nur schwer in bestehende Arbeitspraktiken integriert werden können (Romeo & Lacko, 2026; Soulami et al., 2024). Hinzu kommen organisationale Einschränkungen wie Datenschutzanforderun-

gen, Sicherheitsrichtlinien, Tool-Beschränkungen oder fehlende Freigaben. In solchen Situationen kann sogenannte Shadow AI entstehen, bei der Mitarbeitende KI-Tools informell außerhalb offizieller organisationaler Strukturen verwenden (Catherine et al., 2025).

Ein weiterer Unsicherheitsfaktor betrifft Fragen der Verantwortung und Haftung. Mitarbeitende stehen häufig vor der Frage, wer für Fehler verantwortlich ist, wenn KI-generierte Inhalte in Arbeitsprozesse einfließen (Lin et al., 2026). Unklarheiten darüber, ob und in welchem Umfang KI-generierte Ergebnisse verwendet werden dürfen, können dazu führen, dass KI nur vorsichtig, selektiv oder situationsabhängig eingesetzt wird (Uren & Edwards, 2023; Westenberger et al., 2022). Insgesamt spricht vieles dafür, dass individuelle KI-Nutzung im Arbeitskontext nicht als punktuelle Ja-Nein-Entscheidung, sondern als phasenhafter Verlauf zu verstehen ist. Ob aus einem ersten Ausprobieren eine stabile und routinisierte Nutzungspraxis entsteht, hängt im Arbeitskontext nicht allein von individueller Motivation oder Gewohnheitsbildung ab. Zusätzliche Bedeutung haben vielmehr organisationale Faktoren wie Legitimation, Freigabe, Datenschutzkonformität, technische Einbettung und die Klärung von Verantwortlichkeiten (Achtziger & Gollwitzer, 2007, 2018; Prasad Agrawal, 2024).

Für die theoretische Argumentation ist zudem relevant, dass individuelle KI-Nutzung im Alltag und im Arbeitskontext nicht vollständig voneinander getrennt sind. Vorerfahrungen aus dem Alltag können Vertrautheit mit KI, erste Prompting-Kompetenzen und eine höhere Experimentierbereitschaft fördern (Savolainen et al., 2025). Im Arbeitskontext treffen solche Vorerfahrungen jedoch auf zusätzliche organisationale Anforderungen, etwa in Form von Regularien, Datenschutzvorgaben und der Nutzung freigegebener Tools. Private Nutzungserfahrungen lassen sich daher nicht in jedem Fall unmittelbar übertragen. Damit erscheint individuelle KI-Nutzung im Arbeitskontext als organisational eingebettete Nutzungspraxis, in der subjektive Erfahrungen, situative Nützlichkeit und institutionelle Rahmenbedingungen zusammenwirken (Högemann et al., 2025).

2.3.2 Organisationale KI-Adoption: Sozio-technische Anforderungen und rollenbezogene Spannungen

Trotz erheblicher technologischer Fortschritte und wachsender Investitionen gelingt es vielen Organisationen bislang nur eingeschränkt, KI über einzelne Pilotprojekte hinaus zu skalieren (McKinsey & Company, 2025). Zur theoretischen Rahmung dieses Problems bietet

die sozio-technische Systemtheorie einen plausiblen Ausgangspunkt (Trist & Emery, 2015). Sie geht davon aus, dass organisationale Technologieeinführung insbesondere dann gelingen kann, wenn technisches und soziales Subsystem aufeinander abgestimmt sind. Zum technischen Subsystem gehören etwa Daten, Modelle, Infrastruktur und Prozesse; zum sozialen Subsystem zählen Rollen, Verantwortlichkeiten, Kommunikationsmuster, Entscheidungsrechte und organisationale Routinen (Bauer & Herder, 2009; Trist & Emery, 2015). Für KI-Adoption bedeutet dies, dass nicht allein technische Leistungsfähigkeit relevant ist, sondern ebenso die Art und Weise, wie unterschiedliche organisationale Rollen zusammenarbeiten, Entscheidungen abstimmen und Verantwortung verteilen.

Gerade in frühen Phasen organisationaler KI-Adoption sind häufig zahlreiche heterogene organisationale Rollen gleichzeitig beteiligt, etwa bei der Identifikation von Anwendungsfällen, der Klärung von Zielsetzungen, der Bewertung von Machbarkeit und dem Anstoß erster Initiativen (Benbya et al., 2020). Dieser Klärungsprozess macht eine enge Abstimmung insbesondere zwischen Business-, technischen und funktionalen Rollen erforderlich, da diese unterschiedliche Perspektiven, Prioritäten und Verantwortlichkeiten in die Einführung von KI einbringen (Jöhnk et al., 2021; Selten & Klievink, 2024).

Während auf Business-Seite vor allem Wertbeitrag, Geschwindigkeit und Anwendungsnähe im Vordergrund stehen, fokussieren technische Rollen eher Fragen der technischen Machbarkeit, Daten- und Systemintegration sowie Modellstabilität (Gunklach et al., 2025; Miller, 2022). Funktionale Rollen aus Bereichen wie Einkauf, Legal, Compliance, HR, Projektmanagement oder Governance richten ihren Fokus dagegen stärker auf Kosten, Regelkonformität, Risikoabsicherung, Dokumentation, Budgetfragen und organisationale Legitimation (Malin et al., 2025; Velsberg, 2025). Aus diesem Zusammenspiel unterschiedlicher Logiken, Erfahrungsniveaus, Zielsetzungen und Verantwortungsbereiche können Spannungen entstehen, die sich nicht nur als allgemeine organisationale Dilemmata, sondern häufig auch als konkrete Rollenkonflikte und Rollenunklarheiten manifestieren (Kahn, 1964; Rizzo et al., 1970).

Rollenkonflikte entstehen insbesondere dann, wenn widersprüchliche Erwartungen parallel an beteiligte Akteure herangetragen werden, sodass die Erfüllung einer Erwartung die Erfüllung einer anderen erschwert (Kahn, 1964; Rizzo et al., 1970). Rollenunklarheit zeigt sich

demgegenüber vor allem dann, wenn Zuständigkeiten, Entscheidungsrechte, Budgetverantwortung, Erfolgsmetriken oder Verantwortungszuschreibungen im KI-Adoptionsprozess nicht eindeutig geregelt sind (Weber et al., 2023; Westenberger et al., 2022). Mögliche Konsequenzen können verlängerte Entscheidungs- und Abstimmungsprozesse, unklare Freigabeentscheidungen, widersprüchliche Erfolgskriterien zwischen Business- und Technikbereichen, Nacharbeit infolge später Compliance- oder Architekturanforderungen sowie eine ausbleibende Überführung technisch valider Lösungen in den produktiven Betrieb sein (Miles & Perreault Jr, 1976; Singh, 1993).

Aus dieser Perspektive verschiebt sich der Fokus von einer rein technischen Optimierung hin zu einer sozio-technischen Betrachtungsweise organisationaler KI-Adoption, in der nicht nur das technische Subsystem, sondern ebenso das soziale Subsystem der Organisation in den Blick genommen wird (Emery & Trist, 1960; Trist & Emery, 2015). Gerade in frühen Phasen organisationaler KI-Adoption, in denen viele heterogene organisationale Rollen gleichzeitig aufeinandertreffen, Strukturen noch nicht stabilisiert sind und Verantwortlichkeiten häufig erst ausgehandelt werden, dürfte das Potenzial für Rollenkonflikte und Rollenunklarheit besonders hoch sein. Darin liegt ein zentraler theoretischer Ansatzpunkt für die Frage, warum KI-Initiativen trotz technologischer Machbarkeit im Pilotstatus verbleiben oder nicht erfolgreich skaliert werden.

2.4 Übergreifende theoretische Verdichtung

Die vorangegangenen theoretischen Überlegungen legen nahe, dass die drei in dieser Dissertation unterschiedenen Ebenen – individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption – zwar analytisch voneinander abzugrenzen sind, jedoch für die Fragestellung der Dissertation nicht vollständig isoliert betrachtet werden. Vielmehr erscheint es konzeptionell plausibel, dass zwischen ihnen ein aufeinander bezogener Zusammenhang besteht, in dem subjektive Wahrnehmung, konkrete Nutzungspraxis und organisationale Einbettung miteinander verschränkt sind. Gerade diese mögliche Verschränkung legt nahe, KI-Nutzung im Alltag, KI-Nutzung im Arbeitskontext und organisationale KI-Adoption aus einer zusammenführenden Perspektive zu betrachten.

Die übergreifende theoretische Relevanz der Unterscheidung liegt darin, dass je nach Analyseebene unterschiedliche Mechanismen, Bedingungen und Problemlagen besonders sichtbar werden. Auf Ebene der individuellen KI-Nutzung rücken vor allem subjektive Wahrnehmung, Wissenskalibrierung, Vertrauen, Unsicherheit und KI-Aversion in den Vordergrund (Dietvorst, 2016; Glikson & Woolley, 2020; Logg et al., 2019). Im Arbeitskontext wird KI-Nutzung zusätzlich durch organisationale Regeln, Verantwortungszusammenhänge und Arbeitsprozesse gerahmt, sodass private Vorerfahrungen zwar relevant, aber nicht in jedem Fall unmittelbar übertragbar sind (Romeo & Lacko, 2026; Soulami et al., 2024). Zwischen Alltag und Arbeitskontext zeichnet sich damit eine relevante Differenz ab, insofern KI-Nutzung im Alltag eher freiwillig, risikoarm und weitgehend selbstreguliert erscheint, während sie im Arbeitskontext tendenziell stärker institutionell gerahmt sowie an Legitimation und Verantwortung gekoppelt ist.

Von der individuellen KI-Nutzung im Arbeitskontext ist wiederum die organisationale KI-Adoption zu unterscheiden. Diese verweist nicht auf einzelne Nutzungsakte von Mitarbeitenden, sondern auf die strukturelle Einführung, Verankerung und Skalierung von KI auf Ebene der Organisation (Dwivedi et al., 2021; Jöhnk et al., 2021; Trist & Emery, 2015). Damit verschiebt sich der Blick von der Nutzungspraxis einzelner Mitarbeitender hin zu der Frage, wie KI in organisationale Strukturen, Prozesse und Routinen eingebettet wird. Beide Perspektiven hängen zwar eng zusammen, bezeichnen aber nicht dasselbe, da wiederholte individuelle KI-Nutzung durch Mitarbeitende nicht automatisch organisationale Adoption impliziert und umgekehrt die strategische Einführung von KI in Organisationen nicht zwangsläufig in routinisierte KI-Nutzung durch Mitarbeitende übergeht.

Aus dieser mehrstufigen Betrachtung ergibt sich die Annahme, dass weder rein psychologische Akzeptanzperspektiven noch rein technologische oder organisationale Implementierungsperspektiven für sich genommen hinreichend sind. Eine ausschließlich individualbezogene Sicht würde unterschätzen, dass organisationale KI-Adoption auch dann ins Stocken geraten kann, wenn Mitarbeitende KI grundsätzlich offen gegenüberstehen, solange klare Zuständigkeiten, Entscheidungsrechte und organisationale Einbettung fehlen. Eine ausschließlich organisationale Sicht würde umgekehrt unberücksichtigt lassen, dass die strategische Einführung von KI nicht automatisch dazu führt, dass Mitarbeitende sie im Arbeitsalltag regelmäßig nutzen. Auch formal eingeführte und technisch verfügbare Systeme können in ihrer Nutzung punktuell bleiben und nicht in routinisierte Praxis übergehen. Naheliegend

ist daher eine sozio-technische Perspektive, die KI weder allein als technische Infrastruktur noch allein als Frage individueller Einstellung versteht, sondern als ein in subjektive Wahrnehmungen, konkrete Nutzungspraxen, Rollen und Zuständigkeiten, Entscheidungsprozesse, technische Infrastrukturen sowie organisationale Rahmenbedingungen eingebettetes Phänomen begreift (Dwivedi et al., 2021; Jöhnk et al., 2021; Trist & Emery, 2015).

Vor diesem Hintergrund richtet die vorliegende Dissertation den Blick darauf, die drei Ebenen nicht additiv nebeneinanderzustellen, sondern als zusammenhängendes Erklärungsproblem zu fassen. Damit greift sie ein Forschungsdefizit auf, das darin liegt, dass bisherige Arbeiten häufig entweder einzelne Kontexte individueller KI-Nutzung oder organisationale KI-Adoption isoliert betrachten, ohne ihre wechselseitigen Bezüge systematisch zu berücksichtigen. Die Arbeit zielt daher darauf ab, einen mehrstufigen Erklärungsrahmen der KI-Verankerung in Organisationen zu entwickeln, der individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption in ihrem Zusammenhang betrachtet. Im Zentrum stehen dabei die Übergänge zwischen diesen Ebenen sowie die Spillover-Effekte, Friktionen, Brücken- und Anschlussbedingungen, unter denen nachhaltige KI-Verankerung in Organisationen begünstigt werden kann.

3 Forschungslogik, Forschungsfragen und Beiträge

Aufbauend auf Kapitel 2 verfolgt diese kumulative Dissertation das Ziel, nachhaltige KI-Verankerung in Organisationen als Mehrebenenphänomen zu erklären. Im Mittelpunkt stehen drei analytisch unterscheidbare, aber eng aufeinander bezogene Ebenen: die individuelle KI-Nutzung im Alltag, die individuelle KI-Nutzung im Arbeitskontext und die organisationale KI-Adoption. Ausgehend von dem in Kapitel 2 entwickelten theoretischen Rahmen wird angenommen, dass individuelle KI-Nutzung und organisationale KI-Adoption auf diesen Ebenen unterschiedlichen Logiken folgen und daher nicht mit einer einheitlichen Erklärungsperspektive erfasst werden können. Während auf Ebene der individuellen KI-Nutzung im Alltag vor allem subjektive Wahrnehmung, Wissenskalibrierung und KI-Aversion bedeutsam sind, rücken im Arbeitskontext zusätzlich organisationale Legitimation, Verantwortungszusammenhänge und Nutzungsdynamiken in den Vordergrund. Auf Ebene der organisationalen KI-Adoption werden diese Fragen schließlich um sozio-technische Koordination, Rollenbeziehungen und strukturelle Verankerung erweitert.

Vor diesem Hintergrund lautet die übergreifende Fragestellung der Dissertation, inwiefern nachhaltige KI-Verankerung in Organisationen als Mehrebenenprozess verstanden werden kann, in dem individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption systematisch aufeinander bezogen sind. Die Dissertation geht damit von der Annahme aus, dass weder private KI-Vertrautheit zwangsläufig zu routinisierter KI-Nutzung im Arbeitskontext führt noch wiederholte individuelle KI-Nutzung bereits organisationale KI-Adoption impliziert. Vielmehr ist zu klären, welche Mechanismen auf den einzelnen Ebenen wirksam sind, wie diese Ebenen zusammenhängen und an welchen Übergängen Friktionen, Brüche oder Stabilisierungseffekte auftreten. Daraus werden drei Forschungsfragen abgeleitet, die jeweils eine der drei Analyseebenen empirisch adressieren und zusammen die empirische Grundlage für die übergreifende Argumentationslogik der Dissertation bilden.

Forschungsfrage 1 – Publikation 1: *Subjective Biased Perception on AI Knowledge and AI Aversion*

Wie beeinflusst die Fehlkalibrierung zwischen subjektivem und objektivem KI-Wissen die Akzeptanz bzw. Ablehnung von KI-Tools im privaten Nutzungskontext?

Diese Forschungsfrage adressiert die Ebene der individuellen KI-Nutzung im Alltag. Sie knüpft an den theoretischen Hinweis an, dass KI-Nutzung im Alltag nicht allein von objektiven Systemeigenschaften abhängt, sondern auch durch subjektive Wahrnehmung, Wissenskalibrierung und KI-Aversion geprägt wird.

Forschungsfrage 2 – Publikation 2: ***Crossing the Rubicon of AI Use: How Employees' Experiences, Behaviors, and Mindsets Shape AI Adoption at the Workplace***
Wie überschreiten Beschäftigte psychologische Schwellen von sporadischer KI-Nutzung hin zu routinisierter Nutzung im Arbeitskontext, und welche organisationalen Bedingungen begünstigen oder erschweren diese Übergänge?

Diese Forschungsfrage adressiert die Ebene der individuellen KI-Nutzung im Arbeitskontext. Im Anschluss an Kapitel 2 knüpft sie an die Annahme an, dass KI-Nutzung im Arbeitskontext nicht als punktuelle Ja-Nein-Entscheidung, sondern als phasenhafter Verlauf zu verstehen ist, der durch organisationale Rahmenbedingungen, Legitimation und wahrgenommene Verantwortbarkeit mitgeprägt wird.

Forschungsfrage 3 – Publikation 3: ***A Socio-Technical Lens on AI Adoption: Role Conflict and Ambiguity in Large Organizations***
Welche Rollenkonflikte und Rollenunklarheiten treten in frühen Phasen der KI-Adoption in großen Organisationen auf, und wie wirken sie auf den Übergang von Pilotprojekten zur Skalierung?

Diese Forschungsfrage adressiert die Ebene der organisationalen KI-Adoption. Sie baut auf der in Kapitel 2 entwickelten Annahme auf, dass organisationale KI-Adoption als sozio-technischer Einbettungsprozess verstanden werden kann, in dem technische Voraussetzungen, organisationale Strukturen und menschliches Handeln aufeinander bezogen sind.

Die drei Forschungsfragen sind damit nicht als isolierte Einzelprobleme angelegt, sondern als komplementäre Zugänge zu einem gemeinsamen Erklärungsproblem. Sie erfassen unterschiedliche, aber miteinander verbundene Ebenen der individuellen KI-Nutzung und organisationalen KI-Adoption und schaffen die Grundlage dafür, deren Zusammenhang systematisch zu analysieren.

Studie 4 – ***Bridging Private and Workplace AI Use: Toward an Integrative Framework for Large Organizations***

Studie 4, die sich zum Zeitpunkt der Einreichung dieser Dissertation im Begutachtungsverfahren befindet, knüpft an diese Logik an und nimmt eine zusammenführende Auswertung der drei vorangegangenen Studien vor. Sie bündelt die Befunde, arbeitet kontextübergreifende Mechanismen der KI-Nutzung heraus und entwickelt einen Rahmen, der die Beziehungen zwischen individueller KI-Nutzung im Alltag, individueller KI-Nutzung im Arbeitskontext und organisationaler KI-Adoption theoretisch ordnet. Im Zentrum steht dabei die Frage, inwiefern individuelle KI-Nutzung im Alltag als Lern- und Erfahrungsraum für spätere KI-Nutzung im Arbeitskontext relevant werden kann, wie sich diese Nutzung unter organisationalen Bedingungen stabilisieren lässt und welche organisationalen Voraussetzungen dazu beitragen können, dass solche Vorerfahrungen für stabile, legitimierte und regelkonforme Nutzung sowie für tragfähige organisationale Adoptionsprozesse anschlussfähig werden.

Die in Kapitel 3 dargestellten vier Studien bilden die Grundlage der vorliegenden kumulativen Dissertation. Publikation 1 wurde veröffentlicht, Publikation 2 und Publikation 3 wurden zur Veröffentlichung angenommen, und Studie 4 befindet sich zum Zeitpunkt der Einreichung im Begutachtungsverfahren. Die einleitenden Einordnungstexte wurden an das Layout der Dissertation angepasst; die eingebetteten Publikationsmanuskripte behalten weitgehend ihr jeweiliges Publikationslayout. Dies betrifft insbesondere Überschriften, Seitenlayout, Nummerierungen von Abbildungen und Tabellen sowie den Zitier- und Referenzstil. Inhaltliche Aussagen der Beiträge bleiben davon unberührt.

Abbildung 2 fasst den Aufbau der Forschungsarbeit zusammen und ordnet die Forschungsfragen sowie die vier Studien in eine gemeinsame Forschungslogik ein. Während Publikation 1 bis 3 jeweils eine der drei Analyseebenen empirisch bearbeiten, übernimmt Studie 4 die zusammenführende Auswertung über alle drei Ebenen hinweg. Der wissenschaftliche Mehrwert der Dissertation liegt somit nicht allein in der Untersuchung der einzelnen Ebenen, sondern in ihrer systematischen Zusammenführung. Auf dieser Grundlage entwickelt die Dissertation einen kontextübergreifenden Erklärungsrahmen, der psychologische Mechanismen, prozessuale Übergänge und sozio-technische Spannungen zwischen individueller KI-Nutzung im Alltag, individueller KI-Nutzung im Arbeitskontext und organisationaler KI-Adoption nicht getrennt, sondern in ihrem Zusammenhang betrachtet.

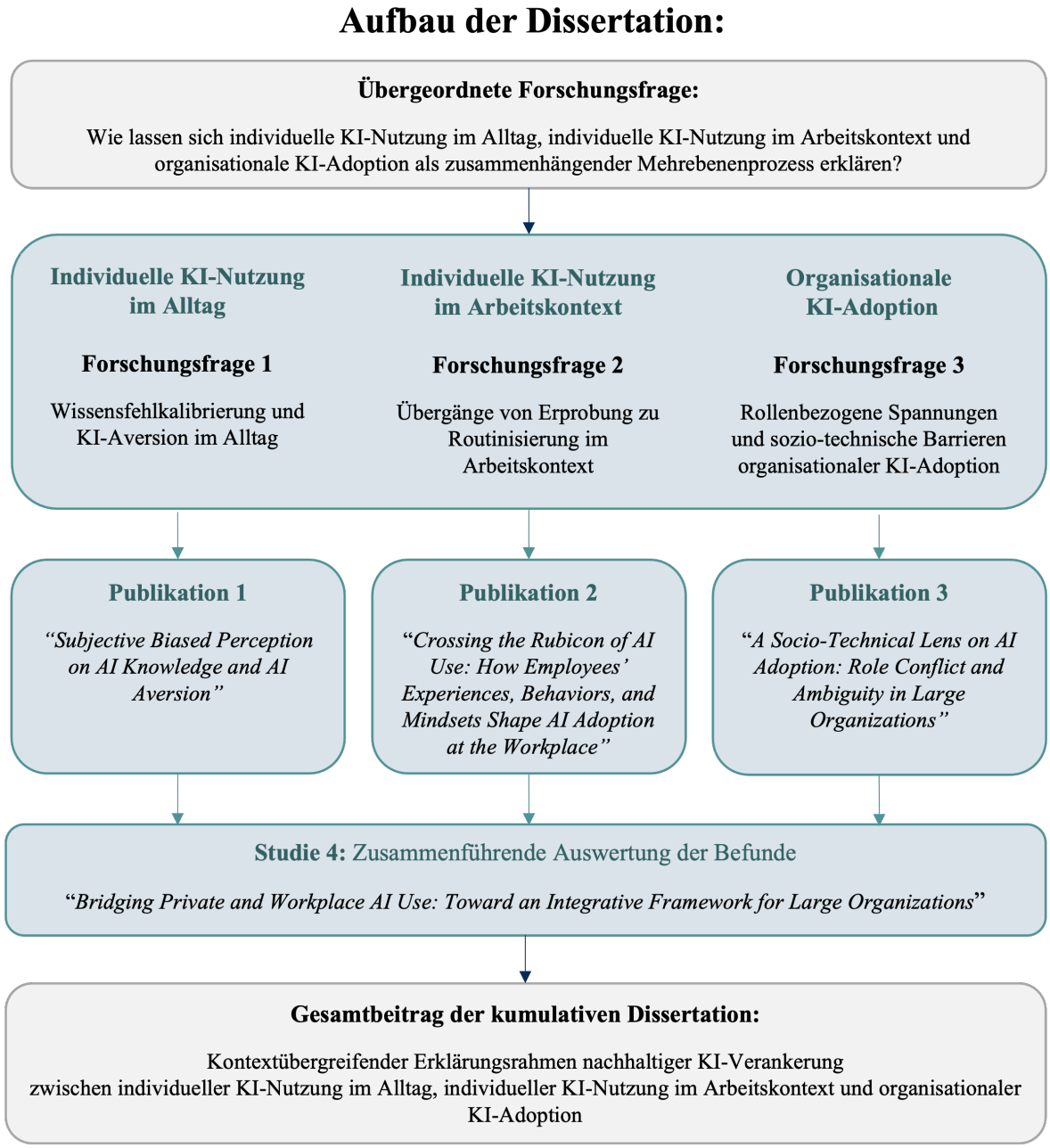


Abbildung 2: Die Forschungslogik der kumulativen Dissertation.

Hinweis: Publikation 1 bis 3 bearbeiten jeweils eine der drei Analyseebenen empirisch, während Studie 4 die Befunde zusammenführend auswertet. Auf dieser Grundlage entwickelt die Dissertation ein kontextübergreifendes Mehrebenenmodell nachhaltiger KI-Verankerung.

3.1 Publikation 1: *Subjective Biased Perception on AI Knowledge and AI Aversion*

"Subjective Biased Perception on AI Knowledge and AI Aversion"

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***Abstract*— The widespread availability of Artificial Intelligence (AI) tools, particularly through wearable devices, has intensified interaction with AI and led to research questioning the human perception of AI advice. Despite of AI's proven efficiency in various tasks, there is a notable reluctance to accept AI recommendations, known as AI aversion. This phenomenon is partly due to a mismatch between users' understanding of AI capabilities and their expectations, which often leads to overconfidence. Efforts like the European Commission's "Ethical Guidelines on the Use of AI" endeavor to enhance AI knowledge from a young age to combat this AI aversion, but academic debate vary. This study among 110 participants showed that people's confidence in AI knowledge influences AI aversion. The more confident an individual about their AI knowledge is, the more likely they are to reject advice from AI input in favor of human advice. The results resolve the conflicting view in the academic debate on this phenomenon and discuss the consequences of biased perceptions of AI technology when people choose between AI and human advice. We also provide evidence for governmental bodies and public to increase the effectiveness of their educational interventions on AI knowledge.**

Keywords—AI knowledge, overconfidence, AI aversion

I. Introduction

As the use Artificial Intelligence (AI) tools is widely accessible through portable AI-powered applications and smartphones, so called wearable AI tools even more motivate people to use AI tools [1]. With these technological developments, academic debate have shown increased interest in better understanding how people treat advice coming from AI systems [2, 3]. It is well known that AI-driven algorithms often outperform human forecasters [4]. Despite this performance advantage, humans are often reluctant to follow AI advice, a term often called AI aversion [2, 3]. Academics and practitioners have suggested increasing individual's AI knowledge to counter this irrational dislike of algorithmic advice [5, 6]. For instance, in cooperation with academia, the private sector, and international organizations, the European Commission published "the Ethical Guidelines on the Use of AI" in which they suggest to increase individual's even in younger ages to engage positively with AI systems [7]. As such, governmental bodies and the public widely agree that individual's is critical to exploiting the full potential of AI, providing better experiences with it, and thus reducing AI aversion.

Importantly, however, existing evidence questions whether AI knowledge has the potential to reduce erroneous skepticism towards AI. On the one hand, studies on AI aversion has shown that people with lower AI knowledge indeed tend to perceive advice from AI systems as more unfair [8] and in general are more aversive towards AI across different domains [6, 9]. This stream of research suggests increasing individual's (e.g., through online courses on learning platforms for AI, [10]) to reduce AI aversion. On the other hand, studies also found that there are many situations and contexts in which increasing AI knowledge (e.g., through interventions) does not have any effect on individuals' AI aversion or could even increase skepticism towards AI [10, 11]. In fact, a study published in 2020 even found in a study involving clinicians that those with lower AI knowledge were seven times *more* likely to select medical treatments recommended by AI [11]. As such, existing research provides an unclear and heterogeneous picture of when and how AI knowledge actually affects AI aversion.

Interestingly, recent research on AI aversion [5, 12] suggest that rather than their objective AI knowledge it is *individuals' confidence in their AI knowledge* (i.e., how they [in]correctly assess their knowledge of AI systems) that can lead to AI aversion. Research on knowledge calibration [13, 14] suggests that individuals' confidence in their knowledge varies by the difference between the individuals' subjective knowledge (what they think or believe they know) and their objective knowledge (what they actually know). In the case of difference between these two variables, a knowledge miscalibration arises that has profound consequences for downstream decisions and behaviors [15, 16]. For instance, people often assume that they understand different kinds of systems (e.g., machines or political regulations) much better than they actually do [17]. In such cases, knowledge miscalibration leads people to be overconfident in their knowledge, with the risk that they neglect support offered by these systems [18]. As such, people's miscalibrated knowledge towards AI can prevent them from delegating tasks to AI systems [5, 6].

Titel: Subjective Biased Perception on AI Knowledge and AI Aversion

Autoren: Özgür Kartal, Jan Spilski, Thomas Lachmann

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Inhalt:

Basierend auf einem quantitativen Forschungsdesign (Feldstudie) wurde untersucht, wie Menschen zwischen menschlichem und KI-basiertem Rat wählen und welche Rolle dabei KI-Aversion spielt, verstanden als die Ablehnung von KI-Ratschlägen zugunsten menschlicher Empfehlungen. Im Fokus steht dabei nicht nur das objektive KI-Wissen, das heißt das tatsächlich vorhandene Wissen über KI, sondern vor allem das subjektive KI-Wissen, das heißt die eigene Einschätzung darüber, wie viel man über KI weiß. Aus beiden Größen wird eine Wissensfehlkalibrierung beziehungsweise die Variable Confidence in AI Knowledge abgeleitet, verstanden als die Differenz zwischen z-standardisiertem subjektivem und objektivem Wissen. Eine Studie mit N = 110 Teilnehmenden aus der EU zeigt mittels logistischer Regression, dass mit zunehmender Überschätzung des eigenen KI-Wissens auch die KI-Aversion steigt. Mit anderen Worten: Je stärker Personen ihr eigenes KI-Wissen überschätzen, desto eher entscheiden sie sich für menschlichen statt für KI-basierten Rat. Die Ergebnisse tragen dazu bei, widersprüchliche Befunde der KI-Aversionsforschung besser einzuordnen, und geben zugleich Hinweise für Bildungs- und politikbezogene Maßnahmen, etwa indem stärker auf Erklärungstiefe gesetzt wird und nicht nur auf die Frage, was KI ist, sondern auch darauf, wie KI funktioniert.

Einordnung in den Gesamtzusammenhang der Arbeit:

- Publikation 1 adressiert die individuelle KI-Nutzung im Alltag und zeigt, dass nicht mangelndes objektives Wissen, sondern eine Fehlkalibrierung zwischen subjektivem und objektivem KI-Wissen dazu beitragen kann, dass KI-Rat trotz seiner Leistungsfähigkeit zugunsten menschlichen Rats abgelehnt wird.
- Damit macht sie sichtbar, dass die Nutzung von KI bereits auf der Ebene individueller Wahrnehmung durch kognitive Verzerrungen beeinflusst werden kann und nicht erst an organisationalen Bedingungen oder fehlender technischer Einbettung.
- Zugleich legt sie nahe, dass zukünftige Forschung zu KI-Aversion sowie angrenzende Forschungsstränge wie KI-Akzeptanz oder Vertrauen in KI nicht nur rationale und organisationale Faktoren berücksichtigen sollte, sondern auch subjektive Verzerrungen und nicht vollständig rationale Bewertungsprozesse.
- Für Bildungs- und politikbezogene Maßnahmen legen die Befunde nahe, dass nicht nur relevant ist, was Menschen über KI wissen, sondern auch, wie sie KI wahrnehmen und ihr eigenes Wissen einschätzen. Bei der Förderung von KI-Kompetenz erscheint es daher sinnvoll, nicht allein den tatsächlichen Wissensstand in den Vordergrund zu stellen, sondern ebenso die Reflexion subjektiver Verzerrungen und psychologischer beziehungsweise kognitiver Mechanismen, die den Umgang mit KI beeinflussen.

“Subjective Biased Perception on AI Knowledge and AI Aversion”

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***Abstract*— The widespread availability of Artificial Intelligence (AI) tools, particularly through wearable devices, has intensified interaction with AI and led to research questioning the human perception of AI advice. Despite of AI’s proven efficiency in various tasks, there is a notable reluctance to accept AI recommendations, known as AI aversion. This phenomenon is partly due to a mismatch between users’ understanding of AI capabilities and their expectations, which often leads to overconfidence. Efforts like the European Commission's "Ethical Guidelines on the Use of AI" endeavor to enhance AI knowledge from a young age to combat this AI aversion, but academic debate vary. This study among 110 participants showed that people’s confidence in AI knowledge influences AI aversion. The more confident an individual about their AI knowledge is, the more likely they are to reject advice from AI input in favor of human advice. The results resolve the conflicting view in the academic debate on this phenomenon and discuss the consequences of biased perceptions of AI technology when people choose between AI and human advice. We also provide evidence for governmental bodies and public to increase the effectiveness of their educational interventions on AI knowledge.**

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I. INTRODUCTION

As the use Artificial Intelligence (AI) tools is widely accessible through portable AI-powered applications and smartphones, so called wearable AI tools even more motivate people to use AI tools [1]. With these technological developments, academic debate has shown increased interest in better understanding how people treat advice coming from AI systems [2, 3]. It is well known that AI-driven algorithms often outperform human forecasters [4]. Despite this performance advantage, humans are often reluctant to follow AI advice, a term often called AI aversion [2, 3]. Academics and practitioners have suggested increasing individual’s AI knowledge to counter this irrational dislike of algorithmic advice [5, 6]. For instance, in cooperation with academia, the private sector, and international organizations, the European Commission published “the Ethical Guidelines on the Use of AI” in which they suggest increasing individual’s even in younger ages to engage positively with AI systems [7]. As such, governmental bodies and the public widely agree that individual’s is critical to exploiting the full potential of AI, providing better experiences with it, and thus reducing AI aversion.

Importantly, however, existing evidence questions whether AI knowledge has the potential to reduce erroneous skepticism towards AI. On the one hand, studies on AI aversion have shown that people with lower AI knowledge indeed tend to perceive advice from AI systems as more unfair [8] and in general are more aversive towards AI across different domains [6, 9]. This stream of research suggests increasing individual’s (e.g., through online courses on learning platforms for AI, [10]) to reduce AI aversion. On the other hand, studies also found that there are many situations and contexts in which increasing AI knowledge (e.g., through interventions) does not have any effect on individuals’ AI aversion or could even increase skepticism towards AI [10, 11]. In fact, a study published in 2020 even found in a study involving clinicians that those with lower AI knowledge were seven times more likely to select medical treatments recommended by AI [11]. As such, existing research provides an unclear and heterogeneous picture of when and how AI knowledge actually affects AI aversion.

Interestingly, recent research on AI aversion [5, 12] suggest that rather than their objective AI knowledge it is individuals’ confidence in their AI knowledge (i.e., how they [in]correctly assess their knowledge of AI systems) that can lead to AI aversion. Research on knowledge calibration [13, 14] suggests that individuals’ confidence in their knowledge

varies by the difference between the individuals' subjective knowledge (what they think or believe they know) and their objective knowledge (what they actually know). In the case of difference between these two variables, a knowledge miscalibration arises that has profound consequences for downstream decisions and behaviors [15, 16]. For instance, people often assume that they understand different kinds of systems (e.g., machines or political regulations) much better than they actually do [17]. In such cases, knowledge miscalibration leads people to be overconfident in their knowledge, with the risk that they neglect support offered by these systems [18]. As such, people's miscalibrated knowledge towards AI can prevent them from delegating tasks to AI systems [5, 6].

In sum, this present research tests a model that integrates literature on overconfidence and algorithm aversion to examine people's confidence in AI knowledge on AI aversion. We do a study among EU-based participants. Our investigations contribute to the conflicting debate on how people's miscalibration in AI knowledge influences their AI aversion. Assuming we find support for our model, this research also provides practical and policy implications for institutes and organizations investing resources in increasing people's AI knowledge (e.g., the EU Commission).

II. Theoretical Background

A. Drivers of AI Aversion

Society has seen a rise in widely accessible AI tools particularly through wearable devices aiming to support people in decision-making across many industry sectors such as finance, healthcare, judiciary, sales, marketing, or personnel selection [19, 20]. People often choose human advice over algorithmic recommendations, despite the proven efficacy of algorithms in tasks such as financial decision-making and great experiences in the use of daily tasks [2, 3]. Surprisingly, even with awareness of their superiority, many exhibit AI aversion–rejecting AI advice in favor of human input [2, 21]. Significantly, studies suggest psychological factors like overconfidence in one's AI knowledge or a preference for gut instinct over analytical reasoning may exacerbate AI aversion, particularly when decisions are deemed important [21, 22]. For instance, users might not understand the complex algorithms behind Netflix's recommendations, similar to how they cannot know others' thoughts but make inferences based on observable behavior. This lack of understanding fosters a preference for human advice, deemed simpler and more comprehensible than AI-generated recommendations [6]. To mitigate AI aversion, experts advocate educating users about AI, enhancing their understanding of how AI works and its potential benefits [6, 12].

B. Subjective Knowledge: A Knowledge Miscalibration Lens

Evidently, besides individual's objective knowledge, that is what they actually know about AI, another stream of research indicates that people's subjective knowledge, what they think or believe they know, about AI can have an impact on AI aversion [18, 23]. Scholars explain that a high subjective knowledge can hinder people from acquiring additional knowledge towards new subjects (e.g., learning more about a new technology), because people incorrectly believe they already know how to use it and what they can expect from that [24]. This leads people to hold on to their prior knowledge towards the subject and only processing new information that is consistent with their previous hypotheses, generally their previous negative beliefs and expectations towards the subject [25]. To illustrate, you can tell someone that AI tools have an average accuracy of 80% and that is enough to make good decisions, i.e., make them learn more about the AI technology. However, in practice, people still focus on the 20% probability of erring and can reject AI recommendations and thus processing with information that is consistent with their individual hypotheses [2, 26].

As such, researchers emphasize the need to consider people's subjective impressions to better understand why people reject AI input over human recommendations [2, 27, 28]. Thus, while scholars and practitioners assume increased objective AI knowledge to reduce AI aversion, it seems possible that their subjective assessment of their AI knowledge may fundamentally shape this relationship. Past research has indicated the critical role of subjective knowledge for other important areas including vaccination, climate change, finance or education [29-32]. We propose that an excess of subjective AI knowledge over objective AI knowledge may cloud people's judgement of AI advice [6, 33]. Yet, the existing human-AI research has failed to consider the possibility of subjective knowledge driving people's AI aversion.

We draw from overconfidence and AI aversion literature to develop a framework that explains the joint impact of objective and subjective AI knowledge on choosing human over AI advice. In general, a difference between individual's subjective and actual knowledge is encompassed under the concept of knowledge calibration [13, 14]. On average, people commonly overestimate their actual knowledge a phenomenon known as knowledge overconfidence and called a cognitive bias [34]. Several studies showed that people consistently overestimated their actual knowledge over subjective knowledge across various everyday objects to areas

such as tax policy, foreign relations, climate change, and personal finances [16, 35]. This is because people generally struggle to completely accurately evaluate their own knowledge, often believing they understand far better than they truly do [16] but sometimes also underestimating their knowledge. To demonstrate, recent studies found that people´s perceptions of what they know (subjective knowledge) may often exceed their actual (objective) knowledge about important scientific issues (e.g., COVID-19 vaccines or climate change) [29, 36, 37]. Scientists suggest that people evaluate their subjective knowledge only on the ease of interpreting subjects (e.g., "what is a crossbow?") and not their knowledge of the complex mechanisms behind them (e.g., "how does the crossbow works?") [29]. Such miscalibration, in turn, can lead them to reject scientific evidence, as people evaluate this evidence on the basis of simplistic information that corresponds to their hypotheses such as expectations and beliefs [29, 36, 37].

C. Confidence in AI Knowledge and AI Aversion

With regard to modern technologies, scholars found evidence that higher knowledge overconfidence influences the acceptance of decision aids, including algorithms and associated AI tools [38, 39]. Generally, knowledge overconfidence can lead to negative evaluation of algorithmic decision aids [39]. Scholars explain that knowledge overconfident people perceive the information they possess as superior, which can make them to be less inclined to acknowledge their limited knowledge about a specific topic or technology [40]. Along the same line, knowledge overconfident people objectively limit themselves to superficial information, while their subjective impressions, i.e., experiences and beliefs about AI, more strongly influence their response to algorithmic decision support [6, 35]. This miscalibrated knowledge, in turn, makes them unwilling to acquire new information from sources such as algorithmic decision aids [38]. As such, a biased subjective AI knowledge can make people to stay on their negative experiences or make to high expectations [2, 26, 41]. Thus, their subjective impressions can shape their response to AI-based decision support [6]. In sum, various studies on AI aversion indicate that people may have incorrect (negative) beliefs and expectations regarding AI that may drive them to reject support from AI tools (e.g., [2, 3]). Building on this basis, we suggest that individuals who underestimate their subjective AI knowledge compared to their actual objective AI knowledge exhibit lower confidence in AI knowledge, while those who overestimate their subjective AI knowledge having a higher confidence in AI knowledge. We propose the hypothesis of this research:

Hypothesis: An individual's confidence in their AI knowledge has a positive influence on their AI aversion, i.e. the greater their confidence in AI knowledge, the more they reject advice from AI in favor of human advice.

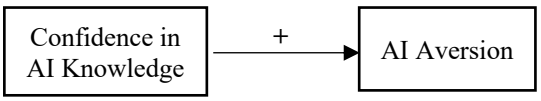

Fig. 1. Research Model of the effect of people's confidence in AI knowledge on AI aversion

III. METHOD

We conducted a field study designed to examine whether the difference between individual's subjective and objective AI knowledge (confidence in AI knowledge) affects their preference for decision support from humans or AI systems (AI aversion). All statistical analyses were performed using IBM SPSS Version 27 [46].

A. Sample

We recruited N = 110 participants from the authors' private network via personal invitations in Germany and the Netherlands by email, targeting academics such as professional researchers and master's students, as well as professionals via social media (LinkedIn). Specifically, we allowed only participants with a working hour of at least 20 hours per week. By doing so, we reached out to participants from a mixed population within the European Union (EU) and filtered out participant's that are unemployed. We used a mechanism of bonus payment (€ 0.50 to the non-profit organization Doctors Without Borders) to increase meaningfulness of the task and further incentivize participants. Our sample comprised N = 110 individuals (60% female; M_{age} = 29.84 years, SD_{age} = 9.40).

B. Measures

The greater people's *subjective AI knowledge* over their objective AI knowledge is, the greater is confidence in AI knowledge is. We again relied on the measurement approach of Light et al. [29].

We measured *objective AI knowledge* by assessing their results on the AI knowledge test including 16 general AI knowledge items [42]. We checked whether the participants chose the correct answer. For each correct answer they received one point, otherwise zero points. We added up all the points and calculated a total objective AI knowledge score (maximum 16).

We calculated the independent variable *confidence in AI knowledge* as a subtraction of the Z-scored subjective AI knowledge and Z-scored objective AI knowledge (Equation 1):

Confidence in AI knowledge = Zscore(Subjective AI knowledge) – Zscore(Objective AI knowledge) (1)

The greater people's subjective AI knowledge over their objective AI knowledge is, the greater is *confidence in AI knowledge* is. We again relied on the measurement approach of Light et al. [29].

We measured *AI aversion* by asking participants to choose to receive advice either from the AI or human agent (see e.g., [3]). Therefore, AI aversion was a dichotomous choice (see also e.g., [43]) in which we coded the AI agent with zero (0, AI) and the human agent with one (human, 1). A participant's choice for human advice rather than AI is an indicator for AI aversion [44]. We chose a task from a subjective domain (e.g., AI recommendations for a joke, see [6]) rather than from an objective domain (e.g., numeric decision task, see [3]) because during decisions in subjective domains, personal and psychological factors such as one's preferences or the protection of one's own identity play a greater role [45]. We derived the decision task from the research on AI aversion and situated a romantic task (see [3], Experiment 1C).

IV. Results

The distribution of the independent variable *Confidence in AI knowledge* shows no extreme values or outliers, and the data both below and above the Z value of 0 are distributed evenly (see Fig. 2).

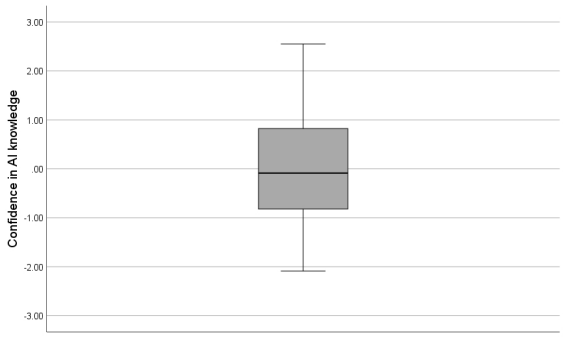

Fig. 2. Distribution of *Confidence in AI knowledge*

The majority of participants preferred the advice of an AI system over a human recommendation (64%, $M_{AI\ aversion}$= 0.36, $SD_{AI\ aversion}$= 0.48). Our hypothesis predicted that an increase in people's confidence in AI knowledge leads to higher AI aversion. We conducted a logistic regression analysis, with people's confidence in AI knowledge as the independent variable and AI aversion as the dependent variable. This logistic analysis revealed a significant positive association between individuals' confidence in AI knowledge and AI aversion (B = 0.462; $OR_{Confidence\ in\ AI\ knowledge}$ = 0.63, $SE_{Confidence\ in\ AI\ knowledge}$ = 0.19, p = 0.017). The more confident an individual about their AI knowledge is, the more likely they are to reject advice from AI input in favor of human advice. Thus, our hypothesis is supported.

TABLE I. Logistic analysis results of our model

Variable	*B*	*S.E.*	Wald	df	Sig.	Exp(B)
Confidence in AI knowledge	0.462	0.193	5.739	1	0.017*	1.587
Constant	-0.592	0.206	8.299	1	0.004*	0.553

Note. * indicates $p < 0.05$.

V. Discussion and Conclusion

We designed this study to expand the literature on algorithm aversion and overconfidence by investigating whether knowledge miscalibration drives individual's decision making when they decide between human and AI supporters. To this end, we investigated whether knowledge miscalibration plays a role in individuals' decision-making processes when they choose between human and AI supporters. To gain insight into this topic, we examined whether there is a discrepancy between individuals' subjective and objective AI knowledge, specifically their confidence in AI knowledge, which may contribute to their aversion to AI. Our findings revealed a significance of individuals' confidence in AI knowledge in their AI aversion. In other words, the more people have a false perception of their actual AI knowledge, the more they are rejecting AI advice in favor of human advice. Past research has indicated the critical role of knowledge overconfidence for other important areas including vaccination, finance or education [29-32]. Light et al. (2022) showed that overconfidence in one's knowledge significantly impacts decision-making, such as the acceptance or rejection of expert recommendations concerning issues like COVID-19 or the climate crisis [29]. Along the same line, our findings propose that an excess of subjective AI knowledge over objective AI knowledge can cloud people's judgement of AI advice [6, 33]. When people have a biased perception on their AI knowledge, an increase on actual AI knowledge through educational facts shows limited effectiveness on reducing AI aversion [29]. Educational interventions can reduce AI aversion, but importantly, the effectiveness of educational interventional requires altering individuals' perceptions of their AI knowledge [29]. This can be achieved by shifting the focus from basic familiarity questions like, "Do you know what AI technology is?" to more in-depth questions such as, "Can you explain how AI technology works and what it is used for?". We thereby recommend augmenting the AI knowledge test [42] with additional items that probe the explanatory depth AI systems, moving beyond simplistic

measures. Asking questions that probe deeper into individual's understanding of AI encourages them to assess their knowledge more realistically and helps mitigate overconfidence [35, 47]. As a result, the risk of knowledge miscalibration reduces, that is a discrepancy between people's perceived (yet often simplistic) understanding of information, and the more complex (and overlooked) aspects of the topic [16]. Information resources that report on AI technology represent another potential risk by influencing individuals' confidence in AI knowledge and their reluctance to adopt AI systems [29]. For instance, if AI technology is often portrayed negatively in the media as a threat to jobs, overconfident individuals are likely to reject AI regardless of their actual level of AI knowledge. Thereby, educational institutions should not only assess individual's objective AI knowledge but also examine the prevailing views within various AI communities, e.g. considering how AI experts communicate about AI in accessible media or in the industry context. Involving AI expert's (positive) views on AI technology on top of fact-based information on AI technology can lay a solid groundwork to increase AI acceptance and reduce AI aversion [48].

Evidently, the academic debate on AI aversion indicates that a biased subjective impression of individual's AI knowledge, driven by people's negative experiences with AI or what they have badly heard so far, may increases AI aversion [5, 6, 12]. This stream of research on AI aversion mainly suggests to decrease distrust factors to reduce AI aversion like negative perceptions, lack of emotional trust [2, 20]. However, the widespread availability of AI tools like OpenAI's ChatGPT, launched in November 2022, garnered 100 million users within only two months, reflecting a significant acceptance and daily use of AI through applications on devices like smartphones [19]. Our findings indicate also a greater interest and basic understanding on AI technology across people. The average AI knowledge score among our participants was 10.71 out of a possible 16 points in our study. In addition, nearly two-third our participants (64%) preferred an AI advice over human recommendations. These results surpass findings from previous studies on AI aversion indicating people may have a low understanding on AI technology and are widely reluctance for AI advice over human recommendations [42, 49]. We propose a review of the psychological factors increasing the AI aversion (distrust factors), noting that recent advancements in AI technology may have significantly altered public perceptions of this technology [20]. Our findings extend this understanding by suggesting that academic research on AI aversion should focus on trust factors such as individual's personal traits, high motivation, curiosity, and openness to AI technology. These trust factors, supported by recent developments in AI technology, could significantly influence AI aversion. [2, 20].

In sum, we found that people's confidence in AI knowledge has a positive influence on AI aversion. Consequently, individuals' biased perceptions of their AI knowledge can lead to flawed decision-making when opting between AI advice and human recommendations, potentially resulting in a stronger reluctance to choose AI advice [2, 3, 29]. Our findings showed that people have a broad interest and solid basic understanding on AI technology [42, 49], highlighting the need to explore trust factors that positively influence AI aversion [20]. Investigating the psychological drivers on AI aversion both before and after ChatGPT became widely available could lead to the identification of new trust factors. Additionally, we propose to investigate the influence of people's confidence in AI knowledge on AI aversion using a more sophisticated AI knowledge test. This AI knowledge test should include complex question items that delve into the depth of understanding, encompassing "how?" questions which explore AI's functionality across diverse use cases and industries [42]. When measuring overconfidence through true or false questions, scholars observed that while respondents accurately assessed true statements, they showed overconfidence in false statements. This phenomenon, known as the veracity effect, reflects the tendency of people to believe statements are true rather than false [50]. This may explain why initial studies on estimating on overconfidence in AI knowledge might not always be fully reliable [42, 49].

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3.2 Publikation 2: *Crossing the Rubicon of AI use: How employees' experiences, behaviors, and mindsets shape AI adoption at the workplace*

Crossing the Rubicon of AI Use: How Employees' Experiences, Behaviors, and Mindsets Shape AI Adoption at the Workplace

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ABSTRACT

Although private use of artificial intelligence (AI) is rapidly increasing, employees in large organizations often remain stuck in experimental or sporadic AI use at work. This exploratory study investigates how employees progress from initial AI intentions to frequent and routinized AI use by drawing on the Rubicon Model of Action Phases. Based on semi-structured interviews with twelve mid- to senior-level practitioners from large organizations and a Gioia-style analysis with substantial inter-coder reliability (κ = .72), this study reconstructs trajectories of employees' use of enterprise AI applications (e.g., internal assistants or copilots) across four Rubicon phases: pre-decisional exploration, pre-actional commitment, actional implementation, and post-actional evaluation. The findings map four phase-typical patterns of experiences, behaviors, and decision mindsets and identify three Rubicon-threshold mechanisms that enable employees to translate initial intentions into routinized use of enterprise AI applications: (1) breakthrough value on real work tasks, (2) organizational legitimacy through secure, governed, and workflow-integrated enterprise AI systems, and (3) stabilization via routines supported by calibrated trust and, for some, an "AI-savvy" professional identity. This study contributes a phase-based process account of workplace AI adoption, a mechanism-based explanation of why strong intentions often remain sporadic, and phase-specific intervention guidance for deploying, governing, and workflow-embedding enterprise AI systems to enable sustained, routinized use.

Keywords: Rubicon Model, AI Adoption, AI at the Workplace

1. INTRODUCTION

Although private use of artificial intelligence (AI) is rapidly increasing, employees in large organizations remain more cautious when using AI in the workplace [1]. Many employees show curiosity and early interest in AI, but they often do not turn this initial enthusiasm into frequent and routinized use of enterprise AI systems [1]. Prior research points to several barriers, such as insufficient skills, unclear value propositions, low organizational readiness, and the novelty and uncertainty of AI technologies [2, 3]. However, these explanations do not fully answer a central question: why do employees use AI readily in their private lives but still struggle to move from experimentation or sporadic AI use to frequent and routinized AI use at work?

Employees also differ in how and whether they integrate AI systems into their daily tasks [4]. Some may never adopt enterprise AI applications, others experiment only from time to time, and a third group uses AI regularly as part of their routines. AI adoption in the workplace follows heterogeneous usage trajectories that depend not only on skills or tool features but also on psychological and contextual factors [4]. For example, employees differ in how they approach AI, ranging from enthusiastic early adopters to cautious or reluctant users [5]. Employees' perceptions of AI, such as whether it increases confidence or triggers career insecurity, also shape whether they move from trial use to sustained use [5]. In addition, AI adoption is influenced by perceived risks, well-being, and social context, which underlines that motivation and workplace conditions are central to whether AI becomes part of everyday routines [4]. Taken together, this work suggests that AI adoption is not only a technical implementation issue but also a motivational and volitional process in which intentions, triggers for commitment, and psychological thresholds determine whether early interest develops into routinized use.

Studies across different industry verticals, such as manufacturing [6] and the public sector [2], show that employees differ widely in how they use AI at work, ranging from non-use to sporadic experimentation to regular, routinized use, and call

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Titel: Crossing the Rubicon of AI Use: How Employees' Experiences, Behaviors, and Mindsets Shape AI Adoption at the Workplace

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Inhalt:

In dieser Studie wurde untersucht, wie Mitarbeitende in großen Organisationen den Übergang von gelegentlichem Ausprobieren zu häufiger und routinisierter KI-Nutzung im Arbeitskontext vollziehen. Als Prozesslinse diente das Rubikon-Modell der Handlungsphasen, um typische Verläufe über vier Phasen hinweg zu rekonstruieren, von frühem Erkunden über eine Commitment-Schwelle bis zur routinisierten Anwendung und späteren Reflexion. Empirische Grundlage bildeten zwölf leitfadengestützte Interviews mit Fach- und Führungskräften auf mittlerer bis höherer Verantwortungsebene, die an der Schnittstelle zu KI-Projekten tätig waren. Die Interviews wurden mithilfe einer Gioia-Analyse ausgewertet und durch eine Intercoder-Reliabilität (κ = .72) abgesichert. Die Ergebnisse zeigen phasentypische Muster in Erleben, Verhalten und Entscheidungsmodus. Daraus werden drei zentrale Schwellenmechanismen herausgearbeitet, die den Übergang zur regelmäßigen Nutzung begünstigen können: spürbarer Nutzen bei realen Arbeitsaufgaben, organisationale Legitimation durch sichere, zugelassene und in Workflows eingebettete Enterprise-Tools sowie Stabilisierung über Routinen. Daraus ergeben sich phasenspezifische Ansatzpunkte für Einführung, Governance und Workflow-Integration von Enterprise-KI.

Einordnung in den Gesamtzusammenhang der Arbeit:

- Publikation 2 rekonstruiert den Übergang von sporadischer zu routinisierter individueller KI-Nutzung im Arbeitskontext und legt nahe, dass KI-Nutzung im Arbeitskontext kein linearer Prozess ist, sondern an motivationalen, situativen und organisationalen Schwellen ins Stocken geraten oder wieder abbrechen kann.
- Damit adressiert sie einen zentralen Übergangspunkt, an dem KI trotz erster Offenheit, verfügbarer Technologie und konkreter Nutzungserfahrungen nicht zwangsläufig in dauerhafte Arbeitspraktiken übergeht, sondern in sporadischer Nutzung verbleibt.
- Zugleich zeigt die Publikation, unter welchen Bedingungen sich dieser Übergang eher stabilisiert, insbesondere durch erlebten Wertbeitrag, organisationale Legitimation und unterstützende Routinen, und macht damit sichtbar, wann individuelle KI-Nutzung im Arbeitskontext für weitergehende organisationale Verankerung anschlussfähig werden kann.

Crossing the Rubicon of AI Use: How Employees' Experiences, Behaviors, and Mindsets Shape AI Adoption at the Workplace

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Abstract

Although private use of artificial intelligence (AI) is rapidly increasing, employees in large organizations often remain stuck in experimental or sporadic AI use at work. This exploratory study investigates how employees progress from initial AI intentions to frequent and routinized AI use by drawing on the Rubicon Model of Action Phases. Based on semi-structured interviews with twelve mid- to senior-level practitioners from large organizations and a Gioia-style analysis with substantial inter-coder reliability ($\kappa = .72$), this study reconstructs trajectories of employees' use of enterprise AI applications (e.g., internal assistants or copilots) across four Rubicon phases: pre-decisional exploration, pre-actional commitment, actional implementation, and post-actional evaluation. The findings map four phase-typical patterns of experiences, behaviors, and decision mindsets and identify three Rubicon-threshold mechanisms that enable employees to translate initial intentions into routinized use of enterprise AI applications: (1) breakthrough value on real work tasks, (2) organizational legitimacy through secure, governed, and workflow-integrated enterprise AI systems, and (3) stabilization via routines supported by calibrated trust and, for some, an "AI-savvy" professional identity. This study contributes a phase-based process account of workplace AI adoption, a mechanism-based explanation of why strong intentions often remain sporadic, and phase-specific intervention guidance for deploying, governing, and workflow-embedding enterprise AI systems to enable sustained, routinized use.

Keywords: Rubicon Model, AI Adoption, AI at the Workplace

1. INTRODUCTION

Although private use of artificial intelligence (AI) is rapidly increasing, employees in large organizations remain more cautious when using AI in the workplace [1]. Many employees show curiosity and early interest in AI, but they often do not turn this initial enthusiasm into frequent and routinized use of enterprise AI systems [1]. Prior research points to several barriers, such as insufficient skills, unclear value propositions, low organizational readiness, and the novelty and uncertainty of AI technologies [2, 3]. However, these explanations do not fully answer a central question: why do employees use AI readily in their private lives but still struggle to move from experimentation or sporadic AI use to frequent and routinized AI use at work?

Employees also differ in how and whether they integrate AI systems into their daily tasks [4]. Some may never adopt enterprise AI applications, others experiment only from time to time, and a third group uses AI regularly as part of their routines. AI adoption in the workplace follows heterogeneous usage trajectories that depend not only on skills or tool features but also on psychological and contextual factors [4]. For example, employees differ in how they approach AI, ranging from enthusiastic early adopters to cautious or reluctant users [5]. Employees' perceptions of AI, such as whether it increases confidence or triggers career insecurity, also shape whether they move from trial use to sustained use [5]. In addition, AI adoption is influenced by perceived risks, well-being, and social context, which underlines that motivation and workplace conditions are central to whether AI becomes part of everyday routines [4]. Taken together, this work suggests that AI adoption is not only a technical implementation issue but also a motivational and volitional process in which intentions, triggers for commitment, and psychological thresholds determine whether early interest develops into routinized use.

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Studies across different industry verticals, such as manufacturing [6] and the public sector [2], show that employees differ widely in how they use AI at work, ranging from non-use to sporadic experimentation to regular, routinized use, and call for investigating these individual AI-use dynamics more closely [7]. This makes an employee-specific investigation of AI-use trajectories increasingly relevant, beyond generic or purely organizational-level views of AI adoption [8, 9]. To investigate these individual threshold dynamics more closely, this study draws on the Rubicon Model of Action Phases (RM) [10] to describe how people move from thinking about an action to actually doing it and later reflecting on it. The RM highlights that adopting a new behavior is not a single decision but a process with different stages [11]. The RM distinguishes four broad phases: considering whether to act (pre-decisional), preparing to act (pre-actional), carrying out the action (actional), and evaluating the outcome afterward (post-actional) [10]. Applied to AI use, the RM could help explain why initial interest or positive intentions do not automatically lead to regular use at work, and why crossing from experimentation to sustained AI use often requires a decisive psychological shift [9].

In this exploratory study, the RM serves as a guiding framework to reconstruct employees' enterprise AI system adoption and integration trajectories in large organizations. The overall goal of this study is on describing phase-specific patterns in experiences (e.g., curious first tries), behaviors (e.g., using AI only occasionally for small tasks), and decision mindsets (e.g., thinking through whether AI is worth using at work) across the four RM phases, thereby providing a foundation for phase-specific, employee-tailored interventions rather than one-size-fits-all organizational programs. More specifically, this phase-based lens aims to clarify when enterprise "intelligent systems" levers, such as secure deployment and approved access to enterprise AI systems, governance and compliance mechanisms, and workflow embedding into existing enterprise information systems become adoption-critical for crossing thresholds from experimentation to routinized use. The study thereby aims to link employees' phase transitions to concrete adoption and integration decisions for enterprise AI systems (secure tooling, governance, and workflow embedding) in organizational contexts. Accordingly, the goals of this study are (1) to provide a phase-based process account of workplace AI adoption by reconstructing trajectories across four RM phases; (2) to specify three Rubicon-threshold mechanisms that explain why strong intentions often remain sporadic use, and (3) to derive phase-specific interventions that inform when and how enterprise AI systems should be introduced, governed, and workflow-integrated to enable routinized use. To address this research focus, the study is based on semi-structured interviews with twelve mid- to senior-level practitioners and a Gioia-style analysis of the qualitative data [12]. Accordingly, this study is guided by the following research question:

> **RQ:** How do employees' experiences, behaviors, and decision mindsets evolve as they progress from initial AI intentions to frequent and routinized AI use across the four Rubicon phases in large organizations?

2. RELATED WORK

2.1 AI Adoption and Individual Use Dynamics

AI adoption in large organizations is an organizational process in which AI tools, infrastructures, and practices are integrated into business operations to improve efficiency, decision making, and innovation [13]. In large organizations, which are characterized by substantial size and highly formalized structures and processes, AI adoption commonly begins with use case identification followed by proof-of-concept development [13, 14]. Many initiatives stall at this stage and work points to organizational conditions like governance arrangements, organizational readiness, decision structures, and compliance requirements as central reasons for this pattern [15]. However, AI adoption is also described as a human-centered trajectory of individuals rather than a solely organizational endeavor, from occasional experimentation to frequent and embedded use [16].

Individual behavior is often modeled with general technology acceptance frameworks such as the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology [17, 18]. These models describe system use as a function of perceived usefulness, perceived ease of use, performance expectancy, effort expectancy, social influence, and facilitating conditions [17, 18]. Extensions for AI-based systems incorporate additional factors such as trust in algorithms, perceived risk, and perceived transparency [19]. This stream of work identifies which beliefs are associated with higher or lower levels of AI use, but it usually measures them at a single point in time and treats adoption as a relatively static outcome.

Beyond usefulness and ease of use, technology acceptance research also models enjoyment-related drivers and the emergence of habitual use. For example, UTAUT2 extends earlier acceptance models by incorporating

hedonic motivation and habit as central predictors of technology use and continuance, emphasizing that repeated usage can become self-reinforcing once users experience the tool as rewarding, effort-saving, or satisfying [15]. This complements the present study's focus on progression from experimentation to frequent and routinized AI use by highlighting that positive affect (e.g., enjoyment) and emerging habit formation can stabilize usage beyond purely rational evaluations and thereby support movement from sporadic AI use toward more frequent AI use in everyday work tasks [17, 18].

However, individual employees could differ strongly in motivation, confidence, and perceived usefulness of AI when integrating it into everyday tasks [15]. Research on AI and career insecurity indicates that trust in AI and perceived risk to one's job are central for whether employees move from occasional trials to more sustained use [4]. Soulami, et al. [4] add that well-being and social context influence whether AI is experienced as supportive or threatening in daily work. Together, these findings suggest that employees occupy different usage states in practice, such as non-use, sporadic use, and more frequent or routinized use, and that these states are shaped by motivation, trust, perceived usefulness, and perceived risk. However, they do not specify when and how individuals cross psychological thresholds, for example from initial experiments to a clear decision to use AI regularly, or from frequent use back to sporadic use after negative experiences or policy changes. The mechanisms that govern these transitions, and the decision mindsets that support or block movement from experimentation or sporadic AI use to frequent and routinized AI use in the workplace, are still poorly understood.

2.2 Rubicon Model of Action Phases

The Rubicon Model of Action Phases is a motivational and volitional framework that explains how individuals move from considering an action to committing to it, implementing it, and evaluating its outcomes [10]. Originally developed in motivational psychology, the model describes four qualitatively distinct phases: pre-decisional, pre-actional, actional, and post-actional (see Figure 1). The shift from the pre-decisional to the pre-actional phase is described as crossing the Rubicon threshold and marks the transition from deliberating about an action to committing to a concrete goal.

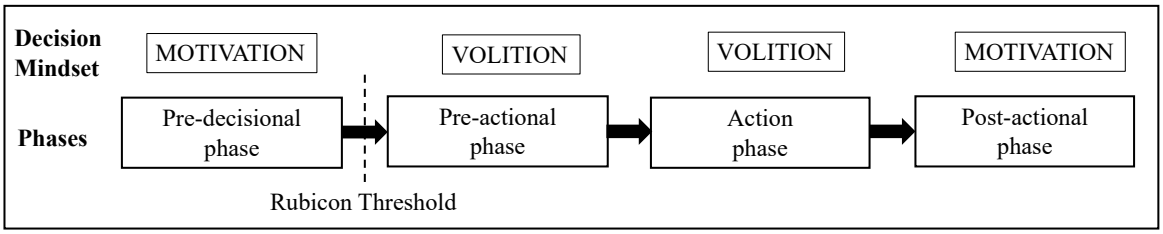

Figure 1: Rubicon Model of Action Phases (adapted from [10]).

In the pre-decisional phase, individuals operate in a motivational mindset. They evaluate whether an action is desirable and feasible, weigh potential risks and benefits, and deliberate on whether it is worth pursuing ("Should I do this?"). Once individuals commit to an action, they cross the Rubicon and enter the pre-actional phase, which is characterized by a volitional mindset. Here, the cognitive focus shifts from deciding whether to act toward planning how to act. Individuals translate intentions into concrete steps, allocate effort, and prepare for implementation ("How do I make this happen?").

The actional phase captures the implementation of the chosen behavior under an action-oriented mindset. Individuals direct their attention toward executing tasks, monitoring progress, and shielding the action from distractions ("What do I need to do right now to keep going?"). After the behavior has been taken, individuals move into the post-actional phase, which involves an evaluative mindset. In this phase, they assess whether the outcomes met expectations, derive lessons from success or failure, and decide whether to maintain, adjust, or abandon the behavior ("Did it work, and what should I do next?").

A key feature of the RM is that each phase involves a distinct decision mindset that shapes how individuals perceive situations, regulate effort, and adapt their behavior [11]. People do not automatically pass through all four phases. They may think about an action for a long time without deciding, decide but never turn this decision into a concrete plan, or start acting and then stop after the first problems appear [10]. Whether they move on depends on how they judge the situation, which resources they have, and which social or organizational conditions support or block the next step [11]. The RM has also been applied in organizational technology

contexts to capture this shift from deliberation to goal striving, for example in research on top managers' support for information systems initiatives [20]. More recently, it has been used to study employees' staged utilization behavior during technology transitions (e.g., e-learning), further supporting its suitability as a process lens for workplace AI use [21].

For AI adoption in the workplace, the RM helps to clarify why employees remain at different levels of AI use [9]. It specifies a sequence of psychological transitions from motivation to intention, to action, to evaluation and thus provides a useful lens for examining how employees either stay with experimentation or sporadic AI use or progress toward frequent and routinized AI use [22]. In large organizations where structures, procedures, or cultural norms do not support these transitions, employees may remain in a state of experimentation or sporadic AI use instead of developing stable, routinized AI use [23]. This study uses the Rubicon Model as a guiding framework to interpret employees' AI-use trajectories by examining their experiences, behaviors, and decision mindsets across the four phases.

3. METHOD

3.1 Research design

This exploratory qualitative study examines how employees in large organizations experience and describe their trajectories of AI use across the four action phases of the Rubicon Model and how these trajectories are reflected in their experiences, behaviors, and decision mindsets. Semi-structured interviews were conducted to achieve sufficient exploratory depth and to surface empirically grounded insights into AI-use trajectories. Participants were mid- to senior-level practitioners who regularly used or oversaw AI tools in their work (e.g., IT development engineers, AI project managers, AI business development managers). All participants (see Table 1) had substantial hands-on experience with AI in their own work tasks and, in many cases, with AI use at the organizational level. This sampling strategy ensured access to practice-embedded expertise on how AI use develops from initial curiosity to more stable, routinized patterns, or stalls along the way.

3.2 Interview procedure

Interview participants were recruited using purposive and snowball sampling to ensure rich, first-hand experience with AI use at work [24]. Initial participants were approached through the authors' professional networks, LinkedIn, telephone contacts, and email invitations, with further participants recruited via referrals. This approach enabled access to practitioners who could describe changes in AI use over time, rather than only early or exploratory impressions.

The final sample comprised twelve mid- to senior-level practitioners working with AI across a variety of roles and organizational settings (see Table 1). Participants represented roles including second-line management, senior IT and presales consulting, IT development engineering, AI project and program management, AI business development, IT operations, and senior and lead AI architecture. The organizations represented sectors including logistics, industrial automation and digital technology, information technology, electronics, transportation, construction, chemicals, and the public sector. To protect confidentiality, participants are referred to using pseudonyms (T1–T12).

Table 1. Interview participants.

ID	Role	Company Industry	Company Type
T1	Second line manager	Logistics	Parcel and Courier
T2	Senior IT consultant	Engineering	Industrial automation and digital technology solutions
T3	Senior IT consultant	Information Technology	IT products and services
T4	Senior presales consultant	Information Technology	IT products and services
T5	IT development engineer	Electronics	High-tech manufacturing and R&D
T6	AI project manager	Transportation	Public infrastructure and mobility services

ID	Role	Company Industry	Company Type
T7	AI business development manager	Information Technology	IT products and services
T8	AI project manager	Construction	Infrastructure and construction services
T9	IT operations lead	Chemicals	Manufacturing of chemicals
T10	Senior AI architect	Information Technology	IT architecture and services
T11	Lead AI architect	Information Technology	IT architecture and services
T12	Senior AI program manager	Public Sector	AI policy and strategy

The interview guide (see Table 2) was developed iteratively to capture AI-use trajectories across the Rubicon phases while avoiding overly theory-laden language. Rubicon phases were translated into behaviorally specific, open-ended questions, complemented by probes tailored to AI use. The interview guide served as a flexible guide rather than a fixed script, ensuring consistency across interviews while allowing for emergent insights.

Table 2. Interview guide for exploring AI-use trajectories across Rubicon phases (pre-decisional, pre-actional, actional, post-actional)

Interview Section	Guiding Interview Questions
Pre-decisional phase	How did your use of AI begin, and what stands out to you from that early period? What kinds of things did you do with AI at that time, and how often did these situations occur in your work or private life? How were you thinking about AI when you were deciding whether to use it or not in those early situations?
Pre-actional phase	What kinds of situations led to noticeable changes in the way you use AI? How did your way of working with AI change after such a situation? What was going through your mind when you decided how you wanted to use AI in your work going forward?
Action phase	What place does AI currently have in a typical workday for you? How does a recent work task unfold when AI is involved, step by step? What guides your decisions in the moment about whether and how to involve AI in a task?
Post-actional phase	In what ways, if any, has your use of AI influenced your work and your life outside of work overtime? What differences, if any, do you notice between the way you use AI now and the way you used it earlier? How do you evaluate afterwards whether using AI in a particular situation was a good way of working for you?

Interviews were conducted one-to-one via video call or telephone. Interviews lasted on average 27 minutes, resulting in a total recording time of approximately five hours and 28 minutes. While moderate in duration, the interviews were narrowly focused on phase transitions and yielded detailed, practice-based reconstructions of concrete AI-use episodes and decision moments, which supported the study's process-oriented aim. Prior to participation, interviewees received an information sheet, provided informed consent, and were assured of anonymity and confidentiality in line with ethical research practices [25]. All interviews were audio-recorded with permission, transcribed verbatim, anonymized, and stripped of identifying information. The transcripts were imported into ATLAS.ti (v.24.2.0) for data analysis.

3.3 Data analysis

Data were analyzed using the Gioia methodology [14], a qualitative and inductive approach designed to capture how individuals move through the Rubicon action phases during AI adoption.

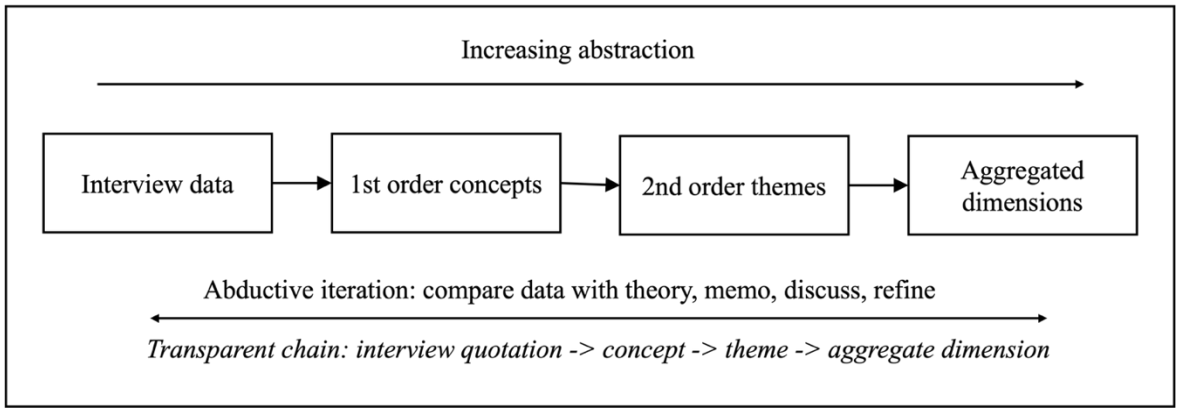

Figure 2: The inferential process in developing a data structure following the Gioia methodology [26, p. 4]

The methodology follows a three-level analytical structure comprising first-order concepts, second-order themes, and aggregate dimensions (see Figure 2). In the first cycle, line-by-line open coding was conducted using participants' own wording to derive informant-centric first-order concepts. In the second cycle, conceptually similar first-order concepts were grouped into second-order themes through iterative comparison, memoing, and discussion among the authors. In a third step, second-order themes were abstracted into aggregate dimensions corresponding to the four Rubicon phases: pre-decisional, pre-actional, actional, and post-actional. For transparency, each coded segment was documented with the verbatim quotation, participant identifier, and timestamp, first-order concept, second-order theme, and aggregate dimension.

Table 3 presents a condensed Gioia-style data structure with representative quotations that illustrate the core phase-specific patterns (e.g., "In the beginning, it was mostly about fun—like a child playing with LEGO for the first time. […]." — T1 [00:07:23] → First-order concept "Playful first experiments with AI; curiosity-driven first trials and early "wow" moments → Second-order theme "Experiences" → Aggregate dimension "Pre-decisional phase"). Table 3 was derived as a curated subset of the full Gioia-style data structure reported in Appendix (Table 7). Within each Rubicon phase and thematic category, a limited number of quotations was selected that most clearly exemplified recurring first-order concepts, while minimizing redundancy and ensuring coverage of all four phases. Importantly, the coding labels reported in Table 3 (first-order concepts, second-order themes, and aggregate dimensions) were taken directly from the complete coding in Table 7; the condensed table therefore reflects selective reporting for readability rather than re-coding or reinterpretation. Given the focused research question, the theoretically guided interview protocol, and the participants' extensive, practice-embedded experience with enterprise AI systems, the dataset provided sufficient information power to reconstruct multi-phase AI-use trajectories across the four Rubicon phases despite the moderate interview length [90, 91]. Appendix (Table 7) reports the full Gioia-style data structure, including all coded segments with original wording and timestamps, thereby enabling full traceability from raw empirical material to higher-order conceptual categories.

Table 3. Gioia-style data structure: Rubicon action phases in AI adoption (*condensed*)

Verbatim; Role & Time stamp	**First-order concept**	**Second-order theme**	**Aggr. dimension**
"In the beginning, it was mostly about fun—like a child playing with LEGO for the first time. I just wanted to see what was possible." — T1 [00:07:23]	Playful first experiments with AI; curiosity-driven first trials and early "wow" moments	Experiences	Pre-decisional phase
"I started using it privately during my master's thesis. I gave it a chapter and saw what it did with my text." — T5 [00:05:35]	Trying AI on personally important but safe tasks; experimenting with AI on small, low-risk personal tasks	Behaviors	Pre-decisional phase
"Initially, it was more experimental—something new and exciting." — T10 [00:05:15]	Treating AI as a novel experiment; open, exploratory attitude; "just trying AI out" without commitment	Decision mindset	Pre-decisional phase

Verbatim; Role & Time stamp	First-order concept	Second-order theme	Aggr. dimension
"There was a moment when I had to answer a lot of emails quickly. I gave AI my bullet points and it wrote the email immediately. From then on I thought: 'I'll use AI regularly.'" — T2 [00:13:23]	Using email overload as a test case for AI; clear productivity gain on a real work task	Experiences	Pre-actional phase
"I would say writing emails, formulating texts. Also for researching certain topics—like when there's a new subject I don't know much about or when I speak with a customer from an unfamiliar industry." — T11 [00:01:46]	First selective uses of AI for emails and new topics; beginning to use AI for specific work tasks (drafting and research)	Behaviors	Pre-actional phase
"When I started using AI to build frameworks and got high-quality results, I realized it really works. Since then I use it regularly." — T1 [00:01:22]	Successful use of AI for complex frameworks; quality-driven commitment to integrate AI into work	Decision mindset	Pre-actional phase
"Actually, I don't even think about it anymore. It's just running in the background. I just open it up without even thinking now." — T8 [00:13:42]	Opening AI tools automatically and intuitively; habitualized, almost unconscious AI use	Experiences	Action phase
"Today I think first: how can I best use ChatGPT for this? How do I phrase my question to get what I need?" — T5 [00:13:07]	Starting many tasks by planning AI use; making AI the default starting point for work tasks	Behaviors	Action phase
"It makes me faster and more efficient. I reach solutions quicker, and that saves time." — T9 [00:06:18]	Feeling faster and more efficient with AI; goal-focused, efficiency-driven orientation that reinforces continued AI use	Decision mindset	Action phase
"I'm better informed and faster than my colleagues. I think the company notices, even if they don't attribute it to AI." — T8 [00:09:30]	Feeling faster and better informed than colleagues; perceiving personal performance advantages through AI use	Experiences	Post-actional phase
"Maybe the biggest benefit would be that I could build a strong internal network. A network of contacts and connections within different projects." — T6 [00:20:50]	Reinvesting saved time into networking and product work; leveraging AI-enabled time savings to take on strategic, higher-level activities	Behaviors	Post-actional phase
"I still find it fascinating, but the novelty has worn off a bit. I've become more critical and more focused on understanding how decisions are made." — T4 [00:30:02]	Moving from wow-effect to sober assessment; developing critical reflection on AI's limits and decision processes	Decision mindset	Post-actional phase
"I'm glad I got into AI early and don't need anyone to explain what it is. It feels like having a personal assistant." — T3 [00:17:51]	Being proud of early adoption and assistant-like support; strengthening identity as an early adopter with an AI "assistant"	Experiences	Post-action phase
"That the questions I ask are answered correctly. … But nowadays… you still need to double-check, stay informed, and verify the AI's outputs to be sure they're accurate." — T8 [00:14:29]	Reinvesting saved time into networking and product work; leveraging AI-enabled time savings to take on strategic, higher-level activities	Behaviors	Post-action phase
"I expect that the questions I ask are answered correctly. But today you still have to double-check and verify the results." — T8 [00:14:29]	Expecting correct answers but still double-checking; calibrated trust and ongoing verification of AI outputs	Decision mindset	Post-action phase

Verbatim; Role & Time stamp	First-order concept	Second-order theme	Aggr. dimension
"AI has significantly increased my productivity. Especially through automated routine tasks and support with research and writing, I save a great deal of time." — T12 [00:20:50]	Evaluating AI's impact on productivity and time; assessing concrete benefits of AI for efficiency and workload	Experiences	Post-action phase
"Now, it feels more like a partner I work with iteratively – bouncing ideas back and forth and exploring different perspectives." — T12 [00:07:31]	Experiencing AI as a collaborative partner; balanced, partnership-oriented view of AI as an ongoing sparring partner	Decision mindset	Post-action phase

(condensed)

3.4 Inter-coder reliability

To enhance analytical rigor, an inter-coder reliability check was conducted in line with qualitative research best practices [27]. Two authors independently coded the interview material after jointly developing the initial codebook from pilot transcripts. Each quotation was treated as a unit of analysis, defined as a contiguous text segment expressing a single idea about AI-use trajectories, decision moments, or consequences of AI use (e.g., *"In the beginning, it was mostly about fun—like a child playing with LEGO for the first time. I just wanted to see what was possible."* — T1 [00:07:23]), resulting in a total of 268 units. Unit boundaries and code definitions were aligned using three pilot transcripts, which were re-unitized and excluded from the κ calculation to avoid inflating agreement [48]. Using the agreed unitization, both authors independently assigned one primary first-order code to each unit from the developing code list, and a coder-by-coder agreement table (see Table 4) was constructed, also known as a confusion matrix [50]. For instance, both authors labeled *"There was a moment when I had to answer a lot of emails quickly. I gave AI my bullet points and it wrote the email immediately. From then on I thought: 'I'll use AI regularly.'"* — T2 [00:13:23] as a productivity-driven commitment under the pre-actional phase, whereas *"Initially, it was more experimental—something new and exciting."* — T10 [00:05:15] received different initial codes and was therefore counted as a disagreement. All disagreements were resolved by consensus, refining the data structure (see Table 3) and ensuring consistency.

Table 4. Cross-table of the coding process, documenting agreements and disagreements between the two authors and serving as the basis for calculating inter-coder reliability.

		Author 1		
		Agreement	Disagreement	Total
Author 2	Agreement	179	14	193
	Disagreement	16	59	75
	Total	195	73	268

Based on the cross table for inter-coder reliability (see Table 4), the authors tallied agreements = 179 and disagreements = 59, giving the observed total agreement = 238:

$$P_0 = \frac{(179+59)}{268} = \frac{238}{268} \approx 0.888 \quad (1)$$

To estimate chance agreement, the analysis computed each coder's marginal proportion of use for every code and then summed the products of corresponding proportions across categories:

$$P_e = \frac{195}{268} x \frac{193}{268} + \frac{73}{268} x \frac{75}{268} \approx 0.600 \quad (2)$$

Cohen's kappa [28] was then calculated using the standard formula:

$$\kappa = \frac{P0-Pe}{1-Pe} = \frac{0.888-0.600}{1-0.600} = 0.72 \quad (3)$$

The corresponding statistical results of the Cohen's Kappa calculations are presented in Table 5.

Table 5. Statistical results of the Cohen's Kappa calculations

Cohen's Kappa	Standard Error	Lower 95% CI	Upper 95% CI	p
0.72	0.05	0.63	0.81	<.001

4. FINDINGS

The analysis of twelve interviews shows that individual AI adoption in everyday work rarely follows a simple "use or don't use" pattern. Instead, participants describe a sequence of experiences, work practices, and mindsets that align closely with the four phases of the Rubicon Model: a pre-decisional exploration phase, a pre-actional threshold phase, an actional implementation phase, and a post-actional evaluation phase. Table 6 summarizes these phases as typical AI-related experiences, work practices and behaviors, and decision mindsets / cognitive orientations. Table 3 provides a representative Gioia-style data structure with illustrative quotes. Below, this study describes each phase and shows how individuals move through, and sometimes back across, these phases as they refine their AI use over time. The interrater reliability yielded substantial agreement between coders, $\kappa = .72$, SE = .05, 95% CI [.63, .81], $p < .001$ (see Table 5). This result indicates a high level of agreement beyond chance, falling within the "substantial agreement" range [29], and thus supports the reliability and consistency of the coding process.

Table 6. Rubicon phases of AI adoption and individuals' experiences, behaviors, and decision mindsets in each phase

Rubicon Phases:	**Pre-decisional phase**	**Pre-actional phase**	**Action phase**	**Post-actional phase**
Experiences	Curiosity-driven first trials and early "wow" moments [T1]; AI feels playful, novel, and low-risk [T10]; early impressions of speed and convenience without real stakes [T8].	Clear productivity and quality improvements on real work tasks [T2]; strong "aha" moments that AI really works [T1, T2]; organizational permission and secure internal tools lower perceived risk and legitimize use [T3]; growing confidence that AI can help in daily work [T1, T2, T11].	Consistently positive experiences and noticeable efficiency gains [T2, T5]; AI becomes embedded in everyday work [T5, T8]; AI is experienced as an assistant or co-pilot [T2, T12]; internal, integrated tools (e.g., linked to CRM or documentation) make AI feel like part of the infrastructure [T7]; use becomes partly habitual and intuitive [T8].	Assessing benefits and limitations [T4, T8]; recognizing accuracy strengths and weaknesses [T8]; noticing concrete productivity and time savings [T12]; experiencing improved work–life balance (less after-hours preparation) [T8]; feeling faster and better informed than colleagues [T8]; developing an early-adopter or "AI-savvy" identity [T3, T7]; experiencing AI as a collaborative partner while becoming more critical of how decisions are made [T12, T4].
Behaviors	Sporadic prompting on small or simple tasks [T5]; experimenting on low-stakes personal tasks (e.g., study work) [T5]; copying examples seen online or from colleagues [T1].	Beginning to use AI for selected, meaningful tasks (emails, drafting, summarizing, rewriting, research, new topics) [T2, T11]; searching for prompts or templates to improve results [T1, T2];	Using AI as a regular starting point for tasks [T5]; keeping AI tools permanently open [T5]; refining prompts and developing routines [T1, T10]; delegating routine tasks to AI and then editing	Adjusting and optimizing routines based on what works [T6, T8]; learning when AI is or is not helpful [T4]; reinvesting saved time into networking, cross-project work, and product improvement [T6]; selectively sharing

Rubicon Phases:	Pre-decisional phase	Pre-actional phase	Action phase	Post-actional phase
		using overload situations (e.g., many emails) as test cases [T2].	[T10]; co-working with AI on core tasks [T2]; structuring complex tasks and meetings [T9]; using enterprise data via integrated AI tools [T7]; applying quality checks and validations [T8].	tips, examples, and good prompts with colleagues [T7, T8].
Decision Mindset	Motivational, open, exploratory mindset [T10]; "just trying it out" without commitment; weighing pros and cons but still treating AI as an experiment [T1, T8].	Volitional, threshold-oriented mindset [T1, T2]; deciding to "take AI seriously" and move from trying to intentional, regular use; quality and productivity gains trigger a commitment to integrate AI into work [T2, T3].	Action-oriented, goal-focused, efficiency-driven mindset [T9]; treating AI as a standard part of the workflow [T5, T7]; accepting occasional errors but continuing use because overall gains are high [T2, T10].	Evaluative mindset with balanced trust ("AI is useful but needs checking") [T8]; critical reflection on AI's limits and decision processes [T4, T12]; seeing AI use as a marker of modern professionalism and future-readiness [T7]; occasionally looping back to earlier phases to refine use or commit to new ways of working with AI [T4, T8].

4. DISCUSSION

Drawing on semi-structured interviews with twelve mid- to senior-level practitioners in large organizations (see Table 1), this study examined how employees progress through distinct phases of AI adoption, from initial curiosity to routinized use, using the Rubicon Model of Action Phases (RM) as a guiding theoretical lens (see Table 7). The discussion focuses on how phase transitions explain why strong intentions often remain sporadic use and how the identified threshold mechanisms translate into phase-specific interventions for the adoption and integration of enterprise AI systems in organizational contexts (secure tooling, governance, workflow embedding). Building on these findings, this section discusses the theoretical and practical implications of conceptualizing workplace AI adoption as a phased motivational–volitional process, followed by limitations and avenues for future research.

5.1 Theoretical implications

Table 7 provides an integrative summary of employees' AI-use trajectories. Table 6 shows that in the pre-decisional phase, AI is approached as playful, novel, and low-risk, often through low-stakes experimentation. In the pre-actional phase, employees face a critical threshold decision to "take AI seriously" and commit to more regular use based on perceived value and feasibility. In the actional phase, AI becomes embedded in everyday routines and is treated as a standard part of task execution. In the post-actional phase, employees evaluate outcomes, recalibrate trust, and refine routines, sometimes looping back to earlier phases when tools, governance, or task demands change. This phase-based perspective shifts attention from whether employees use AI to when, why, and under which conditions AI becomes routinized in day-to-day work. Importantly, it also foregrounds that routinized workplace AI use is coupled to the adoption and integration of enterprise AI systems: employees' transitions depend not only on individual motivation but also on the availability of secure, governed, and workflow-embedded systems that make regular use feasible and legitimate.

Building on the phase patterns summarized in Table 6, Table 7 visualizes workplace AI adoption as a four-stage trajectory. The figure integrates three complementary elements in each phase: (1) what employees experience (e.g., novelty, productivity gains, or the need for verification), (2) what they do in practice (from sporadic trials to routine "AI-first" workflows), and (3) how they think and decide (from exploration to commitment, action focus, and evaluative recalibration). In plain terms, employees typically do not move directly from "not using AI" to "using AI every day." Instead, they progress through phases, with the most consequential shift occurring at the Rubicon threshold, when experimentation turns into committed, intentional use.

Table 7. Employees' AI-use trajectories across Rubicon phases. Within each phase, experiences, behaviors, and decision mindsets co-evolve; transitions are triggered by salient value experiences on real work tasks and enabled by organizational legitimacy through secure and integrated tools. The post-actional phase includes occasional refinement loops back to earlier phases.

	Pre-decisional	**Pre-actional**	**Action**	**Post-actional**
Experiences	• Curiosity-driven "wow" trials • Playful novelty • Low perceived risk	• Breakthrough value on real work tasks • Organizational legitimacy via secure internal tools	• Consistent efficiency gains • AI experienced as an assistant/co-pilot	• Benefits vs. limits salient • Work–life balance • "AI-savvy" identity
Behaviors	• Sporadic prompts for simple tasks • Low-stakes experimentation (often personal/non-workplace use)	• Targeted use for meaningful tasks (emails, drafting summarizing, research) • Prompt search and templates	• AI as default starting point • Delegate → edit → validate	• Optimize routines/boundaries ("when AI helps vs. not") • Reinvest saved time and share selectively with colleagues
Decision mindset	• Exploratory, motivational ("just trying") • Deliberating pros/cons • No commitment	• Threshold decision ("take AI seriously") • Commit to regular use based on value/feasibility	• Action/efficiency focus • Tolerate errors if net gains remain high	• Evaluative, calibrated trust ("useful but needs checking") • Critical reflection

A phase-based process account of workplace AI adoption. Reframing AI adoption as a phased motivational–volitional process shifts the analytical focus from static adoption outcomes (e.g., use vs. non-use) to phase transitions and threshold moments. Prior research on technology adoption emphasizes determinants such as perceived usefulness, ease of use, and organizational readiness [13, 15]. While these frameworks have generated valuable insights, they typically conceptualize adoption as a relatively static outcome and therefore offer limited explanations for how employees move from initial interest to sustained workplace use over time. The findings of this study challenge this binary view by showing that workplace AI adoption unfolds as a sequence of psychologically distinct phases characterized by different experiences, behaviors, and decision mindsets (see Table 6). By doing so, this study supports the view of describing AI adoption as a human-centered trajectory of individuals rather than a solely organizational endeavor, from occasional experimentation to frequent and embedded use [16].

Key Rubicon threshold mechanisms: why intentions often remain sporadic use. The transition into committed workplace use was consistently associated with three interrelated mechanisms. First, employees reported breakthrough value experiences on real work tasks (e.g., clear time savings or quality improvements in emails, drafting, summarizing, or research), which made AI's value tangible. Second, organizational legitimacy, including clear permission, secure approved tools, and workflow integration, reduced perceived risk and friction, making regular use feasible. Third, once use stabilized, employees developed calibrated trust (useful but needs verification) and, for some, an "AI-savvy" professional identity that reinforced continued use. Together, these mechanisms explain why positive intentions alone are often insufficient: employees cross the

Rubicon only when perceived value and organizational conditions align, after which AI becomes easier to sustain and refine.

The findings further indicate that individual's intention alone is insufficient to explain progression from sporadic to routinized AI use. Although technology acceptance models such as TAM [17, 18] and UTAUT [15] position intention as a central predictor of system use, several participants in this study reported strong intentions and repeated experimentation yet remained stuck in occasional AI use. Progression occurred only when specific conditions aligned. In particular, transitions between phases, especially from pre-decisional to pre-actional, and from pre-actional to actional, were shaped by (1) salient breakthrough experiences on real work tasks, (2) organizational legitimization through secure tools, clear policies, and managerial endorsement, and (3) identity gains in the post-actional phase. Together, these mechanisms extend intention-based frameworks by highlighting motivational thresholds, volitional infrastructure, and identity processes as critical links between intention and sustained workplace behavior.

Phase-specific interventions for adoption and integration of enterprise AI systems. Beyond explaining individual phase transitions, the findings also clarify how enterprise AI system integration decisions become phase-contingent. From an intelligent-systems perspective, "AI at work" is often realized through enterprise AI systems (e.g., approved internal assistants/copilots) that require secure deployment, governance, and workflow embedding. The present findings suggest that these system-level levers matter differently across phases: early exploration benefits from safe, low-risk access; the pre-actional threshold depends on legitimacy signals (permission, security assurances, compliance clarity) and reduced friction; routinization in the actional phase is supported by workflow embedding and reusable artifacts (e.g., templates, prompt libraries, integration into everyday systems); and the post-actional phase requires structures for calibrated trust (verification practices, quality checks) and reflective learning. Thus, the study complements individual-level adoption explanations with a phase-based perspective on enterprise intelligent-systems integration, specifying when secure tooling, governance, and workflow embedding become adoption-critical [30].

5.2 Practical Implications

From a managerial perspective, the findings suggest that AI initiatives should be designed as phase-specific, employee-tailored interventions rather than uniform programs [31]. As a first step, organizations can conduct a simple phase-diagnostic assessment to understand where employees currently are in their AI-use trajectories. Such an assessment can combine (a) short survey items that capture curiosity, commitment, routine use, and evaluation; (b) basic usage indicators from internal AI tools; and (c) a small number of qualitative interviews or focus groups to validate patterns [31]. The result is a map of employee segments that predominantly occupy pre-decisional, pre-actional, actional, or post-actional phases.

On this basis, organizations can align interventions with phase-specific needs. For employees in the pre-decisional phase, interventions should focus on safe exploration: sandbox environments, low-risk use cases, and role-specific demonstrations that make AI's possibilities visible without performance pressure [15]. For employees near the pre-actional threshold, interventions should emphasize salient business benefits and legitimacy: concrete success stories on real work tasks, clear communication that AI use is expected and supported, secure and approved enterprise AI systems with clear access rules, and governance clarity [30]. Employees in the actional phase benefit most from support that deepens and stabilizes routines, such as workflow integration, prompt libraries, quality-check guidelines, and lightweight training on advanced use cases. Finally, employees in the post-actional phase require formats that enable reflection and peer learning, such as communities of practice, internal knowledge-sharing platforms, and symbolic recognition of AI fluency as part of professional identity [32]. Across all phases, managers should treat "integration" as more than tool rollout: the adoption of enterprise AI systems depends on visible security assurances, clear governance, and low-friction workflow embedding that aligns with employees' phase-specific decision mindsets.

By combining a phase-diagnostic approach with phase-specific, employee-tailored communication and support, organizations can move beyond generic AI training and create targeted conditions that help employees cross, and recross, their individual Rubicon and sustain meaningful AI use over time [33, 34]. This also supports enterprise intelligent-systems integration by indicating which levers (secure tooling, governance clarity, workflow embedding) should be prioritized at different transition points [33, 34].

5.3 Limitations

This exploratory study aims to uncover phase-specific dynamics in individual AI adoption rather than produce statistically generalizable results [25]. Although the sample size is relatively small, it aligns with established

qualitative research guidelines, which suggest that theoretical saturation is often achieved with 12–15 knowledgeable informants [25]. The twelve participants in this study collectively reported substantial experience with AI across multiple work tasks and projects in large organizations, indicating strong information power. However, all participants were employed in large organizations and held mainly mid- to senior-level roles. Consequently, the findings may not readily transfer to SMEs, start-ups, or junior employees, where AI adoption is shaped by different resource constraints, governance structures, and degrees of decision latitude. In addition, the data rely on retrospective self-reports, which may involve recall bias when participants reconstruct their AI-use trajectories over time.

6. CONCLUSION AND FUTURE WORK

6.1 Conclusion

In summary, this study examined how employees in large organizations move through distinct motivational and volitional phases of AI adoption, from initial experimentation to routinized use. Applying the Rubicon Model of Action Phases, the findings specify micro-level mechanisms, such as salient breakthrough experiences on real work tasks, organizational legitimacy through governance and secure tools, workflow integration, and identity gains, that jointly shape whether AI remains a sporadic experiment or becomes a stable part of everyday work. By integrating psychological action phases with a socio-technical perspective, this study shows that AI adoption is not a smooth or purely rational process but unfolds through qualitatively distinct phases characterized by different experiences, behaviors, and decision mindsets.

The findings further demonstrate that AI adoption differs structurally from traditional, sequential IT projects in large organizations. Rather than progressing through predefined handovers, AI adoption requires employees to repeatedly evaluate value, feasibility, and legitimacy while integrating AI into ongoing work practices. Progression across phases depends not only on individual intention but also on organizational conditions that reduce risk and enable sustained use. Thereby, the study highlights that routinized use emerges when enterprise AI systems are not only available but also secure, governed, and workflow-embedded in ways that match employees' phase-specific decision mindsets. In this way, the study advances AI adoption research by shifting attention from binary adoption outcomes toward phase transitions and threshold moments that explain why many employees remain in sporadic use while others develop routinized AI practices.

6.2 Future Work

Future research could extend this phase-based perspective by using quantitative and mixed-method designs across industry sectors (e.g., public or telecommunications) and other organizational contexts (e.g., SMEs and start-ups). They could also examine whether these phase transition dynamics generalize to junior employees and to organizations outside the current revenue threshold and sector mix, and explore why some employees remain in pre-decisional or pre-actional phases or revert from routinized to sporadic AI use over time. In addition, intelligent-systems research could build on the present findings by evaluating phase-specific enterprise AI system interventions (e.g., secure access models, governance mechanisms, and workflow embedding) and testing which integration levers most effectively support transitions at different phases. For example, future studies could combine interview-based trajectory reconstruction with objective usage traces from enterprise AI systems (where available) to better capture how routinization emerges and how verification practices evolve in the post-actional phase. Finally, intervention-focused research could investigate how communities of practice, prompt libraries, workflow-integrated templates, and formal governance communication interact to stabilize adoption and reduce reversion to sporadic use over time.

APPENDIX

Table 7. Gioia-style data structure: Rubicon action phases in AI adoption (*full-version*)

Verbatim; Role & Timestamp	**First-order concept**	**Second-order theme**	**Aggregate dimension**
"In the beginning, it was mostly about fun—like a child playing with LEGO for the first time. I just wanted to see what was possible." — T1 [00:07:23]	Playful first experiments with AI; curiosity-driven first trials	Experiences	Pre-decisional phase

Verbatim; Role & Timestamp	First-order concept	Second-order theme	Aggregate dimension
	and early "wow" moments		
"Initially, it was more experimental—something new and exciting." — T10 [00:05:15]	Treating AI as a novel experiment; open, exploratory attitude without commitment	Decision mindset	Pre-decisional phase
"At first, I just played around with it a bit. There was no real plan behind it." — T7 [00:04:02]	Unstructured, curiosity-driven experimentation without concrete goals	Behaviors	Pre-decisional phase
"I started using it privately during my master's thesis. I gave it a chapter and saw what it did with my text." — T5 [00:05:35]	Experimenting with AI on personally important but low-risk tasks	Behaviors	Pre-decisional phase
"It felt harmless. I didn't really think about risks at that point." — T3 [00:06:41]	Low perceived risk during early AI exploration	Decision mindset	Pre-decisional phase
"Back then, it was more about curiosity than usefulness." — T9 [00:04:58]	Curiosity outweighs instrumental value considerations	Decision mindset	Pre-decisional phase
"I mostly tried small things, nothing critical." — T2 [00:08:11]	Restricting AI use to low-stakes tasks	Behaviors	Pre-decisional phase
"There was a moment when I had to answer a lot of emails quickly. I gave AI my bullet points and it wrote the email immediately. From then on I thought: 'I'll use AI regularly.'" — T2 [00:13:23]	Breakthrough productivity experience on a real work task	Experiences	Pre-actional phase
"When I started using AI to build frameworks and got high-quality results, I realized it really works." — T1 [00:01:22]	Quality-driven commitment based on successful outcomes	Decision mindset	Pre-actional phase
"I would say writing emails, formulating texts. Also for researching certain topics." — T11 [00:01:46]	First selective integration of AI into meaningful work tasks	Behaviors	Pre-actional phase
"At some point I thought: okay, this is not just a toy." — T4 [00:12:10]	Reframing AI from novelty to serious work tool	Decision mindset	Pre-actional phase
"Once we had an approved internal tool, it felt much safer to really use it." — T3 [00:14:55]	Organizational legitimacy through approved enterprise tools	Experiences	Pre-actional phase
"Knowing that it's allowed and secure made a big difference." — T6 [00:15:42]	Permission and compliance clarity reduce perceived risk	Decision mindset	Pre-actional phase
"That was the point where I decided to actually integrate it into my daily work." — T7 [00:11:08]	Explicit commitment to regular AI use	Decision mindset	Pre-actional phase
"Actually, I don't even think about it anymore. It's just running in the background." — T8 [00:13:42]	Automatic, habitual AI use	Experiences	Actional phase
"Today I think first: how can I best use ChatGPT for this?" — T5 [00:13:07]	AI as default starting point for tasks	Behaviors	Actional phase
"It makes me faster and more efficient. I reach solutions quicker." — T9 [00:06:18]	Efficiency-driven reinforcement of continued AI use	Decision mindset	Actional phase

Verbatim; Role & Timestamp	First-order concept	Second-order theme	Aggregate dimension
“I always have it open when I work.” — T1 [00:09:51]	Persistent availability of AI tools in daily workflow	Behaviors	Actional phase
“I delegate routine stuff to AI and then refine it.” — T10 [00:14:26]	Delegate–edit workflow pattern	Behaviors	Actional phase
“It feels like having an assistant next to you.” — T12 [00:07:31]	AI experienced as assistant or co-pilot	Experiences	Actional phase
“Even if it’s not perfect, the overall gain is worth it.” — T2 [00:16:04]	Tolerance for errors due to net productivity gains	Decision mindset	Actional phase
“I’m better informed and faster than my colleagues.” — T8 [00:09:30]	Perceived personal performance advantage	Experiences	Post-actional phase
“I still find it fascinating, but the novelty has worn off.” — T4 [00:30:02]	Shift from novelty to critical reflection	Decision mindset	Post-actional phase
“You still need to double-check and verify the results.” — T8 [00:14:29]	Calibrated trust and verification practices	Decision mindset	Post-actional phase
“I save a great deal of time.” — T12 [00:20:50]	Evaluating concrete productivity gains	Experiences	Post-actional phase
“I reinvest the saved time into networking and other projects.” — T6 [00:20:50]	Reinvestment of AI-enabled time savings	Behaviors	Post-actional phase
“I’m glad I got into AI early.” — T3 [00:17:51]	Strengthening an AI-savvy professional identity	Experiences	Post-actional phase
“Now it’s more like a partner I work with.” — T12 [00:07:31]	Partnership-oriented view of AI	Decision mindset	Post-actional phase

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3.3 Publikation 3*: A Socio-Technical Lens on AI Adoption: Role Conflict and Ambiguity in Large Organizations*

A Socio-Technical Lens on AI Adoption:
Role Conflict and Ambiguity in Large Organizations

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Abstract. Although AI adoption in private, daily use is accelerating, many initiatives in large organizations stall at the pilot stage and fail to reach production at scale, despite technical optimization. This study examines how heterogeneous organizational roles across business, technical, and functional domains experience role conflict and role ambiguity during AI adoption, and how these role tensions shape adoption outcomes. Based on semi-structured interviews with twelve professionals representing business, technical, and functional organizational roles involved in AI adoption, the Gioia methodology is applied to surface recurrent role conflicts (e.g., business expectations versus technical feasibility; novelty vs. business value) and role ambiguities (e.g., unclear stakeholder responsibilities, risk ownership, and decision-making authority). Substantial inter-coder reliability (κ = .74) supports the consistency of the analysis. By integrating Socio-Technical Systems Theory and Role Conflict Theory, a role-based socio-technical lens is proposed that explains why technically sound AI projects stall when role tensions remain unresolved during the simultaneous engagement of heterogeneous organizational roles. The study contributes a typology of role conflicts and role ambiguities, and discusses their implications for role clarity, decision rights, and cross-functional collaboration.

Keywords: Socio-Technical Systems Theory, Role Conflict Theory, AI Adoption

1 Introduction

The adoption of Artificial Intelligence (AI) in large organizations has accelerated, yet many initiatives stall at the proof-of-concept (PoC) stage and fail to reach production deployment at scale [1]. AI adoption is an organizational process of integrating AI tools, infrastructures, and practices into business operations to improve efficiency, decision-making, innovation, and the realization business value [2, 3]. In large organizations, which are characterized by substantial size and highly formalized structures and processes, AI adoption commonly begins with use case identification followed by PoC development [2, 4]. Technical optimization, such as selecting appropriate AI models, data pipelines, and infrastructure, is widely considered a

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Inhalt:

Basierend auf einem explorativen qualitativen Forschungsdesign (leitfadengestützte Interviews) wurde untersucht, wodurch organisationale KI-Adoption trotz technischer Machbarkeit in frühen Phasen des KI-Adoptionsprozesses stagnieren kann. Im Fokus steht eine sozio-technische Perspektive, die die Zusammenarbeit heterogener organisationaler Rollen aus geschäftsbezogenen, technischen und funktionalen Bereichen sowie die daraus entstehenden Rollenspannungen analysiert. Auf Basis von zwölf Interviews mit Fach- und Führungskräften auf mittlerer bis höherer Verantwortungsebene wird mithilfe einer Gioia-Analyse herausgearbeitet, wie Rollenkonflikte (widersprüchliche Erwartungen) und Rollenunklarheit (unklare Verantwortlichkeiten und Entscheidungsrechte) organisationale KI-Adoption erschweren können. Die Ergebnisse legen nahe, dass organisationale KI-Adoption trotz technischer Machbarkeit vor allem dort ins Stocken geraten kann, wo Rollen, Verantwortlichkeiten und Entscheidungsrechte im KI-Adoptionsprozess nicht hinreichend geklärt sind. Sichtbar werden dabei wiederkehrende, rollenbezogene Spannungen und Unklarheiten, insbesondere in Bezug auf Zuständigkeiten, Entscheidungsrechte sowie Risiko- und Budgetverantwortung. Daraus ergeben sich mögliche Ansatzpunkte für Governance und Koordination, etwa Rollenklärung, abgestimmte Erfolgskriterien und bereichsübergreifende Routinen.

Einordnung in den Gesamtzusammenhang der Arbeit:

- Publikation 3 verschiebt die Perspektive auf die organisationale Ebene und macht sichtbar, dass KI-Adoption nicht nur an individueller Wahrnehmung oder fehlender Routinisierung ins Stocken geraten kann, sondern auch an strukturellen Koordinationsproblemen innerhalb der Organisation.
- Sie macht deutlich, dass durch die gleichzeitige Einbindung heterogener organisationaler Rollen wiederkehrende Rollenkonflikte und Rollenunklarheiten entstehen, die den Übergang von Pilotprojekten in skalierte und dauerhaft verankerte Nutzung erschweren können.
- Damit legt die Publikation nahe, dass selbst akzeptierte und punktuell genutzte KI ohne klare organisationale Einbettung, abgestimmte Entscheidungsrechte und bereichsübergreifende Koordination nur begrenzt in skalierte Nutzung überführt werden dürfte.
- Zugleich liefert sie Ansatzpunkte für Governance, Rollen- und Entscheidungsdesign, um diese strukturellen Spannungen frühzeitig adressierbar zu machen.

A Socio-Technical Lens on AI Adoption: Role Conflict and Ambiguity in Large Organizations

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Abstract. Although AI adoption in private, daily use is accelerating, many initiatives in large organizations stall at the pilot stage and fail to reach production at scale, despite technical optimization. This study examines how heterogeneous organizational roles across business, technical, and functional domains experience role conflict and role ambiguity during AI adoption, and how these role tensions shape adoption outcomes. Based on semi-structured interviews with twelve professionals representing business, technical, and functional organizational roles involved in AI adoption, the Gioia methodology is applied to surface recurrent role conflicts (e.g., business expectations versus technical feasibility; novelty vs. business value) and role ambiguities (e.g., unclear stakeholder responsibilities, risk ownership, and decision-making authority). Substantial inter-coder reliability ($\kappa = .74$) supports the consistency of the analysis. By integrating Socio-Technical Systems Theory and Role Conflict Theory, a role-based socio-technical lens is proposed that explains why technically sound AI projects stall when role tensions remain unresolved during the simultaneous engagement of heterogeneous organizational roles. The study contributes a typology of role conflicts and role ambiguities, and discusses their implications for role clarity, decision rights, and cross-functional collaboration.

Keywords: Socio-Technical Systems Theory, Role Conflict Theory, AI Adoption

1 Introduction

The adoption of Artificial Intelligence (AI) in large organizations has accelerated, yet many initiatives stall at the proof-of-concept (PoC) stage and fail to reach production deployment at scale [1]. AI adoption is an organizational process of integrating AI tools, infrastructures, and practices into business operations to improve efficiency, decision-making, innovation, and the realization business value [2, 3]. In large organizations, which are characterized by substantial size and highly formalized structures and processes, AI adoption commonly begins with use case identification followed by PoC development [2, 4]. Technical optimization, such as selecting appropriate AI models, data pipelines, and infrastructure, is widely considered a primary driver of successful AI adoption [5, 6]. However, a narrow technical view underestimates the fact that AI adoption outcomes depend not only on technical systems, but also on socio-technical dynamics shaped by heterogeneous organizational roles from business, technical, and functional domains involved in the AI adoption process [3]. These organizational roles are professional roles that influence, design, or execute decisions and actions related to AI adoption in large organizations [7]. Each organizational role brings role-specific tasks, responsibilities, and expectations into the AI adoption process [5]. Taken together, the simultaneous involvement of heterogeneous organizational roles may lead to situations in which competing role demands complicate cross-functional coordination, decision-making, and consensus-building across roles in AI adoption processes.

A simultaneous involvement of heterogeneous organizational roles from different domains can enhance but also introduce barriers to AI adoption in large organizations [8]. To illustrate, the diverse expertise of heterogeneous organizational roles may improve the assessment of business value and organizational risk [e.g., 9]. In contrast, divergent priorities can slow down go/no-go decisions, delay deployment, and weaken commitment to specific use cases [e.g., 10]. For example, business executives may emphasize strategic ROI, technical developers may focus on technical feasibility and data constraints, legal and compliance teams may prioritize regulatory assurance, and end-users may demand usability and workflow fit.

A recent AI adoption study in healthcare demonstrates that heterogeneous organizational roles are often engaged unevenly and at different stages of AI projects [11]. While diverse expertise from different domains is critical, the study found that unclear responsibilities and divergent priorities across these heterogeneous organizational roles create coordination challenges that slow the adoption process [11]. Similarly, a study from

the manufacturing sector [12] demonstrated that heterogeneous organizational roles from different domains often pursue divergent priorities, from Return-on-Investment (ROI) calculations to model accuracy, resulting in misaligned expectations and unclear task responsibilities.

However, a dominant technical perspective on AI adoption provides limited insight into the specific role conflicts and role ambiguities that arise across business, technical, and functional domains and how these role tensions influence AI adoption processes. This study integrates Socio-Technical Systems Theory (STS) [13] and Role Conflict Theory [14] to examine how the divergent priorities of heterogeneous organizational roles generate role tensions in AI adoption processes. Role conflict tensions may arise when balancing strategic goals with technical feasibility, regulatory assurance with innovation speed, or model optimization with workflow usability. This often leaves accountability, risk ownership, and decision rights unclear [14]. STS Theory emphasizes that technology adoption succeeds only when the social and technical subsystems are optimized together. The social subsystem comprises human capabilities, incentives, and work practices, while the technical subsystem focuses on technical performance and efficiency [15, 16]. Role Conflict Theory explains how overlapping responsibilities and contradictory expectations among individuals within this social subsystem disrupt coordination and alignment during technology adoption in organizations [14]. By combining STS Theory and Role Conflict Theory, a socio-technical lens is applied on AI adoption, thus extending the predominantly technical perspective of AI adoption by incorporating the social subsystem and examining how heterogeneous organizational roles navigate conflicting expectations that can either hinder or enable progress. The study is guided by the following research question:

> **RQ:** Which role conflict and role ambiguity tensions arise through the simultaneous engagement of heterogeneous organizational roles, and how do these role tensions shape AI adoption processes in large organizations?

To address this research question, a qualitative study is conducted based on semi-structured interviews with twelve mid- to senior-level professionals representing business, technical, and functional organizational roles involved in AI adoption processes. Building on the Gioia methodology [17], the analysis identifies recurrent role conflict and role ambiguity tensions and examines how these role tensions shape AI adoption processes. Implications are discussed for both research and practice, including ways to strengthen role clarity, decision rights, and cross-functional coordination. This study extends the predominantly technical perspective on AI adoption by introducing a role-based socio-technical lens that foregrounds organizational role dynamics.

2 Related Work

2.1 A socio-technical lens on AI adoption

AI adoption is an organizational process in which organizations integrate AI systems to generate business value, enhance efficiency, and foster innovation [4]. Prior research conceptualizes technology adoption as a staged integration process, moving from initiation and decision-making to implementation and scaling [2]. It is also described as a human-centered trajectory from occasional experimentation to frequent and embedded use [18]. However, AI adoption differs from traditional IT adoption because it involves unique challenges such as high data dependency, model opacity, ethical and regulatory uncertainties, significant demands for specialized skills, and operationalization requirements (e.g., AIOps, monitoring, retraining) [19].

Despite efforts to generate positive organizational outcomes, more than half of AI initiatives in large organizations fail to progress beyond the early stage [20]. Studies attribute these failures not only to technical issues but also to a lack of strategic alignment, unclear business cases, cultural resistance, insufficient AI expertise and gaps in AI governance and ownership [21]. This suggests that the success of AI adoption depends not only on overcoming technical deficits but also on aligning technological and human subsystems within the organization [22, 23]. Moreover, the adoption of AI should not be understood as a strictly linear process, as it often involves iterative cycles of experimentation, learning, and refinement that require coordination across multiple organizational roles and perspectives [24].

These diverse facets highlight the importance of applying a socio-technical lens to AI adoption, where outcomes emerge from the interactions between human roles within the social subsystem and the technical subsystem [16].

2.2 Human organizational roles in AI adoption

During AI adoption, heterogeneous organizational roles interact simultaneously to scope use cases, set goals, launch PoCs, and assess feasibility. Such activities require close collaboration across business, technical, and functional domains to ensure alignment of priorities and resources [7, 24]. Within this process, organizational roles contribute distinct perspectives and responsibilities that collectively shape the direction and success of AI initiatives in large organizations [7, 24].

Business roles such as executive leaders (e.g., CEOs, CIOs, CTOs, and CDOs) set the strategic vision, allocate budgets, and sponsor governance structures including AI governance [25]. Business units including marketing, sales, production, and finance provide domain knowledge, articulate value hypotheses, and define success criteria [26, 27]. Functional roles such as project and product managers translate business objectives into deliverables, scope initiatives, and coordinate cross-functional collaboration [24, 28]. Functional roles also include legal and compliance officers who interpret regulatory requirements, prepare documentation, and identify risks in AI adoption [23]. Human resources and change managers anticipate workforce effects, plan reskilling, and manage communication [29, 30]. Procurement departments evaluate vendor proposals, manage cost calculations, and ensure contractual and budgetary compliance during AI solution sourcing [31]. Technical roles such as IT leaders in architecture and operations provision secure environments, safeguard data, and ensure scalability for production deployment [32]. Additionally, data scientists, AI engineers, and data engineers carry out the technical experimentation by preparing data pipelines, training models, and implementing explainability and monitoring as part of AIOps practices [24, 33].

Together, these constitute the internal organizational roles within large organizations. External stakeholders such as consultants, technology vendors, and regulators also shape adoption trajectories by providing expertise, infrastructure, or binding requirements [28, 34]. However, the present study focuses on organizational roles within large organizations, as they are central to the socio-technical dynamics of AI adoption [7, 24].

2.3 Role conflict and role ambiguity in AI adoption

When heterogeneous organizational roles interact simultaneously, alignment and coordination do not occur automatically [14]. Differences in perspectives and expectations can create two central tensions: role conflict and role ambiguity [35]. The quality of coordination depends on whether expectations are specified clearly, communicated consistently, and reconciled effectively when they diverge [36]. Prior work shows that such role conflict and ambiguity can lead to unclear ownership, contested decision rights, extended approval queues, rework due to divergent interpretations, inconsistent metrics across domains, and compliance failures when accountability chains are missing [35, 37].

Role conflict arises when expectations from different senders or from the same sender cannot be satisfied at the same time [37]. In AI adoption, this may occur when business leaders push for rapid delivery and visible results, while compliance and legal roles emphasize documentation, validation, and regulatory traceability before deployment [24, 27]. Technical roles like data scientists and developers may seek flexible experimentation with tools and architectures, whereas IT leaders enforce standardized stacks and security protocols to meet production-readiness requirements [32, 33]. These role conflicts are not simply “miscommunication” but reflect legitimate, yet incompatible expectations rooted in different role logics.

Role ambiguity occurs when expectations are insufficiently specified, leading to uncertainty about objectives, responsibilities, permissible methods, or evaluation criteria [38]. In AI adoption, role ambiguity may emerge when it is unclear who owns business outcomes, who defines success metrics, or who is accountable for ongoing monitoring and retraining once a PoC is complete [39]. For example, data scientists may see themselves as responsible for model performance, while business units expect to control targets and KPIs, and risk or compliance teams expect veto rights on deployment decisions, i.e., unclear decision rights [32, 40]. Role ambiguity can also arise around budget authority for AI infrastructure or around evolving regulatory obligations, where teams are unsure which role is responsible for documentation and risk controls, i.e., unclear risk ownership [41].

Building on these role dynamics, Figure 1 presents the research framework of this study by integrating Socio-Technical Systems Theory [13] and Role Theory [14]. By foregrounding the social subsystem, the framework moves beyond predominantly technical optimization perspectives. It examines how interactions among heterogeneous organizational roles from business, technical, and functional domains give rise to role-based tensions, manifested as role conflict and role ambiguity, which shape AI adoption processes in large organizations.

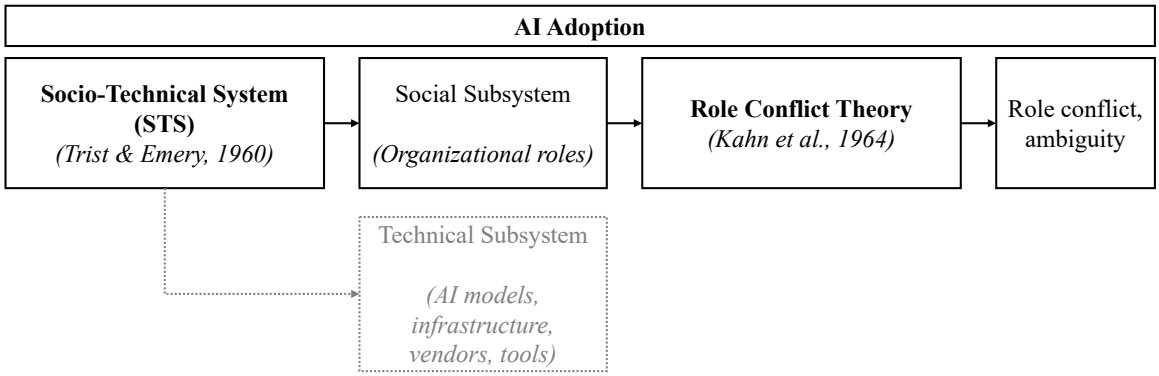

Fig. 1. Conceptual research framework integrating Socio-Technical Systems Theory [13] and Role Conflict Theory [14] to examine how role-based tensions among heterogeneous organizational roles within the social subsystem shape AI adoption in large organizations.

3 Method

3.1 Research design

This exploratory qualitative study was designed to examine how heterogeneous organizational roles experience role conflicts and role ambiguities and how these role tensions influence the adoption of AI. Semi-structured expert interviews were conducted to create a common structure while ensuring the flexibility needed to study an emergent socio-technical context [42].

Mid-to senior-level AI professionals with substantial experience in AI projects were selected from both within their own organizations and in customer-facing contexts. This sampling approach ensured access to practice-based expertise across large organizations and aligns with socio-technical research traditions that emphasize understanding organizational realities through the perspectives of those directly engaged in relevant tasks [43].

3.2 Interview procedure

The recruitment of interview participants was based on purposive and snowball sampling [44]. Initial participants were identified through the authors' professional networks, LinkedIn, phone calls, and emails, with further participants recruited via referrals. The final sample comprised twelve mid- to senior-level professionals from seven large organizations (annual revenues ≥ USD 100 million) in the United States, the United Kingdom, and Germany, representing business, technical, and functional organizational roles (see Table 1). To protect confidentiality, role-based pseudonyms (e.g., ARCH1, DS1, CONS1) were used.

Table 1. Overview of participants in interviews

ID	Role	Industry	Country	Type	Revenue
SLM1	Second line manager	Manufacturing	GER	IT solutions	>$1.0B
DS1	Managing data scientist	Information technology	GER	IT solutions	>$100M
AIPM1	Senior AI product manager	Information technology	GER	IT solutions	>$1.0B
AIPM2	Senior AI project manager	Consulting	GER	IT services	>$200M
FLM1	First line manager	Information technology	USA	IT solutions	>$1.0B
CONS1	Managing AI consultant	Consulting	USA	IT services	>$200M
FLM2	First line manager	Information technology	USA	IT solutions	>$1.0B
ARCH1	Senior AI solutions architect	Software	GER	Analytics and AI	>$1.0B
CONS2	Senior AI consultant	Consulting	GER	IT solutions	>$900M

ID	Role	Industry	Country	Type	Revenue
ARCH2	Senior AI architect	Information technology	GER	IT solutions	>$1.0B
ARCH3	Senior AI architect	Information technology	USA	IT solutions	>$1.0B
DS2	Senior data scientist	Broadcasting, streaming	UK	Broadcasting	>$1.0B

Interviews were conducted one-to-one and lasted on average 31 minutes, resulting in a total recording time of six hours and 12 minutes. Prior to participation, all interviewees were informed about the study, provided informed consent, and were assured of anonymity and confidentiality in line with ethical research practices [45]. With consent, interviews were recorded, transcribed verbatim, anonymized, and stripped of identifying information.

The interview guide (see Table 2) was systematically developed to cover all relevant themes and avoid ad-hoc questioning. The constructs of role conflict and role ambiguity [14] were translated into behaviorally specific, open-ended questions, supplemented by subdimensions tailored to AI adoption. We emphasized open-ended, incident-focused prompts and probes (e.g., "What were your experiences with conflicts between task priorities?", "Where do you see overlaps in tasks between different roles?") to surface boundaries, tensions, and early signals of conflict or ambiguity [46]. Thus, the interview guide served as guide rather than a fixed script.

The final guide comprised three sections aligned with the study's theoretical focus. First, questions on participants' roles in AI adoption captured how they defined their responsibilities, project involvement, and evolving tasks. Second, a core section explored unclear and conflicting expectations, structured into (a) role conflict and (b) role ambiguity in AI adoption. Third, a section on consequences asked participants to reflect on how these tensions affected AI adoption outcomes (e.g., delays, trust issues, stalled projects) and to describe practices or mechanisms that helped to reduce them.

Table 2. Interview guide for exploring role conflict and role ambiguity in AI adoption.

Interview Section	Guiding Interview Questions
Understanding Participants' Organizational Role	How would you describe your role and involvement in AI adoption? How do you see your role evolving over time? What are your responsibilities during this phase?
Exploring Role Conflict in AI adoption	**Role Conflict** (contradictory expectations and tensions between roles) What were your experiences with conflicts between task priorities? In what ways have you encountered conflicts when working with other roles? How have differing expectations across roles affected your work in AI adoption? When priorities compete, how are trade-offs decided and by whom?
Exploring Role Ambiguity in AI adoption	**Role Ambiguity** (unclear responsibilities, ownership, or success measures) What situations have you experienced where responsibilities were unclear? Where do you see overlaps in tasks between different roles? When working across teams, when was it unclear who should make final decisions? Where have you encountered uncertainty about who is accountable for maintaining or monitoring an AI solution?
Consequences for AI adoption	What effects have these role dynamics had? How are role dynamics typically solved in your organization? What approaches have reduced tensions between organizational functions?

3.3 Data analysis

Gioia Methodology. To capture the role dynamics, the Gioia methodology [17] was used, a qualitative and inductive analytical approach designed to structure and interpret complex organizational phenomena from participants' perspectives. The methodology follows a three-level analytical process consisting of *first-order concepts* (informant terms), *second-order themes* (researcher interpretations), and *aggregate dimensions*, thereby ensuring analytical rigor and traceability from empirical data to theoretical insights. Figure 2 illustrates this analytical logic by visualizing how interview data are progressively transformed into higher-level conceptual explanations.

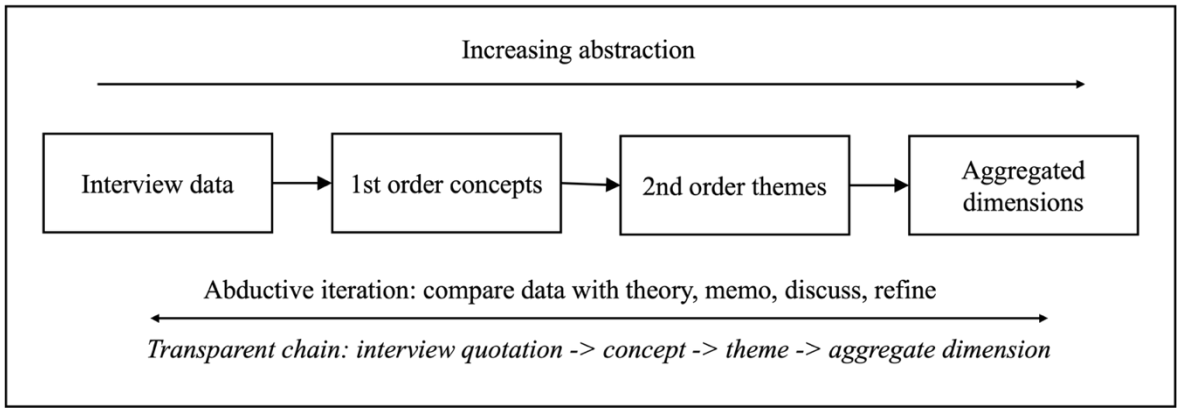

Fig. 2. The inferential process in developing a data structure following the Gioia methodology [47, p. 4]

The Gioia analysis [47] begins at the informant-centered level (Figure 2), where verbatim interview quotations are coded line by line into first-order concepts using participants' own language. This inductive step ensures that the analysis remains closely grounded in empirical evidence. The analysis then moves to a theory-informed level, where conceptually related first-order concepts are compared and grouped into second-order themes by identifying recurring relationships, tensions, and contrasts in how participants described their roles and interactions. This step involved multiple iterations of comparison, memoing, and discussion among the authors to ensure that each theme represented a distinct and theoretically meaningful pattern in the data. Second-order themes were then abstracted into aggregate dimensions, which capture higher-level organizational mechanisms of alignment and tension shaping AI adoption. Throughout this analysis process, data and theory were iteratively combined through abductive reasoning, allowing grounded theoretical insights to emerge while maintaining a transparent link between raw evidence and conceptual development.

All interviews were transcribed verbatim, anonymized, and analyzed using ATLAS.ti (v.24.2.0). To ensure transparency and traceability, a comprehensive Gioia-style data structure was developed that documented each coded segment: (1) the verbatim excerpt with participant ID and timestamp, (2) the assigned first-order concept, (3) the corresponding second-order theme, and (4) the resulting aggregate dimension. Table 3 presents this data structure, linking representative quotations to their conceptual interpretations (e.g., "IT wants scalability, business wants quick wins, and compliance wants safety […]." — CONS2 [00:05:08] → First-order concept "*Competing priorities (speed/scale/safety)"* → Second-order theme "*Risk Control vs. Delivery Speed"* → Aggregate dimension "*Role Conflict"*).

Table 3. Resulting data structure after applying the Gioia methodology, linking interview data to first-order concepts, second-order themes, and aggregate dimensions [17].

Verbatim; Role & Time stamp	**First-order concept**	**Second-order theme**	**Aggr. dimension**
"IT wants scalability, business wants quick wins, and compliance wants safety. Bridging those differences is hard." — CONS2 [00:05:08]	Competing priorities (speed/scale/safety)	**Risk Control vs. Delivery Speed**	*Role Conflict*
"There's also a gap in understanding between business leaders and IT… This misalignment creates delays and technical debt." — ARCH1 [00:04:40]	Business leadership expectations vs. IT feasibility	**Business Expectations vs. Technical Feasibility**	*Role Conflict*
"Sales teams may downplay risks to close deals, while implementers see the real challenges. Sometimes projects are oversold…" — SLM1 [00:23:08]	Sales–delivery expectation conflict	**Business Expectations vs. Technical Feasibility**	*Role Conflict*
"The higher up someone is, the more they focus on the project narrative… but with data science… there's no room for vague results." — FLM1 [00:08:32]	Narrative vs. numeric precision (senior management vs. data scientists)	**Cross-Functional Coordination vs. Technical Feasibility**	*Role Conflict*
"Clients want guarantees, but AI projects are exploratory. We can't promise success, only potential." — FLM1 [00:21:59]	Experimentation vs. certainty	**Novelty vs. Business Value**	*Role Conflict*
"If we suggest something risky—like using public cloud for confidential data—they might push back." — SLM1 [00:27:53]	Risk pushback vs. speed or innovation	**Legal Risk vs. Usage**	*Role Conflict*
"Another challenge is balancing standardization with flexibility, so we don't stifle innovation." — ARCH3 [00:04:01]	Standardization vs. flexibility trade-offs	**Standardization vs. Flexibility**	*Role Conflict*

Verbatim; Role & Time stamp	First-order concept	Second-order theme	Aggr. dimension
"We use value-feasibility matrices… avoid chasing technically interesting but low-impact ideas." — CONS1 [00:07:28]	Technically interesting vs. business value-first	**Novelty vs. Business Value**	*Role Conflict*
"The model was technically solid but raised concerns about fairness and explainability… we had to slow down, redesign… and allow humans to intervene." — AIPM2 [00:21:21]	Ethics/fairness/explainability vs. automation speed	**Risk Control vs. Delivery Speed**	*Role Conflict*
"I work as a full-lifecycle AI developer… both technical and coordination responsibilities." — FLM2 [00:00:12]	Dual technical & coordination workload	**Cross-Functional Coordination vs. Technical Feasibility**	*Role Conflict*
"My main tasks include model development… and I also facilitate meetings… and help build internal confidence." — FLM2 [00:01:52]	Delivery plus stakeholder enablement	**Outcome Delivery vs. Stakeholder Management**	*Role Conflict*
"I assess whether our IT architecture is ready… meet compliance and security… coordinate with DevOps…" — ARCH1 [00:01:45]	Breadth of cross-functional coordination	**Cross-Functional Coordination vs. Technical Feasibility**	*Role Conflict*
"Explainability, AI regulation, and cost-efficient computing. We're adapting architectures to support these trends—such as energy-efficient model deployment and audit logs that satisfy legal requirements." — ARCH1 [00:24:17]	Resource/energy efficiency vs. model performance needs	**Cost Efficiency vs. Model Performance**	*Role Conflict*
"Building a governance structure… guiding colleagues… promoting AI literacy…" — AIPM1 [00:01:51]	Simultaneous governance and enablement	**Governance Structures vs. Organizational Enablement**	*Role Conflict*
"Over the past five years, I've done everything from presales… project management and technical implementation… I'm deeply involved in every stage." — SLM1 [00:01:08]	Multi-hatting across the lifecycle	**Traditional Tasks vs. AI-Specific Role Tasks**	*Role Conflict*
"No clear ownership, no identified end user, and no data strategy." — CONS1 [00:15:47]	Unclear ownership & missing end user	**Unclear allocation of business ownership**	*Role Ambiguity*
"Yes—lack of stakeholder involvement, unclear KPIs, and ignoring organizational change." — AIPM2 [00:27:15] · "Often, KPIs are too focused on the number of models or use cases." — AIPM1 [00:10:24]	Unclear or ill-defined KPIs & success criteria	**Unclear evaluation criteria across business and technical areas**	*Role Ambiguity*
"It varies… The client sets business expectations, and we as Data Scientists adjust technically. It's a negotiation process." — SLM1 [00:10:32]	Negotiating targets under uncertainty	**Unclear business objectives**	*Role Ambiguity*
"I'd improve tooling for monitoring and make infrastructure budgeting more agile. But I don't know who to turn to with this. AI is fast paced, but our infrastructure cycles are still slow." — ARCH2 [00:25:00]	Funding pace/ownership not aligned with AI needs	**Unclear budget authority for AI initiatives**	*Role Ambiguity*
"Lack of clarity… There's often a disconnect between business goals and what AI can actually deliver." — CONS1 [00:04:12]	Disconnect between AI capabilities and business goals	**Unclear business objectives**	*Role Ambiguity*
"We need to know who has access to what… and how decisions are being made… and regular compliance checks—especially with new AI regulations coming up." — ARCH2 [00:06:55]	Evolving rules create uncertainty about obligations	**Unclear compliance requirements**	*Role Ambiguity*
"They evolve during the project. You start with rough goals, then refine them based on data availability and business relevance." — FLM1 [00:10:32]	Evolving and initially rough goals	**Unclear business objectives**	*Role Ambiguity*
"We embed ethics from the beginning… bias testing, stakeholder reviews… for high-risk use cases, we include external advisors and legal experts in the decision-making process." — AIPM2 [00:19:28]	Risk management spread across AI, cybersecurity, and legal	**Unclear allocation of risk ownership**	*Role Ambiguity*
"Yes—lack of stakeholder involvement, unclear KPIs…" — AIPM2 [00:27:15]	Lack of stakeholder involvement	**Unclear stakeholder responsibilities**	*Role Ambiguity*
"It's a cross-functional effort… We ensure that everyone understands their role in the AI lifecycle and that communication flows both ways." — AIPM2 [00:02:44]	Ambiguity around responsibilities across build–deploy–operate	**Unclear model ownership across AI lifecycle stages**	*Role Ambiguity*
"Resistance comes when people worry about losing decision-making authority to a system…" — AIPM1 [00:05:15]	Anxiety about shifting authority / decision rights	**Unclear decision-making authority**	*Role Ambiguity*

Inter-coder reliability. To enhance the transparency and rigor of the coding process, a reliability check was conducted consistent with best practices for ensuring dependability in qualitative research [48]. Both authors independently coded the data, and agreement was evaluated using Cohen's kappa (κ), a standard statistic for

categorical coding reliability [49]. Each quotation was treated as a unit of analysis, defined as a contiguous text segment expressing a single idea about roles or role interactions (e.g., "No clear ownership, no identified end user, and no data strategy." — CONS1 [00:15:47]), resulting in a total of 340 units. Unit boundaries and code definitions were aligned using three pilot transcripts, which were re-unitized and excluded from the κ calculation to avoid inflating agreement [48]. Using the agreed unitization, both authors independently assigned one primary first-order code to each unit from the developing code list, and a coder-by-coder agreement table (see Table 4) was constructed, also known as a confusion matrix [50]. For instance, both coders labeled "IT wants scalability, business wants quick wins, and compliance wants safety […]."— CONS2 [00:05:08] as "*Competing priorities"* under the "*Role Conflict"* theme, whereas "Legacy systems are a constant issue […] expectations are high, but feasibility checks are rarely done early enough"— ARCH1 [00:04:40] received different initial codes and was therefore counted as a disagreement. All disagreements were resolved by consensus, refining the data structure (see Table 3) and ensuring consistency.

Table 4. Cross-table of coding process, documenting agreements and disagreements between the two coders and serving as the basis for calculating inter-coder reliability.

		Author 1		
		Agreement	Disagreement	Total
Author 2	Agreement	243	12	255
	Disagreement	20	65	85
	Total	263	77	340

Based on the cross-table in Table 4, diagonal agreements were tallied as = 243 + 65 = 308, giving the observed total agreement = 308:

$$P_0 = \frac{(243+65)}{340} = \frac{308}{340} \approx 0.906 \quad (1)$$

To estimate chance agreement, each coder's marginal proportion of use for every code was computed, and the products of corresponding proportions across categories were summed:

$$P_e = \frac{255}{340} x \frac{263}{340} + \frac{85}{340} x \frac{77}{340} \approx 0.637 \quad (2)$$

Cohen's kappa [51] was then calculated using the standard formula:

$$\kappa = \frac{P0-Pe}{1-Pe} = \frac{0.906-0.637}{1-0.637} \approx 0.741 \quad (3)$$

The corresponding statistical results of the Cohen's Kappa calculations are presented in Table 5.

Table 5. Statistical results of the Cohen's Kappa calculations

Cohen's Kappa	Standard Error	Lower 95% CI	Upper 95% CI	p
0.74	0.04	0.66	0.82	<.001

4 Findings

The Gioia-based data structure (see Table 3) reveals role conflict and role ambiguity among heterogeneous organizational roles, highlighting recurring role dynamics in AI adoption in large organizations. These role patterns capture how overlapping responsibilities, competing expectations, and unclear ownership shape AI adoption processes across business, technical, and functional roles in large organizations. As shown in Table 5, the inter-coder reliability yielded substantial agreement between coders, κ = .74, SE = .04, 95% CI [.66, .82], p < .001. This result indicates a high level of agreement beyond chance, falling within the "substantial agreement" range [52], and thus supports the reliability and consistency of the coding process.

According to Table 3, role conflicts among business (executives and business units), technical (IT leaders, data scientists, AI engineers and data engineers), and functional (project and product managers, HR, legal and compliance, and procurement) domains arose at the intersection of strategic, governance, and delivery issues

(e.g., business expectations versus technical feasibility, novelty versus business value, risk control versus delivery speed). Role conflict is not a single event but a recurring negotiation among these domains as AI adoption evolves. Conflicts emerged when incompatible expectations collided, such as speed versus scalability, innovation versus compliance, or experimentation versus standardization. Participants linked these conflicts to longer decision cycles, delayed releases, and, in some cases, stalled transitions from pilot to production stages.

Role ambiguity centered on unclear responsibilities, ownership, decision-making authority, and business objectives (e.g., unclear model ownership across lifecycle stages, unclear allocation of risk ownership, and KPIs not tied to user value). Ambiguity was especially pronounced at organizational interfaces where responsibilities and decision rights were insufficiently specified. Participants reported uncertainty about ownership, approval rights, success metrics, and accountability for compliance and risk management. These unclear boundaries led to delayed reviews, inconsistent evaluation practices, and gaps in auditability.

The resulting key role conflict and role ambiguity tensions in AI adoption are described in Table 6.

Table 6. Overview of key role conflict and ambiguity tensions observed during AI adoption in large organizations

Category	Tensions	Description
Role Conflict	**Novelty vs. Business Value**	Technical teams explore emerging AI methods, while business leaders expect clear and measurable business value.
Role Conflict	**Business Expectations vs. Technical Feasibility**	Ambitious business goals conflict with the constraints in data quality, legacy systems, and available tools.
Role Conflict	**Legal Risk vs. Usage**	Business seeks broad AI usage, whereas legal and compliance roles restrict adoption to mitigate regulatory risk.
Role Conflict	**Standardization vs. Flexibility**	IT enforces standardized platforms, while developers and data scientists request flexible tools to innovate.
Role Conflict	**Governance Structures vs. Organizational Enablement**	Centralized governance slows decision-making even as teams are expected to accelerate AI adoption.
Role Conflict	**Outcome Delivery vs. Stakeholder Management**	Pressure to deliver AI results competes with the need to align, inform, and manage stakeholders.
Role Conflict	**Risk Control vs. Delivery Speed**	Compliance checks and documentation delay releases that business units expect quickly.
Role Conflict	**Traditional vs. AI-specific Role Tasks**	New responsibilities expand roles into unfamiliar areas (e.g., technical roles incorporating legal considerations).
Role Conflict	**Cross-Functional Coordination vs. Technical Feasibility**	Extensive coordination across heterogeneous organizational roles reduces time for solving core technical feasibility issues.
Role Conflict	**Cost Efficiency vs. Model Performance**	Procurement prioritizes cost efficiency, while technical teams seek greater computing resources to maximize model performance.
Role Ambiguity	**Unclear stakeholder responsibilities**	Role responsibilities are insufficiently defined, creating uncertainty about participation and weakening coordinated decisions.
Role Ambiguity	**Unclear allocation of business ownership**	Business ownership is undefined, generating ambiguity about who is accountable for a use case and its outcomes.
Role Ambiguity	**Unclear business objectives**	AI adoption lacks clear problem statements or target outcomes, leading to ambiguous expectations.
Role Ambiguity	**Unclear evaluation criteria across business and technical areas**	Business and technical roles apply different success metrics (e.g., cost-saving vs. model accuracy), resulting in inconsistent evaluations.
Role Ambiguity	**Unclear decision-making authority**	It is unclear who holds final approval or stop/go authority in AI adoption.
Role Ambiguity	**Unclear allocation of risk ownership**	Multiple roles influence risk decisions, but none is assigned final ownership.
Role Ambiguity	**Unclear budget authority for AI initiatives**	Heterogeneous organizational roles lack clarity on which domain funds AI pilots, IT infrastructure, or platform costs.

Category	Tensions	Description
Role Ambiguity	**Unclear compliance requirements**	Compliance responsibilities are unclear because legal, business, and technical roles jointly shape requirements.
Role Ambiguity	**Unclear model ownership across AI lifecycle stages**	Ownership of models across development, deployment, and operation is not clearly assigned between technical and functional roles.

Figure 3 synthesizes the role tensions identified in the Gioia-based data structure (see Table 3) by mapping them onto the business, technical, and functional organizational roles involved in AI adoption. The figure groups these role tensions by domain to illustrate where they predominantly arise and where they intersect across domains. The arrows indicate where interactions between different organizational roles give rise to recurring role tensions during AI adoption. Unshaded boxes indicate role conflict tensions, while shaded boxes indicate role ambiguity tensions, corresponding to the categories summarized in Table 6. Together, Figure 3 provides a consolidated view of how role-based tensions are distributed across heterogeneous organizational roles within AI adoption processes in large organizations.

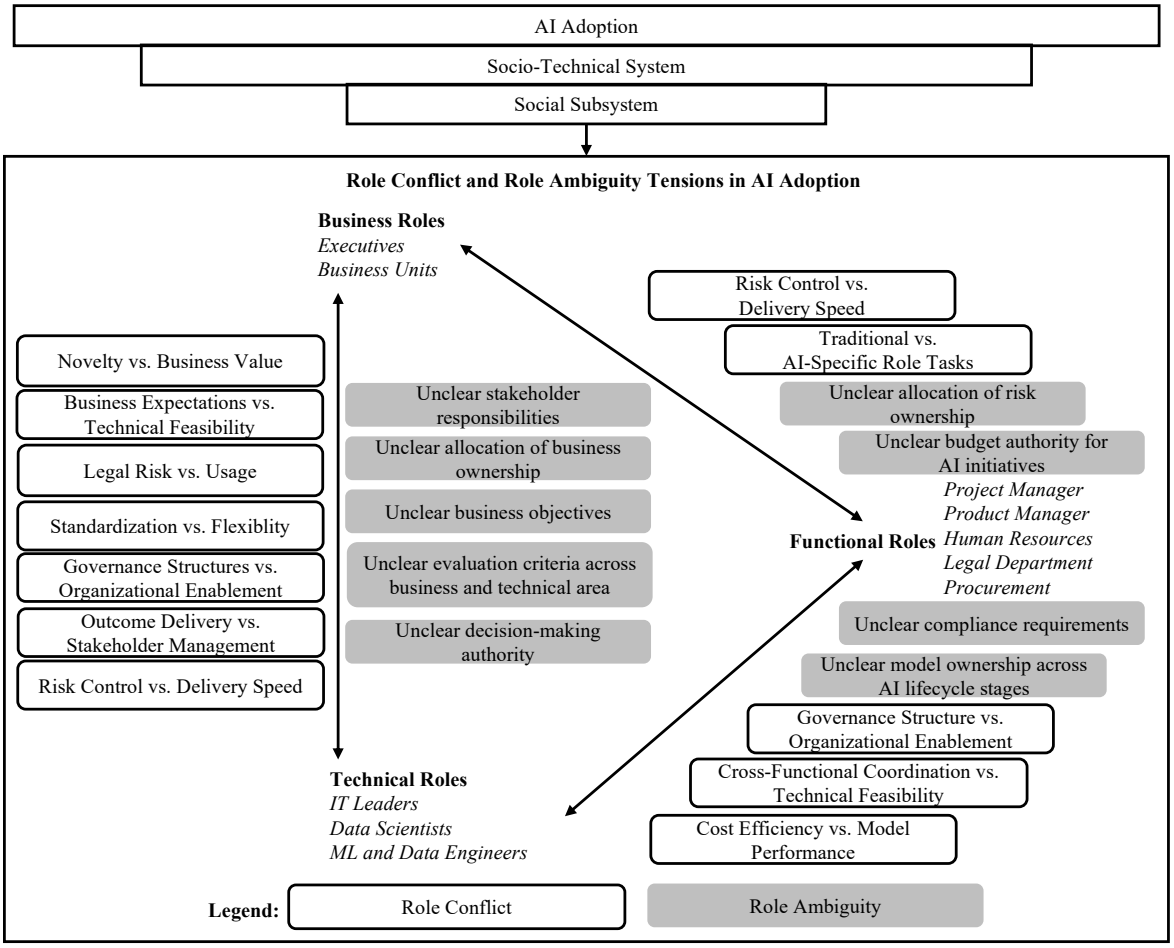

Fig. 3. Key role conflict and role ambiguity tensions across business, technical, and functional organizational roles in large organizations involved in AI adoption. Unshaded boxes indicate role conflict tensions, while shaded boxes indicate role ambiguity tensions, as derived from the Gioia-based data structure (see Table 3).

5 Discussion

Drawing on semi-structured interviews with twelve mid- to senior-level professionals across business, technical, and functional organizational roles in large organizations (see Table 1), this study identified recurring role conflict and role ambiguity tensions between those role domains, which can hinder progression in AI

adoption (see Figure 3). Building on these findings, the following section discusses the theoretical and practical implications through a role-based, socio-technical lens on AI adoption.

5.1 Theoretical and practical implications

Enriching AI adoption processes by integrating a socio-technical lens. While prior studies emphasize that organizations must jointly optimize their social and technical subsystems during technology adoption [3, 7], they offer limited insight into *how* heterogeneous organizational roles engage in AI adoption. The findings (see Figure 3) show how role-based tensions unfold between heterogeneous organizational roles: business roles emphasize strategic returns and delivery speed, functional roles balance organizational governance with enablement, and technical roles focus on feasibility, scalability, and model performance [7, 24]. This shifts the focus away from aggregate, organizational-level factors, such as organizational culture, strategy, readiness, and IT capability [e.g., 23, 53], to the level of individual organizational roles. At this level, day-to-day coordination, role-specific expectations, and decision rights determine whether AI adoption accelerates or stalls [54]. The findings specify concrete micro-level mechanisms through which conflicting expectations across heterogeneous organizational roles disrupt collaboration. More specifically, the findings (see Table 6) describe tensions of role conflict and role ambiguity that can cause otherwise technically sound AI adoption efforts to stall. Unclear ownership, inconsistent decision rights, divergent risk appetites, and fragmented evaluation criteria can all undermine scaling. In this way, the study advances a socio-technical lens on AI adoption processes by demonstrating that the simultaneous engagement of heterogeneous organizational roles within the social subsystem shapes AI adoption outcomes.

Extending Role Theory in the context of AI adoption. Although role conflict and role ambiguity have been widely examined in large organizational settings [55], their application to AI adoption reveals dynamics not fully captured by earlier work [e.g., 24, 56]. The study contributes to Role Theory [14] by presenting novel, AI-specific forms of role conflict and ambiguity between heterogeneous organizational roles (see Figure 3) that earlier work has not yet captured. The role tensions between business, tech-nical, and functional domains (see Figure 3) show that AI adoption structurally diverges from traditional IT adoption [57]. Clas-sic enterprise systems (e.g., ERP, CRM, HRIS) typically follow sequential waterfall logic, where role tasks and responsibilities are predefined within a development protocol, and adoption moves step-by-step from business analysis to design, implementa-tion, and testing [58]. In contrast, AI adoption requires the simultaneous involvement of these business, technical, and functional roles from the beginning. This simultaneity requires organizational roles to negotiate feasibility, governance, and value as AI adoption evolves, rather than in sequential handovers. When role expectations and constraints collide in real time, the likelihood of misunderstandings, duplicated work, unclear ownership, and delayed decisions increases sharply [55]. In practice, this can slow down AI adoption, lead to repeated rework, and prevent AI projects from moving beyond the pilot phase.

Complementing technical approaches with role dynamics to improve AI adoption outcomes. Finally, the study contributes to AI adoption research by clarifying why many AI initiatives in large organizations fail despite being technically well-conceived. While existing studies [5, 6] often attribute stalled AI adoption to technical barriers, the findings show that unresolved role tensions across organizational roles can block scaling, even when the AI technology operates effectively. The findings (see Table 3) describe validated AI models that could not advance to production because business and data science teams disputed ownership of success criteria, legal and compliance requirements surfaced only at the end of the development cycle, or procurement and technical teams disagreed on vendor solutions. Other examples involved architectural constraints introduced after model development or inconsistent ROI expectations among business leaders and executives. Thus, the findings suggest that the AI adoption process can stall when organizational roles are unclear about who is responsible, who makes decisions, and how competing priorities should be balanced. These cases indicate that social misalignment, rather than technical inadequacy, frequently prevents AI adoption from progressing beyond the PoC stage. This aligns with socio-technical arguments that technical optimization alone is insufficient for successful adoption [15, 16]. By identifying role tensions across business, technical, and functional domains (see Figure 3), this study demonstrates that AI adoption outcomes arise from the joint optimization of social and technical subsystems [22, 23].

Practical Implications. Based on the role-based socio-technical perspective developed in this study, the effective adoption of AI requires optimizing collaboration among heterogeneous organizational roles. First, formal role-mapping frameworks, such as RACI matrices [e.g., 59], can help ensure that responsibilities and decision rights are transparent and mutually understood across business, technical, and functional domains. Second, large organizations can strengthen collaboration in cross-functional teams by introducing agile-inspired routines and flatter coordination structures, which are widely established in SMEs and start-ups [18, 60]. Agile methodologies, such as Scrum or Kanban [61], enable short, iterative sprints and regular, cross-functional sessions. This can reduce decision delays by jointly addressing feasibility, governance, and strategic priorities rather than sequentially. Large organizations may avoid misunderstandings, surface constraints earlier, and strengthen the overall AI adoption process by complementing top-down decision processes with more simultaneous, role-inclusive coordination [62]. Finally, targeted AI literacy programs tailored to executives, business roles, technical users, and functional experts can help create a shared understanding of AI's capabilities and limitations, which can reduce fear, unrealistic expectations, and resistance to AI adoption [63, 64].

5.2 Limitations

This exploratory study aims to uncover role conflict and role ambiguity tensions among heterogeneous organizational roles in AI adoption rather than produce statistically generalizable results. Although our sample size was relatively small, it aligns with qualitative guidelines, which suggest that theoretical saturation is often achieved with 12 to 15 experts [65]. Additionally, our sample included twelve professionals who collectively had experience with more than 50 AI projects in various organizational environments. Therefore, we have likely achieved strong information power. However, all participants worked in large organizations with revenues above USD 100 million, so the findings may not transfer to SMEs or startups, where AI adoption tends to be more agile and less formal, and is shaped by different resource constraints and role structures. The sample also reflects similar levels of seniority and organizational context.

6 Conclusion and Future Work

In summary, this study examined how role conflict and role ambiguity among heterogeneous organizational roles shape AI adoption in large organizations. Applying a socio-technical lens, micro-level role mechanisms are specified through which the social and technical subsystems jointly shape AI adoption outcomes rather than the technical subsystem alone. Across business, technical, and functional domains, recurring role tensions were identified at the intersection of strategic priorities, governance requirements, and delivery constraints. Role conflict emerged when incompatible expectations collided (e.g., business expectations versus technical feasibility, novelty versus business value, risk control versus delivery speed). Role ambiguity centered on unclear responsibilities, ownership, decision-making authority, and success criteria across lifecycle stages. Together, these role tensions were associated with delays in collaboration and decision-making across heterogeneous organizational roles and could slow progress in AI adoption.

The findings show that AI adoption differs structurally from traditional, sequential IT projects in large organizations. Rather than progressing through predefined handovers, AI adoption requires the simultaneous involvement of business, technical, and functional roles, which must continuously negotiate feasibility, governance, and value as adoption evolves. Practically, the results suggest that improving AI adoption outcomes requires strengthening cross-domain collaboration through role clarity and decision rights, earlier alignment on evaluation criteria and risk responsibilities, and coordination practices that support simultaneous, role-inclusive collaboration (e.g., role mapping and agile-inspired routines).

Future research could extend this role-based, socio-technical perspective by using quantitative and mixed-method studies across industry sectors (e.g., healthcare, manufacturing, banking) and in small-to-medium enterprises (SMEs) and start-ups. These studies could compare how different organizational contexts and types experience, negotiate, and manage role tensions in AI adoption and examine whether these role-based dynamics also apply to junior employees and to organizations outside the current revenue threshold and sector mix.

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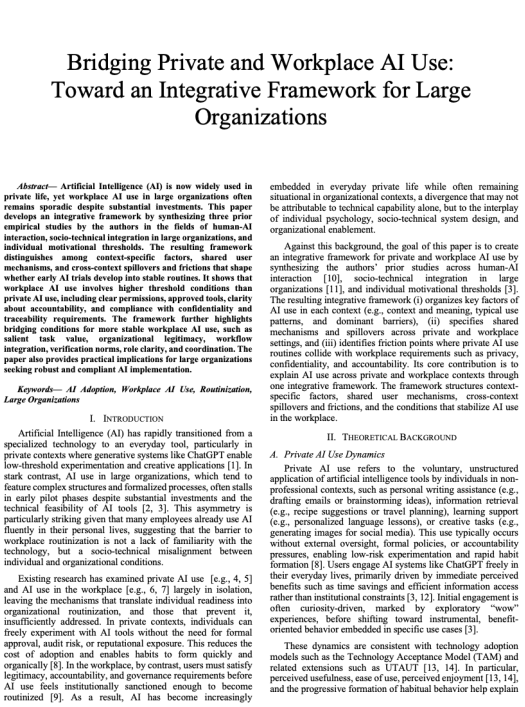
3.4 Studie 4: *Bridging Private and Workplace AI Use: Toward an Integrative Framework for Large Organizations*



Bridging Private and Workplace AI Use:
Toward an Integrative Framework for Large Organizations

***Abstract*— Artificial Intelligence (AI) is now widely used in private life, yet workplace AI use in large organizations often remains sporadic despite substantial investments. This paper develops an integrative framework by synthesizing three prior empirical studies by the authors in the fields of human-AI interaction, socio-technical integration in large organizations, and individual motivational thresholds. The resulting framework distinguishes among context-specific factors, shared user mechanisms, and cross-context spillovers and frictions that shape whether early AI trials develop into stable routines. It shows that workplace AI use involves higher threshold conditions than private AI use, including clear permissions, approved tools, clarity about accountability, and compliance with confidentiality and traceability requirements. The framework further highlights bridging conditions for more stable workplace AI use, such as salient task value, organizational legitimacy, workflow integration, verification norms, role clarity, and coordination. The paper also provides practical implications for large organizations seeking robust and compliant AI implementation.**

Keywords*— *AI Adoption, Workplace AI Use, Routinization, Large Organizations

I. Introduction

Artificial Intelligence (AI) has rapidly transitioned from a specialized technology to an everyday tool, particularly in private contexts where generative systems like ChatGPT enable low-threshold experimentation and creative applications [1]. In stark contrast, AI use in large organizations, which tend to feature complex structures and formalized processes, often stalls in early pilot phases despite substantial investments and the technical feasibility of AI tools [2, 3]. This asymmetry is particularly striking given that many employees already use AI fluently in their personal lives, suggesting that the barrier to workplace routinization is not a lack of familiarity with the technology, but a socio-technical misalignment between individual and organizational conditions.

Existing research has examined private AI use [e.g., 4, 5] and AI use in the workplace [e.g., 6, 7] largely in isolation, leaving the mechanisms that translate individual readiness into organizational routinization, and those that prevent it, insufficiently addressed. In private contexts, individuals can freely experiment with AI tools without the need for formal approval, audit risk, or reputational exposure. This reduces the cost of adoption and enables habits to form quickly and organically [8]. In the workplace, by contrast, users must satisfy legitimacy, accountability, and governance requirements before AI use feels institutionally sanctioned enough to become routinized [9]. As a result, AI has become increasingly embedded in everyday private life while often remaining situational in organizational contexts, a divergence that may not be attributable to technical capability alone, but to the interplay of individual psychology, socio-technical system design, and organizational enablement.

Against this background, the goal of this paper is to create an integrative framework for private and workplace AI use by synthesizing the authors' prior studies across human-AI interaction [10], socio-technical integration in large organizations [11], and individual motivational thresholds [3]. The resulting integrative framework (i) organizes key factors of AI use in each context (e.g., context and meaning, typical use patterns, and dominant barriers), (ii) specifies shared mechanisms and spillovers across private and workplace settings, and (iii) identifies friction points where private AI use routines collide with workplace requirements such as privacy, confidentiality, and accountability. Its core contribution is to explain AI use across private and workplace contexts through one integrative framework. The framework structures context-specific factors, shared user mechanisms, cross-context spillovers and frictions, and the conditions that stabilize AI use in the workplace.

II. Theoretical Background

A. Private AI Use Dynamics

Private AI use refers to the voluntary, unstructured application of artificial intelligence tools by individuals in non-professional contexts, such as personal writing assistance (e.g., drafting emails or brainstorming ideas), information retrieval (e.g., recipe suggestions or travel planning), learning support (e.g., personalized language lessons), or creative tasks (e.g., generating images for social media). This use typically occurs without external oversight, formal policies, or accountability pressures, enabling low-risk experimentation and rapid habit formation [8]. Users engage AI systems like ChatGPT freely in their everyday lives, primarily driven by immediate perceived benefits such as time savings and efficient information access rather than institutional constraints [3, 12]. Initial engagement is often curiosity-driven, marked by exploratory "wow" experiences, before shifting toward instrumental, benefit-oriented behavior embedded in specific use cases [3].

These dynamics are consistent with technology adoption models such as the Technology Acceptance Model (TAM) and related extensions such as UTAUT [13, 14]. In particular, perceived usefulness, ease of use, perceived enjoyment [13, 14], and the progressive formation of habitual behavior help explain

Titel: Bridging Private and Workplace AI Use: Toward an Integrative Framework for Large Organizations

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Inhalt:

Basierend auf einer zusammenführenden Auswertung der drei vorangegangenen empirischen Studien (Publikation 1 bis 3) untersucht diese Studie, wie individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption zusammenhängen und unter welchen Bedingungen aus ersten KI-Erfahrungen stabile Nutzung im Arbeitskontext sowie tragfähige organisationale Adoptionsprozesse entstehen können. Methodisch erfolgt dies über eine Cross-Study-Auswertung mit Comparative-Factor-Mapping, bei der die Ergebnisse der drei Studien systematisch verglichen und zu einem zusammenführenden Erklärungsrahmen verdichtet werden. Die Ergebnisse legen nahe, dass individuelle KI-Nutzung im Alltag meist freiwillig, niedrigschwellig und mit geringem Risiko erfolgt, während KI im Arbeitskontext und auf organisationaler Ebene deutlich stärkeren Anforderungen unterliegt, etwa klaren Freigaben, Datenschutz, Nachvollziehbarkeit, Verantwortlichkeit, Rollenabstimmung und bereichsübergreifender Koordination. Damit solche Vorerfahrungen in stabile Nutzung im Arbeitskontext und darüber hinaus in organisationale Adoptionsprozesse übergehen können, erscheinen organisationale Bedingungen wie erkennbarer Aufgabenwert, sichere und freigegebene Tools, Einbindung in Arbeitsabläufe, Überprüfungsroutinen sowie klare Zuständigkeiten zentral. Daraus werden theoretische und praktische Implikationen für eine stabile, legitime und regelkonforme KI-Nutzung in großen Organisationen entwickelt.

Einordnung in den Gesamtzusammenhang der Arbeit:

- Studie 4 nimmt die zusammenführende Auswertung der vorangegangenen empirischen Publikationen 1 bis 3 vor.
- Sie legt nahe, dass individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption nicht vollständig isoliert voneinander betrachtet werden können, da sie über Übergänge, Spillover-Effekte, Friktionen sowie Brücken- und Anschlussbedingungen systematisch miteinander verbunden sein können.
- Damit leistet Studie 4 den Beitrag, die zuvor getrennt untersuchten Ebenen in ihrem Zusammenhang sichtbar zu machen und die Grundlage für die spätere übergreifende Diskussion der Dissertation zu schaffen.
- Zugleich macht Studie 4 deutlich, unter welchen Bedingungen private KI-Erfahrungen für KI-Nutzung im Arbeitskontext und darüber hinaus für tragfähige organisationale Adoptionsprozesse anschlussfähig werden können.

Bridging Private and Workplace AI Use: Toward an Integrative Framework for Large Organizations

Abstract— **Artificial Intelligence (AI) is now widely used in private life, yet workplace AI use in large organizations often remains sporadic despite substantial investments. This paper develops an integrative framework by synthesizing three prior empirical studies by the authors in the fields of human-AI interaction, socio-technical integration in large organizations, and individual motivational thresholds. The resulting framework distinguishes among context-specific factors, shared user mechanisms, and cross-context spillovers and frictions that shape whether early AI trials develop into stable routines. It shows that workplace AI use involves higher threshold conditions than private AI use, including clear permissions, approved tools, clarity about accountability, and compliance with confidentiality and traceability requirements. The framework further highlights bridging conditions for more stable workplace AI use, such as salient task value, organizational legitimacy, workflow integration, verification norms, role clarity, and coordination. The paper also provides practical implications for large organizations seeking robust and compliant AI implementation.**

Keywords— AI Adoption, Workplace AI Use, Routinization, Large Organizations

I. Introduction

Artificial Intelligence (AI) has rapidly transitioned from a specialized technology to an everyday tool, particularly in private contexts where generative systems like ChatGPT enable low-threshold experimentation and creative applications [1]. In stark contrast, AI use in large organizations, which tend to feature complex structures and formalized processes, often stalls in early pilot phases despite substantial investments and the technical feasibility of AI tools [2, 3]. This asymmetry is particularly striking given that many employees already use AI fluently in their personal lives, suggesting that the barrier to workplace routinization is not a lack of familiarity with the technology, but a socio-technical misalignment between individual and organizational conditions.

Existing research has examined private AI use [e.g., 4, 5] and AI use in the workplace [e.g., 6, 7] largely in isolation, leaving the mechanisms that translate individual readiness into organizational routinization, and those that prevent it, insufficiently addressed. In private contexts, individuals can freely experiment with AI tools without the need for formal approval, audit risk, or reputational exposure. This reduces the cost of adoption and enables habits to form quickly and organically [8]. In the workplace, by contrast, users must satisfy legitimacy, accountability, and governance requirements before AI use feels institutionally sanctioned enough to become routinized [9]. As a result, AI has become increasingly embedded in everyday private life while often remaining situational in organizational contexts, a divergence that may not be attributable to technical capability alone, but to the interplay of individual psychology, socio-technical system design, and organizational enablement.

Against this background, the goal of this paper is to create an integrative framework for private and workplace AI use by synthesizing the authors' prior studies across human-AI interaction [10], socio-technical integration in large organizations [11], and individual motivational thresholds [3]. The resulting integrative framework (i) organizes key factors of AI use in each context (e.g., context and meaning, typical use patterns, and dominant barriers), (Savolainen et al.) specifies shared mechanisms and spillovers across private and workplace settings, and (iii) identifies friction points where private AI use routines collide with workplace requirements such as privacy, confidentiality, and accountability. Its core contribution is to explain AI use across private and workplace contexts through one integrative framework. The framework structures context-specific factors, shared user mechanisms, cross-context spillovers and frictions, and the conditions that stabilize AI use in the workplace.

II. Theoretical Background

A. Private AI Use Dynamics

Private AI use refers to the voluntary, unstructured application of artificial intelligence tools by individuals in non-professional contexts, such as personal writing assistance (e.g., drafting emails or brainstorming ideas), information retrieval (e.g., recipe suggestions or travel planning), learning support (e.g., personalized language lessons), or creative tasks (e.g., generating images for social media). This use typically occurs without external

oversight, formal policies, or accountability pressures, enabling low-risk experimentation and rapid habit formation [8]. Users engage AI systems like ChatGPT freely in their everyday lives, primarily driven by immediate perceived benefits such as time savings and efficient information access rather than institutional constraints [3, 12]. Initial engagement is often curiosity-driven, marked by exploratory "wow" experiences, before shifting toward instrumental, benefit-oriented behavior embedded in specific use cases [3].

These dynamics are consistent with technology adoption models such as the Technology Acceptance Model (TAM) and related extensions such as UTAUT [13, 14]. In particular, perceived usefulness, ease of use, perceived enjoyment [13, 14], and the progressive formation of habitual behavior help explain how private AI use can become embedded in everyday practices [15, 16]. Nevertheless, routinization remains fragile rather than automatic, as frustrating early experiences, perceived loss of control, or performance below expectations may prevent regular use from stabilizing and instead lead users back to occasional, situational use [17]. In private AI use, there is typically no institution-level quality assurance or formal guidance that standardizes how outputs should be evaluated [18, 19]. At the same time, users often have limited visibility into how AI systems process, retain, or govern data, which makes disclosure and verification decisions more user-dependent [19]. Prior work on algorithm aversion and trust in AI further suggests that people frequently rely on subjective impressions (e.g., perceived competence, trust, and prior experiences) rather than consistent verification standards when judging AI output quality [20, 21]. Moreover, AI users tend to overestimate their understanding of AI, such that overconfidence in their AI literacy can lead to greater rejection of recommendations from AI tools [10]. Another study in this stream shows that people tend to overgeneralize prior AI successes or failures when judging system reliability, affecting their verification behavior [22]. In summary, private AI users are often largely left to themselves when deciding whether an AI-generated answer is "good enough," and they therefore rely strongly on subjective perceptions.

B. Workplace AI Use Dynamics

Workplace AI use refers to employees' use of AI tools within organizational contexts under formal rules and oversight, for example for data analysis, customer service support, HR screening, meeting productivity, or workflow automation [7]. In contrast to private use, workplace use is tied to performance expectations and bounded by compliance requirements, data governance protocols, and role-dependent decision rights [6, 9].

From a socio-technical systems perspective, employees' AI use in the workplace becomes stable when they can integrate AI outputs into everyday work in a way that is experienced as useful, safe, and legitimate [23, 24]. This depends on technically reliable and accessible tools, but also on governance structures that clarify permissible use, accountability expectations, and decision authority [11, 23]. When these conditions are weak, employees often keep AI use sporadic even if the technology performs well, because routinization is constrained by uncertainty regarding coordination, accountability, and organizational fit rather than by model limitations alone [11, 23].

A recurring source of uncertainty and therefore a barrier to AI use in large organizations tends to be role conflict and role ambiguity across heterogeneous organizational roles, for example when business expectations for speed and innovation collide with technical feasibility or risk controls, or when ownership of compliance-sensitive decisions and approval authority remains unclear [11, 25]. Under these conditions, technically viable AI initiatives may not translate into stable work practices. Even employees with strong intentions can hesitate if they lack the capability and confidence to prompt effectively, evaluate outputs critically, and integrate results responsibly into compliance-sensitive workflows [11].

Employees' progression toward routinized AI use tends to require reinforcing conditions in their day-to-day work. AI needs to deliver clear task value in real work activities, organizations need to signal legitimacy through approved enterprise tools and explicit data-use policies, and residual uncertainty needs to be reduced through workflow integration and structured verification routines [3, 11]. When these conditions align, employees are more likely to move from cautious experimentation to role-consistent practice; when they do not, workplace AI use often remains fragmented despite individual motivation [3, 11]. Organizational frame conditions function as legitimacy signals that can enable or constrain this progression [26, 27]. Explicit governance policies, approved enterprise tooling, and workflow-integrated AI solutions tend to lower perceived risk and help employees justify AI use in performance-critical contexts [3, 24]. Leadership communication, role modeling, and cross-functional coordination can further stabilize adoption by signaling that AI-supported work is expected, institutionally supported, and appropriately governed, whereas ambiguous or restrictive signals tend to sustain cautious, sporadic use patterns [3, 28]

Beyond structural organizational constraints, AI use in the workplace is also shaped by employees' motivational and volitional processes [3]. Employees vary in how they progress from initial curiosity to stable use; many remain in sporadic experimentation, particularly when perceived risks to job security, professional identity, or error attribution are salient

[24, 29]. A phase-based perspective views AI use as a process that unfolds over time, moving from initial exploration to more stable and frequent use. Crossing the psychological threshold between these stages is often triggered by strong task value experiences, repeated positive reinforcement, and the perception that AI use aligns with one's professional role and identity [3, 23].

III. Synthesis Approach

Rather than generating new primary data, this paper applies a cross-study synthesis to integrate findings from three previously conducted studies by the authors into an integrative framework spanning private AI use and workplace AI use. Cross-study synthesis refers to the systematic integration and comparison of findings across multiple studies in order to identify shared patterns, context-specific factors, and higher-level conceptual relationships [30]. In this paper, this process was operationalized through comparative-factor-mapping, meaning that relevant findings from the three studies were aligned under comparable factors and systematically compared across studies and contexts [31].

Within the comparative-factor-mapping [31], the relevant findings from the three studies were grouped according to whether they primarily described private AI use factors, workplace AI use factors, or cross-context patterns linking both contexts. Conceptually related findings were aligned under shared labels and compared across the three studies in order to identify context-specific factors, recurring patterns, and relationships between private and workplace AI use. The resulting comparative-factor-mapping is documented in Table II (see Appendix) and provides the intermediate synthesis structure from which the higher-level integrative framework in Table I was derived. While Table II documents the detailed comparative mapping and source traceability, Table I condenses these mapped factors into a higher-level framework that highlights the main contextual differences, shared mechanisms, cross-context dynamics, and bridging conditions. To ensure transparency, Table II links each factor to at least one of the three studies and thereby documents its empirical origin within the comparative factor mapping. In this way, Table II provides traceability from the integrative framework (Table I) to its underlying evidence base and shows how the synthesized structure was derived from the three studies.

One study examines private AI reliance and AI aversion and shows how miscalibration between subjective and objective AI knowledge is associated with reluctance to follow recommendations from AI tools, thereby highlighting the role of subjective user perceptions, trust, and early experiences in shaping private AI use [10]. Another study examines socio-technical constraints on AI use in large organizations with annual revenues above €1 billion and identifies how role conflict, role ambiguity, governance requirements, and accountability structures across business, technical, and functional organizational roles can prevent workplace AI use from becoming stabile despite high technical feasibility [11]. A further study contributes a phase-based perspective on AI use trajectories in large organizations by reconstructing how employees move from initial experimentation to more frequent and routinized AI use, while also showing why many remain in situational use [3]. This perspective informs the framework's emphasis on conditions for stabile workplace AI use, such as task value, legitimacy signals, verification practices, and workflow embedding.

IV. Integrative framework

Table I summarizes the integrative framework of AI use across private and workplace contexts. It organizes the synthesis into four dimensions: context-specific factors, shared mechanisms, cross-context spillovers and frictions, and bridging conditions for stabile workplace use.

As shown in Table I, AI use differs substantially across private and workplace contexts. In private life, AI use is typically self-chosen, low stake, and associated with convenience and empowerment. Its routinization is shaped by rapid trial-and-error learning, everyday task applicability, and a "good enough" quality threshold. The dominant barriers in this context are largely self-managed and include inconsistent verification, lower barriers to informal data sharing with AI tools, and the possibility that salient errors reduce future use.

In the workplace, by contrast, AI use is embedded in company rules, approved tools, and established workflows and unfolds under higher reputation and liability risk. It is further shaped by legitimacy and stigma concerns as well as accountability requirements regarding the explanation and checking of outputs. Accordingly, workplace routinization is characterized by defensible use, including verification, documentation, policy adherence, and stronger emphasis on traceability and justification. Dominant workplace barriers include unclear permissions and legitimacy signals from management, limited access to approved tools, confidentiality and audit requirements, cross-role frictions, and an AI-unfriendly climate marked by low psychological safety and fear of judgment.

At the same time, Table I identifies several mechanisms shared across both contexts. In both private and workplace settings, users weigh expected benefits against the effort of use, build trust through repeated experience, and develop habitual interaction routines such as prompting, iteration, and selective verification. The framework also captures cross-context relationships. Positive spillovers from private

to workplace use include prompting competence, confidence from prior experiences, and a willingness to experiment, whereas workplace use can spill over into private use through stronger verification habits, governance awareness, and more output-oriented use. In parallel, the framework shows frictions where private habits, such as informal data sharing, ad hoc use, relaxed verification, or personal account use, intersect with workplace expectations regarding confidentiality, accountability, traceability, and approved enterprise tools.

Finally, Table I includes bridging conditions associated with more stabile workplace AI use. These conditions include salient task value, organizational legitimacy through clear permissions and secure approved tools, and stabilization mechanisms such as verification norms, documentation expectations, workflow embedding, role clarity, decision rights, and coordination.

TABLE I. AN INTEGRATIVE FRAMEWORK SYNTHESIZED FROM THE AUTHOR'S STUDIES ACROSS HUMAN-AI INTERACTION [10], SOCIO-TECHNICAL INTEGRATION IN LARGE ORGANIZATIONS [11], AND INDIVIDUAL MOTIVATIONAL THRESHOLDS [3]: COMPARING PRIVATE AND WORKPLACE AI USE, INCLUDING CONTEXT, ROUTINIZATION, BARRIERS, SHARED MECHANISMS, SPILLOVERS, FRICTIONS, AND BRIDGING CONDITIONS FOR STABILE WORKPLACE USE

Private AI Use (low stake, autonomy)	**AI Use in the Workplace (higher stakes, constraints)**
Context and meaning • Self-chosen by personal goals and boundaries • Low reputation risk (errors rarely affect personal reputation) • AI experienced as convenience and empowerment	**Context and meaning** • AI use only inside company rules, tools, and workflows. • Higher reputation and liability risk (errors or misuse can be attributed to the employee) • Legitimacy and stigma concerns (AI use may be seen as "shortcutting" or low competence) • Accountability required (ability to explain what was used, why, and how outputs were checked)
Typical use routinization • Rapid trial-and-error learning loops • Everyday tasks (writing, learning, planning, searching) • "Good enough" is often sufficient	**Typical use routinization** • Defensible use: verify, document, and follow policy boundaries • Task-specific adoption (value-driven rather than curiosity-driven) • Greater emphasis on traceability and justification
Dominant barriers • Inconsistent verification of results • Lower barriers to informal data sharing with AI tools • Salient errors on a topic can reduce future use	**Dominant barriers** • Unclear permissions/legitimacy signals from management • Limited access to approved tools • Confidentiality and traceability/audit requirements • Cross-role frictions between business, technical, and functional roles • AI-unfriendly climate (low psychological safety; fear of judgment)
Shared mechanisms (private AI use and workplace use) • Weighing benefits against the effort of use • Building trust through repeated experience • Developing habitual prompting routinization: prompting, iteration, selective verification	
Spillovers between private AI use and the workplace • **Private → Work Spillover:** Prompting competence, more confidence from good experiences, and a willingness to try and improve through trial and error driven by curiosity • **Work → Private Spillover:** Stronger verification of usefulness, governance awareness, more output-oriented use	
Frictions between private AI use and the workplace • Informal data sharing ↔ confidentiality rules • Relaxed verification ↔ accountability / error liability • Ad hoc use ↔ traceability / auditability expectations • Personal accounts ↔ approved enterprise tools and data boundaries • Social norms: "normal" privately ↔ "risky / unproductive" at work	

Bridging conditions for a better workplace trajectory:
AI Use in the workplace is more likely to stabilize when:

- **Task value is salient** (clear productivity/quality gains on real tasks)
- **Organizational legitimacy** exists (permission clarity and secure, approved, integrated tools)
- **Stabilization mechanisms are in** place (verification norms, documentation expectations, workflow embedding, role clarity/decision rights, coordination)

V. Discussion

This paper extends current understandings of AI adoption by showing that differences in AI use between private and workplace contexts are not adequately explained by the technology alone, but by the surrounding threshold conditions under which AI use becomes acceptable, routinized, and sustainable. While private AI use often unfolds under voluntary, low-stakes, and identity-safe conditions, workplace AI use is embedded in legitimacy demands, accountability structures, and cross-role coordination requirements. The resulting gap is therefore not merely a usage gap, but a context-dependent adoption gap.

A. Theoretical Implications

The findings (Table I) suggest that the gap between private and workplace AI use is not primarily a question of technological access or technical capability, but of the conditions under which employees can use AI in ways that are seen as legitimate, defensible, and worth routinizing [11]. Private AI use usually develops in settings where people use AI voluntarily, face relatively low risks, and worry less about being judged by others [4, 10]. By contrast, employees' AI use in workplace settings is shaped by whether AI use is permitted for a given task, whether approved tools are available, whether outputs must be verified and documented, whether data boundaries are clear, and whether using AI is interpreted as competent support or as risky shortcutting [3]. Organizational AI adoption should therefore not be understood as one uniform acceptance process, but rather as a context-dependent process in which individual threshold conditions shape whether employees move from occasional experimentation to repeated, role-consistent, and policy-aligned AI use in everyday work [3, 11]. This also implies that organizational AI adoption is shaped in part by the individual user's pre-adoption status quo, including prior familiarity with AI, established usage routines, trust formation, prompting competence, and willingness to experiment [3, 16].

At the same time, the findings (Table I) show that private AI use should not be treated as fully separate from employees' AI use at work. Rather, private use can function as a pre-stage of AI adoption in organizations in which users learn how to prompt, iterate, assess output usefulness, and integrate AI into small recurring tasks before encountering organizational constraints [26]. While the existing literature separates AI use in private settings [e.g., 4, 5] and in the workplace [e.g., 6, 7], the present framework highlights how both contexts are connected through spillovers, frictions, and different routinization conditions. However, routines developed in private settings do not transfer automatically into organizational work [3]. Habits such as ad hoc prompting, limited verification, informal data sharing, or using personal accounts may clash with workplace expectations of confidentiality, traceability, accountability, approved tools, and clear decision rights [3]. The key challenge of organizational AI adoption is therefore not simply making AI available but translating possible AI use into legitimate and routinized workplace use under organizational conditions. Organizations may block this dynamic when legitimacy remains unclear, when role structures create ambiguity, when accountability is high, but guidance is weak, or when motivational barriers such as fear of judgment and low psychological safety remain unresolved. In this sense, AI adoption emerges as a socio-technical and motivational process in which user perceptions, legitimacy signals, role structures, governance expectations, and coordination requirements jointly shape whether employees' AI use remains cautious and situational or becomes stable in everyday work [11].

B. Practical Implications for Large Organizations

For organizations, the framework suggests that the main challenge is not just to increase the frequency of AI use, but also to translate private AI experience into legitimate, compliant, and routine workplace practice. Many employees already gain familiarity, trust, and prompting competence through private AI use, so organizations do not start from zero. However, private AI fluency should not be equated with workplace readiness, because familiarity and confidence in private AI use do not automatically translate into legitimate, compliant, and accountable AI use at work. The practical barrier lies in adapting this prior and private experience of AI use to organizational rules, role expectations, and accountability requirements.

This means that employees are often unsure whether AI use is permitted, how it will be evaluated, and who is accountable if errors occur. To overcome these barriers, organizations need to reduce ambiguity around AI use through clear policy boundaries and consistent leadership communication [29]. Employees need guidance on whether AI may be used, for which tasks, with which tools, and under which data, verification, and documentation rules. They also need approved and accessible AI tools with

clear data boundaries and integration into daily workflows, so that use does not depend on personal accounts or informal workarounds [18, 27]. In addition, organizations should specify what must be checked, what must be documented, and how decision rights are distributed across business, technical, and functional roles [32]. Finally, the findings indicate that legitimacy and psychological safety also matter in practice. When AI use is associated with stigma, fear of judgment, or unclear responsibility, employees seem to be more likely to use it cautiously or avoid it altogether, even when the technology itself is available [3].

C. Limitations

This present work preliminarily synthesizes the authors' prior evidence into an integrative framework intended to support managerial understanding and decision making in large organizations rather than to introduce new empirical data or provide statistically generalizable estimates. The synthesis draws on three prior studies by the authors, which constrains the breadth of empirical coverage and may reflect context-specific patterns that do not generalize across industries or cultural settings. The integrative framework has also not been empirically validated as a whole, since the factors and bridging conditions are derived from separate studies rather than tested jointly within a single design. The organizational anchors further reflect large organizations with mainly mid to senior level participants, so the implications may not readily transfer to SMEs, start-ups, or junior employees, where AI use is shaped by different company resource constraints or organizational structures.

D. Conclusion

In summary, the integrative framework on AI suggests that the sustainable use of AI in the workplace depends less on increasing usage frequency and more on the professionalization of AI use through legitimacy, governance, and stabilization mechanisms. When organizations deliberately professionalize AI use through approved tools, clear permissions, proportional verification norms, workflow embedding, role clarity, and a psychologically safe environment, the anchor studies collectively indicate that private AI experience can be translated into robust and compliant workplace routinization rather than remaining sporadic or shifting into risky informal workarounds. In addition, private AI use can be treated as a pre-adoption stage and an individual-level antecedent of workplace AI adoption, where employees bring experiential priors (e.g., skills, expectations, and trust calibration) from private contexts that condition whether and how AI use stabilizes at work under confidentiality, accountability, and traceability constraints.

E. Future Work

Future work should empirically validate the integrative framework on AI use across diverse organizational contexts (e.g., public versus private organizations), across different industry sectors (e.g., healthcare, manufacturing, and banking), and across cultural settings. Quantitative and mixed methods designs would be particularly valuable for testing phase-based progression assumptions of AI use and identifying which factors and governance interventions have the strongest effects. Research should also examine whether these dynamics generalize to junior employees, SMEs, and start-ups, as well as across additional industry sectors.

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APPENDIX

TABLE II. COMPARATIVE-FACTOR-MAPPING INDICATING THE ORIGINATING ANCHOR(S) AND THE EVIDENCE TYPE

Private AI Use Factors

Factor	Anchor(s)
Self-chosen by personal goals and boundaries	[10]
Low reputation risk (errors rarely affect personal reputation)	[10]
Rapid trial-and-error learning loops	[10] [11]
Everyday tasks (writing, learning, planning, searching)	[11]
“Good enough” is often sufficient	[11]
Inconsistent verification of results	[10]
Lower barriers for informal data sharing with the AI tools	[10] [11]
Salient errors on a topic can reduce future use	[10]

Workplace AI Use Factors

Factor	Anchor(s)
AI use only inside company rules, tools, and workflows	[3]
Higher reputation/liability risk (errors/misuse attributed to employee)	[3]
Legitimacy/stigma concerns (“shortcutting”/low competence)	[3] [11]
Accountability required (explain use, checks)	[3]
Defensible use: verify, document, policy boundaries	[3] [11]
Task-specific adoption (value-driven rather than curiosity-driven)	[11]
Greater emphasis on traceability/justification	[3]
Unclear permissions/legitimacy signals from management	[3] [11]
Limited access to approved tools	[3]
Confidentiality + traceability/audit requirements	[3]
Cross-role frictions (business/technical/functional)	[3]
AI unfriendly climate (low psychological safety, fear of judgment)	[3]

Cross-Context Elements

Element	**Anchor(s)**
Weighing benefits against the effort of use	[10] [11]
Building trust through repeated experience	[10] [11]
Developing habitual prompting routinization: prompting, iteration, selective verification	[11]
Private → Work: Prompting competence, confidence from experiences, trial-and-error willingness	[11]
Work → Private: Stronger verification of usefulness, governance awareness, output-oriented use	[3] [11]
Informal sharing ↔ confidentiality rules	[3]
Relaxed verification ↔ accountability/error liability	[10] [3]
Ad-hoc use ↔ traceability/auditability expectations	[3]
Personal accounts ↔ approved enterprise tools/data boundaries	[3] [11]
“Normal” private ↔ “risky/unproductive” at work	[3]
Task value salient	[11]

Organizational legitimacy (permissions, secure/approved/integrated tools)	[3] [11]
Stabilization mechanisms (verification norms, documentation, expectations, workflow embedding, role clarity/decision-rights, coordination)	[3] [11]

4 Diskussion

Die Dissertation basiert auf drei Publikationen, die KI-Nutzung und KI-Adoption auf drei analytisch unterschiedenen Ebenen – individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption – untersuchen, sowie auf einer vierten Studie, die diese Befunde zu einer übergreifenden Mehrebenenbetrachtung zusammenführt. Das übergeordnete Erkenntnisinteresse der Dissertation besteht darin, nachhaltige KI-Verankerung in Organisationen als Mehrebenenprozess zu erklären. Dafür werden psychologische Mechanismen, prozessuale Übergänge und sozio-technische Spannungen nicht isoliert, sondern in ihrem Zusammenwirken betrachtet. Die Ergebnisse der vier Beiträge legen nahe, dass KI-Nutzung auf jeder Ebene unterschiedlichen Logiken folgt und dass das Überschreiten der Grenzen zwischen diesen Ebenen an spezifische Schwellen und Bedingungen geknüpft ist, die weder durch rein psychologische Akzeptanzperspektiven noch durch rein technologische Implementierungslogiken hinreichend erklärt werden können (Dietvorst et al., 2015; Gollwitzer, 1990; Jöhnk et al., 2021; Trist & Emery, 2015).

4.1 Gegenüberstellung und zusammenführende Diskussion der Einzelstudien

Publikation 1 adressiert eine grundlegende Ausgangsbedingung von KI-Nutzung: das individuelle Verständnis von KI und die Einschätzung des eigenen KI-Wissens. Die Befunde legen nahe, dass nicht allein mangelndes objektives Wissen, sondern insbesondere eine Fehlkalibrierung zwischen subjektivem und objektivem KI-Wissen dazu beitragen kann, dass KI-Rat trotz seiner Leistungsfähigkeit zugunsten menschlichen Rats zurückgewiesen wird. Damit verweist die Studie auf einen kognitiven Mechanismus, der bereits auf Ebene individueller Wahrnehmung mitprägt, ob und wie KI akzeptiert wird (Kartal et al., 2025). Zugleich relativiert sie die in Teilen der Literatur angelegte lineare Annahme, dass mehr Wissen automatisch zu höherer Akzeptanz führt, und macht die KI-Aversionsforschung stärker anschlussfähig an Arbeiten zu Wissenskalibrierung, Overconfidence und Illusion of Explanatory Depth (Alba & Hutchinson, 2000; Rozenblit & Keil, 2002; Sloman & Fernbach, 2018).

Publikation 2 untersucht den Übergang von initialer zu stabiler KI-Nutzung im Arbeitskontext und adressiert damit die mittlere der drei Analyseebenen zwischen privater Vertrautheit

und organisationaler Verankerung. Sie zeigt, dass KI-Nutzung im Arbeitskontext kein fortlaufend progressiver Prozess ist, sondern an motivationalen, situativen und organisationalen Schwellen ins Stocken geraten oder wieder abbrechen kann (Kartal et al., in press-a). Damit identifiziert sie den kritischen Punkt, an dem KI trotz positiver Einstellung, verfügbarer Technologie und erster Nutzungserfahrungen nicht zwangsläufig in dauerhafte Arbeitspraktiken übergeht, sondern in sporadischer Nutzung verbleiben oder nach ersten Erfahrungen wieder abnehmen kann. Zugleich wird sichtbar, unter welchen Bedingungen sich dieser Übergang stabilisiert, insbesondere durch erlebten Wertbeitrag, organisationale Legitimation und unterstützende Routinen (Achtziger & Gollwitzer, 2007; Prasad Agrawal, 2024).

Publikation 3 verschiebt die Perspektive auf die organisationale Ebene und zeigt, dass organisationale KI-Adoption nicht nur durch individuelle Wahrnehmung oder fehlende Routinisierung beeinflusst wird, sondern auch durch strukturelle Koordinationsprobleme innerhalb der Organisation ins Stocken geraten kann (Kartal et al., in press-b). Sie macht deutlich, dass durch die gleichzeitige Einbindung heterogener organisationaler Rollen wiederkehrende Rollenkonflikte und Rollenunklarheiten entstehen, die den Übergang von Pilotprojekten in skalierte und dauerhaft verankerte Nutzung erschweren oder verhindern können (Kahn, 1964; Rizzo et al., 1970; Trist & Emery, 2015). Im Zusammenspiel mit Publikation 2 wird damit sichtbar, dass die Bedingungen stabiler KI-Nutzung im Arbeitskontext nicht allein auf Ebene individueller Nutzung entstehen. Organisationale Legitimation, sichere Nutzungsspielräume und verlässliche Freigaben hängen vielmehr davon ab, ob Rollen, Entscheidungsrechte und Governance-Strukturen hinreichend geklärt sind. Die organisationale Ebene erscheint damit nicht nur als nachgelagerter Ort der Skalierung, sondern bereits als Rahmenbedingung dafür, ob individuelle KI-Nutzung im Arbeitskontext stabilisiert werden kann.

Studie 4 führt die Befunde der drei vorangegangenen Studien zusammen und überführt sie in einen gemeinsamen Erklärungsrahmen (Kartal et al., under review). Sie legt nahe, dass individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption nur begrenzt als getrennte Phänomene erklärt werden können, weil sie über Übergänge, Spillover-Effekte, Friktionen sowie Brücken- und Anschlussbedingungen systematisch miteinander verbunden sind. Damit wird zugleich präzisiert, worin die zusammenführende Betrachtung besteht. Sie eröffnet eine Mehrebenenperspektive, die in der bisherigen Theorie so nicht systematisch ausgearbeitet ist, weil sie die Übergänge zwischen

Wahrnehmung, Nutzungspraxis und organisationaler Einbettung selbst zum Erklärungsgegenstand macht. Der übergreifende Erkenntnisbeitrag der Dissertation liegt folglich darin, nachhaltige KI-Verankerung weder allein aus individueller Akzeptanz noch allein aus organisationaler Implementierung zu erklären, sondern aus dem Zusammenspiel subjektiver Wahrnehmung, routinisierter Nutzungspraxis und organisationaler Einbettung.

In ihrer Zusammenschau verweisen die vier Studien damit auf eine gemeinsame Grundspannung: Weder individuelles Wissen noch technische Verfügbarkeit noch private Nutzungsvertrautheit führen für sich genommen automatisch zu stabiler, legitimer und organisational eingebetteter KI-Nutzung. Gerade diese mehrstufige Betrachtung macht sichtbar, warum KI-Verankerung in Organisationen häufig fragil bleiben kann: Auf der Alltagsebene kann bereits die Wissensfehlkalibrierung die KI-Akzeptanz begrenzen (Dietvorst et al., 2015; Logg et al., 2019; Yeomans et al., 2019), im Arbeitskontext können fehlende Legitimation und Stabilisierung den Übergang von Intention zu Routine erschweren (Prasad Agrawal, 2024; Romeo & Lacko, 2026; Soulami et al., 2024), und auf organisationaler Ebene können ungelöste Rollenspannungen die Skalierung selbst technisch valider Lösungen blockieren (Jöhnk et al., 2021; Tursunbayeva & Gal, 2024).

4.2 Theoretische Implikationen

Im Zentrum der theoretischen Implikationen steht das in Abbildung 3 verdichtete Mehrebenenmodell nachhaltiger KI-Verankerung in Organisationen. Dieses konzeptionelle Modell fungiert als Erklärungsrahmen, der die drei Analyseebenen der Dissertation – individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption – in ihrem Zusammenhang sichtbar macht. Es baut auf der theoretischen Verdichtung in Kapitel 2, der übergreifenden Forschungslogik in Kapitel 3 und der zusammenführenden Auswertung von Studie 4 auf. Sichtbar wird dabei nicht nur, dass auf jeder Ebene unterschiedliche Mechanismen besonders hervortreten, sondern auch, dass nachhaltige KI-Verankerung vor allem an den Übergängen zwischen diesen Ebenen erklärungsbedürftig wird. Spillover-Effekte, Friktionen sowie Brücken- und Anschlussbedingungen erscheinen damit nicht als nachträgliche Ergänzungen, sondern als zentrale Bestandteile eines mehrstufigen Verankerungsprozesses. In diesem Sinne folgt das Modell einer Mehrebenenlogik, nach der KI in Organisationen nur unzureichend erklärt werden kann, wenn individuelle KI-

Nutzung, KI-Nutzung im Arbeitskontext und organisationale KI-Adoption getrennt betrachtet werden. Erst wenn auch die Übergänge und Wechselwirkungen zwischen diesen Ebenen berücksichtigt werden, lässt sich genauer erklären, wie nachhaltige KI-Verankerung entstehen kann (Bankins et al., 2024; Mathieu & Chen, 2011).

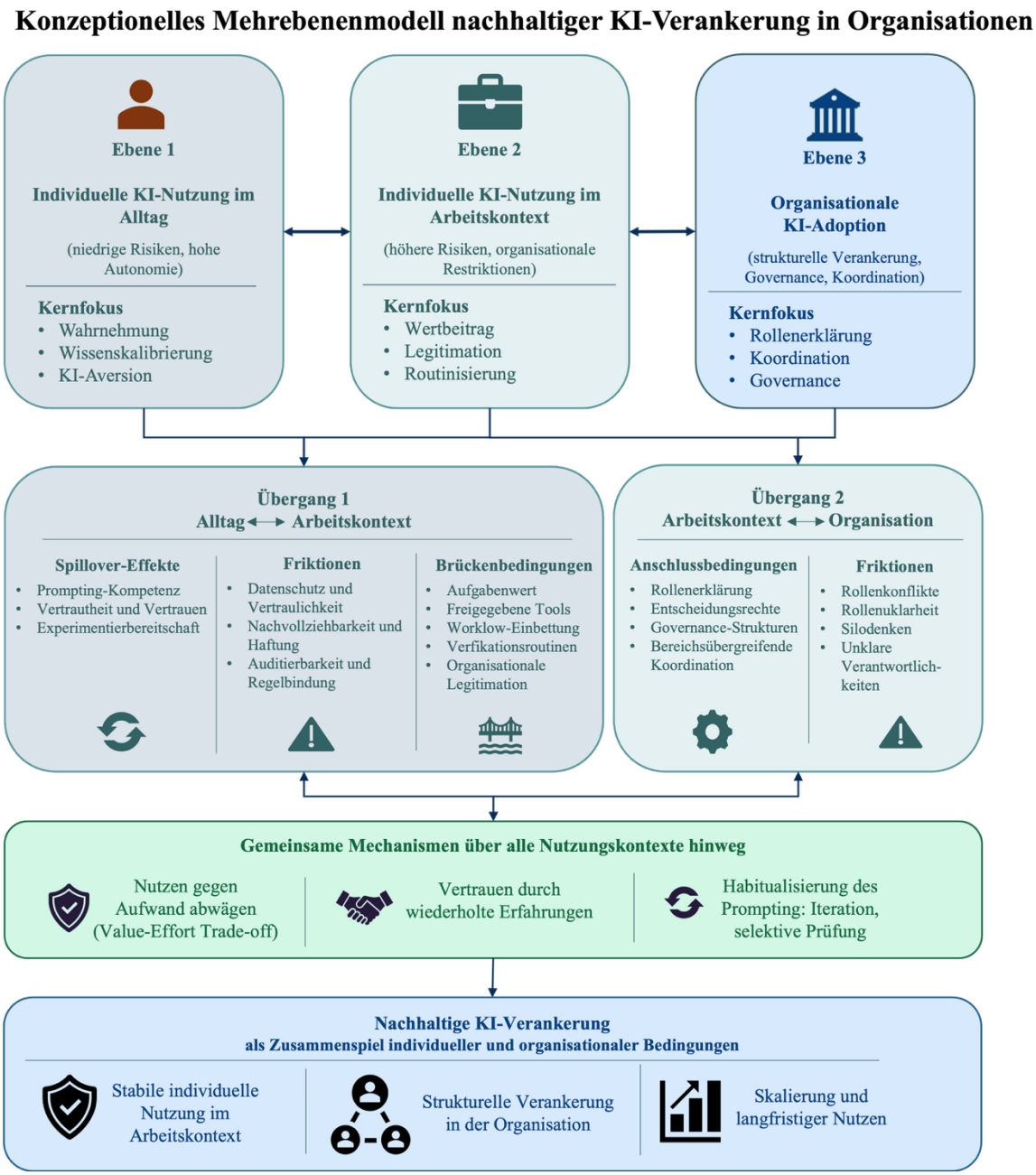

Abbildung 3: Konzeptionelles Mehrebenenmodell der Beziehungen zwischen individueller KI-Nutzung im Alltag, individueller KI-Nutzung im Arbeitskontext und organisationaler KI-Adoption sowie der damit verbundenen Spillover-Effekte, Friktionen, Brücken- und Anschlussbedingungen.

Wie Abbildung 3 verdeutlicht, entstehen die zentralen Herausforderungen nachhaltiger KI-Verankerung nicht auf einer einzelnen Ebene, sondern vor allem an den Übergängen zwischen ihnen. Auf der Alltagsebene sind insbesondere Wahrnehmung, Wissenskalibrierung und KI-Aversion relevant. Im Arbeitskontext rücken dagegen Wertbeitrag, organisationale Legitimation und Routinisierung in den Vordergrund. Auf Ebene der organisationalen KI-Adoption werden diese Nutzungsdynamiken schließlich durch Rollenklärung, Governance und bereichsübergreifende Koordination strukturell gerahmt. Die in Abbildung 3 ausgewiesenen Spillover-Effekte, Friktionen sowie Brücken- und Anschlussbedingungen machen deutlich, warum private KI-Vertrautheit den Einstieg in den Arbeitskontext zwar erleichtern kann, aber weder routinisierte berufliche Nutzung noch organisationale KI-Adoption automatisch hervorbringen muss. Gerade darin liegt der theoretische Ertrag der Mehrebenenbetrachtung: Psychologische, prozessuale und sozio-technische Perspektiven werden nicht nebeneinandergestellt, sondern in ein gemeinsames Erklärungsmodell überführt.

Ausgehend von dieser Mehrebenenlogik erhält auch die Forschung zu Algorithmus- und KI-Aversion eine breitere theoretische Einordnung. Die bisherige Literatur erklärt KI-Aversion vor allem über wahrgenommene Fehler, mangelnde Transparenz oder fehlendes Vertrauen in algorithmische Systeme (Dietvorst, 2016; Dietvorst et al., 2015; Mahmud et al., 2022). Die Befunde von Publikation 1 legen nahe, dass nicht nur fehlendes Wissen, sondern gerade die Überschätzung des eigenen Wissens Ablehnung begünstigen kann. Damit wird KI-Aversion stärker an epistemische Selbstwahrnehmung rückgebunden und an Forschung zu Overconfidence, Knowledge Calibration und Illusions of Understanding anschlussfähig gemacht (Alba & Hutchinson, 2000; Light et al., 2022; Walters et al., 2017). In der Logik des Mehrebenenmodells erscheint Akzeptanz damit nicht mehr als stabiler Endzustand, sondern als frühe Schwelle eines längeren Verankerungsprozesses. Die bislang häufig implizit unterstellte lineare Annahme, mehr Wissen führe unmittelbar zu mehr Akzeptanz und mehr Nutzung, wird dadurch in eine kontextsensitivere Sicht überführt, in der subjektive Wahrnehmung zwar den Einstieg in KI-Nutzung prägt, spätere Nutzungsverläufe jedoch von zusätzlichen Bedingungen abhängen (Glikson & Woolley, 2020; Logg et al., 2019; Yeomans et al., 2019).

Auch die Anschlussfähigkeit an klassische Technologieakzeptanzforschung verschiebt sich dadurch. Modelle wie TAM und UTAUT erklären Technologiegebrauch vor allem über

wahrgenommenen Nutzen, Benutzerfreundlichkeit, soziale Einflüsse und unterstützende Bedingungen (Davis, 1985; Venkatesh & Davis, 2000). Im theoretischen Hintergrund der Dissertation war bereits angelegt, dass ein solches Verständnis für KI nur begrenzt ausreicht, weil Nutzungserfahrungen, Unsicherheiten und situative Rückkopplungen den Umgang mit der Technologie fortlaufend verändern (Ajibade, 2018; Mogaji et al., 2024; Venkatesh et al., 2024). Die Befunde aus Publikation 2 konkretisieren diese prozessuale Perspektive für den Arbeitskontext, indem sie zeigen, dass individuelle KI-Nutzung am Arbeitsplatz nicht angemessen als bloßer Zustand von Nutzung oder Nicht-Nutzung beschrieben werden kann. Mit dem Rubikon-Modell wird sichtbar, an welchen Schwellen zwischen Exploration, Commitment, Handlung und Evaluation sich Nutzung stabilisiert oder wieder abbricht (Gollwitzer, 2012; Keller et al., 2020). Akzeptanz erscheint damit nicht als hinreichende Bedingung routinisierter Nutzung, sondern als ein Bestandteil eines längeren motivational-volitionalen Verlaufs.

Gerade in Verbindung mit den übrigen Befunden aus Publikation 1, Publikation 3 und Studie 4 wird jedoch deutlich, dass dieser Verlauf nicht bei individueller Nutzungsintention beginnt und auch nicht dort endet. Prozessuale Übergänge im Arbeitskontext schließen an vorgelagerte Wahrnehmungs-, Wissens- und Bewertungsprozesse an, werden aber zugleich durch organisationale Legitimation, sichere Tools, Freigaben und Workflow-Einbettung mitgeprägt (Pinski & Benlian, 2023; Prasad Agrawal, 2024; Soulami et al., 2024). Die technologieakzeptanzbezogene Perspektive verschiebt sich damit von einer primär individuellen und statisch gedachten Erklärung hin zu einem kontextsensitiven und mehrebenenbezogenen Verständnis, in dem sich KI-Nutzung insbesondere an den Übergängen zwischen Alltag, Arbeitskontext und Organisation stabilisiert. Für die Theorie bedeutet das, dass die Bruchstelle zwischen Akzeptanz und Routinisierung nicht länger als Randproblem verstanden werden kann, sondern selbst zum zentralen Gegenstand der Erklärung wird. Zusammenfassend zeigt sich damit, dass die Stabilisierung von KI-Nutzung nicht durch individuelle Akzeptanz allein erklärbar ist, sondern als mehrebenenbezogener Prozess, dessen zentrale Dynamik insbesondere in den Übergängen zwischen Wahrnehmung, Nutzung und organisationaler Einbettung liegt.

Besonders deutlich wird dieser Mehrwert am Begriff der Spillover-Effekte, der in der bisherigen Literatur häufig eher implizit bleibt. Spillover bezeichnet in dieser Arbeit die kontextspezifische Übertragung von Erfahrungen, Routinen und Erwartungen aus privater KI-

Nutzung in Nutzung im Arbeitskontext; anders als ein allgemeiner Transfer macht der Begriff zugleich sichtbar, dass diese Übertragung durch neue Regeln, Rollen, Verantwortlichkeiten und Risikobedingungen verändert, ermöglicht oder begrenzt wird (Savolainen et al., 2025; Venkatesh et al., 2024). Zugleich wird sichtbar, warum Spillover allein keine stabilen Nutzungsroutinen hervorbringt. Vorhandene KI-Kompetenzen aus privater Nutzung können zwar für berufliche Zwecke relevant sein, treffen im Arbeitskontext jedoch auf Anforderungen wie Vertraulichkeit, Nachvollziehbarkeit, Haftung, Auditierbarkeit oder Rollengrenzen (Chen et al., 2024; Soulami et al., 2024; Uren & Edwards, 2023). Damit ist Spillover kein automatischer Kompetenztransfer, sondern ein erklärungsbedürftiger Übergang zwischen Kontexten.

An diese Übergangslogik schließt die Weiterentwicklung sozio-technischer Perspektiven auf organisationale KI-Adoption durch eine rollentheoretische Perspektive an. Publikation 3 verbindet sozio-technische Systemtheorie mit Role-Conflict- und Role-Ambiguity-Forschung und zeigt, dass organisationale Barrieren nicht nur als diffuse soziale Faktoren beschrieben werden können, sondern als konkrete, wiederkehrende Spannungsmuster zwischen organisationalen Rollen (Kahn, 1964; Rizzo et al., 1970; Trist & Emery, 2015). Dadurch wird die Literatur zu KI-Adoption um Begriffe für unterschiedliche Formen von Rollenkonflikten, Rollenunklarheiten und Verantwortungsdiffusion präzisiert (Gupta et al., 2024; Horani et al., 2025). Zugleich legen die in Abbildung 3 verdichteten Befunde nahe, dass Rollenklarheit, Governance und bereichsübergreifende Koordination nicht erst für die spätere organisationale Skalierung relevant werden, sondern bereits mit beeinflussen, ob individuelle KI-Nutzung im Arbeitskontext überhaupt legitimiert, abgesichert und routinisiert werden kann (Horani et al., 2025; Miller, 2022; Selten & Klievink, 2024).

Darüber hinaus zeigt das Mehrebenenmodell, dass individuelle KI-Nutzung im Arbeitskontext nicht nur Gegenstand organisationaler Rahmung ist, sondern selbst einen relevanten Inputfaktor für organisationale KI-Adoption darstellt (Bankins et al., 2024; Savolainen et al., 2025). Gerade weil KI im Arbeitskontext nicht ausschließlich als rational zu bewertende Technologie erscheint, sondern auch durch subjektive Wahrnehmung, Neugier, Unsicherheit, Vertrauen und wahrgenommenen Nutzen mitgeprägt wird (Frenkenberg & Hochman, 2025; Högemann et al., 2025), kann organisationale KI-Adoption nicht als rein technisches oder rein strategisches Implementierungsprojekt verstanden werden (Dwivedi et al., 2021; Gupta et al., 2024; Schweitzer et al., 2025). Vielmehr baut sie

auf vorgelagerten individuellen Nutzungserfahrungen auf, deren Stabilisierung anschließend durch Rollenklärung, Governance und Koordination organisatorisch ermöglicht, begrenzt oder erschwert werden kann (Horani et al., 2025; Schweitzer et al., 2025; Westenberger et al., 2022). Individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption scheinen damit analytisch unterscheidbar, empirisch jedoch eng miteinander verschränkt zu sein.

Gerade an diesem Punkt wird auch deutlicher, warum bisherige Erklärungsansätze zu individueller KI-Nutzung und organisationaler KI-Adoption jeweils nur einen Teil des Problems erfassen. Eine rein psychologische Akzeptanzperspektive kann erklären, warum Personen KI annehmen oder ablehnen, unterschätzt aber, dass Nutzung im Arbeitskontext und organisationale Adoption institutionell gerahmt sind und an Rollen, Regeln und Governance gebunden bleiben (Davis, 1985; Soulami et al., 2024; Venkatesh, 2000; Workman, 2005). Eine rein organisationale oder institutionalistische Perspektive kann wiederum erklären, warum Governance, Ressourcen und Entscheidungsrechte relevant sind, vernachlässigt aber die subjektive Wahrnehmung, Neugier, Skepsis und Vertrauensentwicklung, die bereits auf Alltagsebene darüber mitprägen, wie Menschen KI überhaupt in ihre Praktiken aufnehmen (Glikson & Woolley, 2020; Logg et al., 2019; Mahmud et al., 2022). Und eine ausschließlich verhaltensökonomische oder aversionsbezogene Perspektive bleibt zu eng, wenn sie Akzeptanz als Endpunkt betrachtet, ohne Routinisierung, Workflow-Einbettung und organisationale Verankerung mitzudenken (Dietvorst et al., 2015; Mogaji et al., 2024; Yeomans et al., 2019). Die Reichweite des Mehrebenenmodells besteht gerade darin, diese bisherigen Perspektiven nicht zu ersetzen, sondern in ihren jeweiligen Stärken und Grenzen sichtbar zu machen und in einen umfassenderen Zusammenhang zu stellen.

Aus dem Modell lassen sich schließlich mehrere theoretische Propositionen ableiten, die zukünftige Forschung systematisch prüfen kann. Erstens ist zu erwarten, dass Fehlkalibrierung zwischen subjektivem und objektivem KI-Wissen nicht nur frühe Akzeptanzentscheidungen beeinflusst, sondern auch die Richtung späterer Übergänge in andere Nutzungskontexte mitprägt. Zweitens dürfte sich der Übergang von sporadischer zu routinisierter KI-Nutzung im Arbeitskontext insbesondere dann stabilisieren, wenn individueller Aufgabenwert und organisationale Legitimation gleichzeitig gegeben sind. Drittens spricht die zusammenführende Perspektive dafür, dass Rollenklarheit, Governance

und bereichsübergreifende Koordination nicht bloß Bedingungen organisationaler Skalierung sind, sondern bereits als Voraussetzungen routinisierter KI-Nutzung wirken. Viertens ist zu erwarten, dass Spillover aus privater KI-Nutzung insbesondere dann produktiv werden kann, wenn privat erworbene Kompetenzen und Routinen nicht ungefiltert übertragen, sondern organisational gerahmt und stabilisiert werden. Fünftens legt das Modell nahe, dass nachhaltige KI-Verankerung wahrscheinlicher wird, wenn subjektive Wahrnehmung, konkrete Nutzungspraxis und organisationale Einbettung über die Ebenen hinweg aufeinander abgestimmt sind.

4.3 Praktische Implikationen

Das in Abbildung 3 verdichtete Mehrebenenmodell legt nahe, dass nachhaltige KI-Verankerung in Organisationen nicht durch einen einzelnen Hebel entsteht. Weder technische Bereitstellung noch Schulung noch Governance allein reichen aus. Praktisch relevant wird vielmehr das Zusammenspiel von subjektiver Wahrnehmung, individueller Nutzungspraxis im Arbeitskontext und organisationaler Einbettung. Die Befunde legen daher nahe, KI weniger als reine Tool-Einführung, als isoliertes Weiterbildungsprogramm oder als ausschließliches Governance-Thema zu behandeln, sondern als mehrstufigen Verankerungsprozess, in dem Übergänge zwischen Alltag, Arbeitskontext und organisationaler Adoption bewusst adressiert werden (Bankins et al., 2024; Schweitzer et al., 2025; Uren & Edwards, 2023).

Ein erster praktischer Ansatzpunkt liegt im Umgang mit bereits vorhandenen privaten KI-Erfahrungen der Mitarbeitenden. Die zusammenführende Betrachtung der Dissertation macht deutlich, dass Organisationen hier nicht bei null beginnen. Viele Beschäftigte bringen bereits Vertrautheit mit KI-Tools, erste Prompting-Erfahrungen, Neugier und eine gewisse Experimentierbereitschaft aus dem Alltag mit (Savolainen et al., 2025). Diese Erfahrungen können den Einstieg in die berufliche KI-Nutzung erleichtern, sollten aber nicht mit hinreichender Bereitschaft für eine dauerhafte Nutzung im Arbeitskontext verwechselt werden. Gerade die Befunde zu Wissenskalibrierung und KI-Aversion legen nahe, dass subjektive Sicherheit im Umgang mit KI nicht automatisch mit reflektiertem, belastbarem oder regelkonformem Einsatz gleichzusetzen ist (Alba & Hutchinson, 2000; Light et al., 2022; Yeomans et al., 2019). Für Organisationen legt dies nahe, KI-Qualifizierung nicht auf bloßes

Faktenwissen zu beschränken, sondern stärker bei Erklärungstiefe, realistischer Selbsteinschätzung und der Fähigkeit zur kritischen Prüfung von KI-generierten Ergebnissen anzusetzen. Nicht nur die Frage, was KI ist, sondern wie sie funktioniert, wo ihre Grenzen liegen und wann Ergebnisse verifiziert werden sollten, wird damit für die praktische Qualifizierung zentral (Cadario et al., 2021; Rozenblit & Keil, 2002; Walters et al., 2017).

Zugleich legen die Befunde nahe, dass private KI-Erfahrungen vor allem dann produktiv für den Arbeitskontext werden können, wenn passende Brückenbedingungen bestehen. Aus individueller Offenheit oder sporadischer Nutzung entsteht noch keine stabile Nutzungspraxis. Damit sich KI im Arbeitskontext stabilisieren und routinisieren kann, erscheinen Aufgaben mit erkennbarem Wertbeitrag, sichere und freigegebene Tools, klare Nutzungsspielräume sowie eine Einbettung in bestehende Arbeitsabläufe erforderlich (Prasad Agrawal, 2024; Romeo & Lacko, 2026; Soulami et al., 2024). Praktisch bedeutet dies, dass Beschäftigte nicht nur Zugang zu KI benötigen, sondern auch Anwendungsfälle, in denen der Nutzen für reale Arbeitsaufgaben unmittelbar erfahrbar wird. Ebenso wichtig sind Freigabesignale, technische Integration und Routinen zur Überprüfung von Ergebnissen. Für Organisationen erscheint es daher sinnvoll, sichere Explorationsräume zu schaffen, in denen Mitarbeitende KI mit geringem Risiko erproben können, bevor die Nutzung auf sensible oder verantwortungskritische Tätigkeiten ausgeweitet wird. Damit aus Erprobung Routinisierung wird, sollten Lerngelegenheiten, Verifikationspraktiken und technische Einbettung aufeinander abgestimmt werden (Pinski & Benlian, 2023; Übellacker, 2025).

Eine weitere praktische Implikation der zusammenführenden Betrachtung liegt darin, dass individuelle KI-Nutzung im Arbeitskontext und organisationale KI-Adoption nicht vollständig getrennt betrachtet werden sollten. Die Dissertation legt nahe, dass individuelle KI-Nutzung im Arbeitskontext nicht nur von individuellen Einstellungen abhängt, sondern von organisationaler Legitimation und strukturellen Rahmenbedingungen mitgeprägt wird. Umgekehrt hängt organisationale KI-Adoption nicht nur von strategischen Entscheidungen über Einführung und Skalierung ab, sondern auch davon, ob sich auf Ebene der Mitarbeitenden überhaupt tragfähige Nutzungsmuster ausbilden. Die Befunde sprechen daher dagegen, KI-Verankerung als rein top-down gesteuertes Implementierungsprojekt zu begreifen. Vielmehr sind Nutzungserfahrungen von Mitarbeitenden und organisationale Steuerung gemeinsam zu betrachten. Wenn Beschäftigte KI als hilfreich erleben, aber keine

klaren Freigaben, keine sicheren Tools oder keine nachvollziehbaren Regeln vorfinden, bleibt Nutzung fragmentiert oder wandert in informelle Schattenpraktiken ab. Wenn hingegen zwar ein organisationaler Rahmen vorhanden ist, aber keine anschlussfähigen Nutzungssituationen entstehen, bleibt organisationale KI-Adoption weitgehend formal und entfaltet kaum nachhaltigen Nutzen für Beschäftigte (Horani et al., 2025; Schweitzer et al., 2025; Westenberger et al., 2022).

Vor diesem Hintergrund rückt die praktische Bedeutung von Rollenklärung, Entscheidungsrechten und bereichsübergreifender Koordination in den Vordergrund. Die Ergebnisse der Dissertation legen nahe, dass organisationale KI-Adoption besonders dann stagniert, wenn unklar bleibt, wer Entscheidungen trifft, wer Risiken trägt, wer Budgets verantwortet und nach welchen Kriterien Erfolg bewertet wird. Für Organisationen lässt sich daraus ableiten, dass frühe Rollen- und Verantwortlichkeitsklärung für KI-Initiativen besonders relevant sein dürfte. RACI-Matrizen, abgestimmte KPIs, gemeinsame Erfolgskriterien und bereichsübergreifende Abstimmungsroutinen sind dabei nicht nur klassische Managementinstrumente, sondern können eine wichtige Voraussetzung dafür darstellen, KI aus Pilotphasen heraus in tragfähige Nutzung zu überführen (Benbya et al., 2020; Weber et al., 2023; Westenberger et al., 2022). Solche Strukturen reduzieren nicht nur Abstimmungsaufwand, sondern machen auch sichtbar, welche Rolle welche Entscheidung verantwortet, welche Risiken akzeptiert werden und wann ein Pilot in den Regelbetrieb überführt werden kann. Gerade weil Business-, technische und funktionale Rollen unterschiedliche Logiken und Prioritäten einbringen, erscheint es plausibel, einen organisationalen Rahmen frühzeitig zu etablieren und nicht erst dann, wenn Konflikte bereits die Skalierung blockieren (Benbya et al., 2020; Miller, 2022; Selten & Klievink, 2024).

Aus der zusammenführenden Betrachtung ergibt sich schließlich die praktische Lesart, KI-Verankerung als Übergangsmanagement zu verstehen. Praktisch relevant ist nicht nur, ob KI eingeführt wird, sondern wie Übergänge gestaltet werden: vom privaten Vorwissen zur beruflichen Nutzung, von sporadischer Erprobung zur Routinisierung und von individueller Nutzung zur organisationalen Verankerung. Für diese Übergänge erscheinen unterschiedliche Interventionen relevant. Früh sind sichere Explorationsräume, Orientierung und legitime Nutzungssignale wichtig. Danach gewinnen die Einbettung in Arbeitsabläufe, Verifikationsroutinen und rollenklare Entscheidungswege an Bedeutung. Später erscheint entscheidend, ob Koordination, Governance und organisationsweite Anschlussfähigkeit so

gestaltet sind, dass aus lokalen Nutzungsvorteilen auch dauerhafte organisationale Wertschöpfung entstehen kann (Bankins et al., 2024; Selten & Klievink, 2024).

4.4 Limitationen und Ausblick

Die folgenden Abschnitte reflektieren die Limitationen der Dissertation und zeigen Ansatzpunkte für zukünftige Forschung auf. Dabei stehen insbesondere die methodische Anlage, die Reichweite der Befunde und die weitere empirische Prüfung des entwickelten Mehrebenenmodells im Vordergrund.

4.4.1 Limitationen

Die Dissertation bringt spezifische Limitationen mit sich, da die Verknüpfung der drei Analyseebenen nicht innerhalb eines einheitlichen Forschungsdesigns erfolgt, sondern auf unterschiedlichen empirischen Zugängen und einer nachgelagerten zusammenführenden Auswertung beruht. Während Publikation 1 auf einer quantitativen Feldstudie basiert, beruhen Publikation 2 und 3 auf explorativen qualitativen Interviewstudien; Studie 4 führt die Befunde dieser drei Studien in einer Cross-Study-Auswertung zusammen. Da Studie 4 zum Zeitpunkt der Einreichung noch im Begutachtungsverfahren ist, ist der Mehrebenenrahmen innerhalb der Dissertation theoretisch begründet, aber noch nicht als externer Publikationsbeitrag publiziert. Diese methodische Vielfalt ist für den Erkenntnisgewinn produktiv, weil sie psychologische, prozessuale und sozio-technische Perspektiven auf KI-Nutzung und KI-Adoption verbindet. Zugleich bedeutet sie jedoch, dass die angenommenen Zusammenhänge zwischen den Ebenen nicht in einem einheitlichen, kausal angelegten Mehrebenendesign geprüft wurden. Die zusammenführende Auswertung liefert daher vor allem eine theoretische Verknüpfung der Befunde, nicht jedoch eine vollständige empirische Prüfung aller Übergänge, Spillover-Effekte und Friktionen zwischen den Ebenen.

Die empirischen Studien beziehen sich überwiegend auf Teilnehmende aus der EU beziehungsweise auf Mid- bis Senior-Professionals in großen Organisationen. Für kleine und mittlere Unternehmen, Start-ups, öffentliche Organisationen, außereuropäische Kontexte oder jüngere Beschäftigtengruppen können sich andere Bedingungen ergeben. Gerade die qualitative Evidenz zur individuellen KI-Nutzung im Arbeitskontext und zur organisationalen KI-Adoption ist bewusst explorativ angelegt und auf theoretischen Erkenntnisgewinn

ausgerichtet, nicht auf statistische Repräsentativität. Dies entspricht der Logik qualitativer Forschung, die besonders geeignet ist, subjektive Deutungen, Prozessverläufe und organisationale Spannungen in frühen Forschungsfeldern sichtbar zu machen (Gioia et al., 2013; Ritchie et al., 2013). Gleichwohl sollten die entwickelten Zusammenhänge in künftigen Studien mit größeren, diverseren und stärker vergleichenden Stichproben weiter geprüft werden. Damit bleibt die Generalisierbarkeit der Befunde begrenzt.

Hinzu kommt, dass insbesondere die qualitativen Befunde auf retrospektiven Selbstbeschreibungen beruhen (Schwarz, 2007). Solche Daten sind wertvoll, weil sie rekonstruieren, wie Akteure KI-Nutzung, Entscheidungsprozesse, Rollenspannungen und organisationale Rahmenbedingungen selbst wahrnehmen und deuten. Gleichzeitig können sie durch Erinnerungsverzerrungen, nachträgliche Rationalisierung oder selektive Hervorhebung beeinflusst sein (Small & Cook, 2023). Dies betrifft insbesondere phasenhafte Nutzungsverläufe im Arbeitskontext sowie organisationale Konfliktlagen, die von den Befragten aus ihrer heutigen Perspektive rekonstruiert wurden. Für die Interpretation der Befunde bedeutet dies, dass die identifizierten Phasen, Schwellen und Spannungen nicht als vollständig objektive Prozessabbildungen verstanden werden sollten, sondern als theoretisch verdichtete Rekonstruktionen subjektiver Erfahrungen und organisationaler Deutungsmuster (Gioia et al., 2013).

Eine weitere Einschränkung ergibt sich aus dem Untersuchungsgegenstand selbst. Generative KI, Enterprise-KI, Governance-Strukturen und regulatorische Rahmenbedingungen verändern sich derzeit mit hoher Geschwindigkeit (Janssen, 2025). Einige der in dieser Dissertation identifizierten Mechanismen dürften vergleichsweise stabil sein, etwa die Bedeutung von Wissenskalibrierung, Legitimation, Verifizierung, Rollenklarheit und Koordination. Andere konkrete Ausprägungen, beispielsweise bestimmte Tool-Landschaften, Freigabeprozesse oder Compliance-Anforderungen, können sich dagegen kurzfristig verändern. Zudem ist nicht auszuschließen, dass ein Teil der beobachteten Diskrepanz zwischen individueller Nutzung und organisationaler Adoption weniger eine dauerhafte strukturelle Kluft als eine zeitliche Verzögerung darstellt. Organisationen könnten private und individuelle Nutzungspraktiken erst mit zeitlichem Abstand in formalisierten Prozessen, Governance-Strukturen und skalierbaren Lösungen aufgreifen. Die Dissertation liefert daher weniger eine zeitlose Beschreibung bestimmter Werkzeuge oder Einführungsprogramme als einen theoretischen Rahmen zur Analyse von Stabilisierung, Friktion und Verankerung unter Bedingungen schnellen technologischen Wandels (Maslej et al., 2025; Venkatesh et al., 2024).

4.4.2 Ausblick

Besonders naheliegend erscheinen Längsschnittstudien, die individuelle KI-Nutzung im Alltag, individuelle KI-Nutzung im Arbeitskontext und organisationale Adoptionsentscheidungen gleichzeitig erfassen. Solche Mehrebenendesigns könnten genauer prüfen, ob und wie private KI-Erfahrungen in berufliche Nutzung übergehen, wann diese Nutzung routinisiert wird und unter welchen organisationalen Bedingungen daraus tragfähige KI-Adoption entstehen kann. Besonders aufschlussreich wären Studien, die die in Abbildung 3 angenommenen Übergänge, Spillover-Effekte, Friktionen, Brückenbedingungen und Anschlussbedingungen direkt empirisch untersuchen. Damit ließe sich genauer prüfen, unter welchen Bedingungen private KI-Vertrautheit für berufliche Nutzung produktiv werden kann und welche Rolle Aufgabenwert, Legitimation, Verifikationsroutinen, Workflow-Einbettung und Rollenklärung dabei spielen.

Darüber hinaus könnte die Forschung zu Wissenskalibrierung und KI-Aversion durch experimentelle oder quasi-experimentelle Designs vertieft werden. Dabei wäre insbesondere zu untersuchen, ob Interventionen, die nicht nur objektives KI-Wissen, sondern auch die realistische Einschätzung des eigenen Wissens fördern, tatsächlich zu reflektierterer KI-Nutzung führen. Ebenso wäre es sinnvoll, qualitative Rekonstruktionen individueller KI-Nutzung im Arbeitskontext mit objektiven Nutzungsdaten aus Enterprise-KI-Systemen zu kombinieren. So ließe sich besser nachvollziehen, wann aus Erprobung tatsächlich Routinen entstehen, wann Routinen wieder abbrechen und welche Rolle Verifizierungspraktiken, Tool-Zugänge oder organisationale Freigaben dabei spielen. Schließlich erscheint es sinnvoll, die identifizierten Rollendynamiken vergleichend in unterschiedlichen Sektoren, Organisationsgrößen und regulatorischen Kontexten zu untersuchen. Gerade die Frage, wie Business-, technische und funktionale Rollen in verschiedenen organisationalen Strukturen zusammenwirken, bleibt für die weitere KI-Adoptionsforschung zentral (Bankins et al., 2024; Jöhnk et al., 2021; Tursunbayeva & Gal, 2024).

Die nächste logische Forschungsstufe besteht damit darin, die in dieser Dissertation theoretisch rekonstruierte Verknüpfung von Alltag, Arbeitskontext und organisationaler Adoption in einem methodisch enger gekoppelten Design zu prüfen. Zukünftige Forschung könnte daher nicht nur einzelne Ebenen isoliert untersuchen, sondern gezielt die Übergänge zwischen ihnen in den Blick nehmen. Genau dort dürfte sich besonders deutlich zeigen, ob KI

lediglich erprobt, punktuell eingesetzt oder tatsächlich langfristig in Organisationen verankert wird.

5 Fazit

Die Dissertation macht sichtbar, dass nachhaltige KI-Verankerung in Organisationen nicht mit einer einheitlichen Adoptionslogik erklärt werden kann. Weder technische Leistungsfähigkeit noch individuelle Akzeptanz allein reichen aus, um zu verstehen, warum KI im Alltag schnell angenommen wird, im Arbeitskontext aber häufig situativ bleibt und auf organisationaler Ebene oft nicht über den Pilotstatus hinauskommt. Der zentrale Beitrag der Arbeit besteht darin, diese Unterschiede nicht als getrennte Phänomene zu behandeln, sondern als Ausdruck eines zusammenhängenden Mehrebenenprozesses (siehe Abbildung 3).

Auf Ebene der individuellen KI-Nutzung im Alltag verweist die Dissertation auf die zentrale Bedeutung subjektiver Wahrnehmung, Wissenskalibrierung und KI-Aversion. Auf Ebene der individuellen KI-Nutzung im Arbeitskontext zeigt sie, dass der Übergang von Erprobung zu Routinisierung phasenhaft verläuft und unter Bedingungen von Aufgabenwert, organisationaler Legitimation und Stabilisierung gelingt. Auf Ebene der organisationalen KI-Adoption macht sie deutlich, dass technische Machbarkeit allein keine Skalierung erzeugt, solange Rollenkonflikte, Rollenunklarheit und fehlende sozio-technische Koordination die Verankerung erschweren. Erst die zusammenführende Betrachtung dieser Ebenen macht nachvollziehbar, warum private KI-Vertrautheit nicht automatisch in berufliche Routinen übergeht und warum wiederholte individuelle Nutzung noch keine organisationale Adoption erzeugt.

Der übergreifende Erkenntnisgewinn der Dissertation liegt damit nicht nur in den Einzelbeiträgen der drei Publikationen und der vierten Studie, sondern in dem zusätzlichen Erklärungsrahmen, der aus ihrer systematischen Verbindung entsteht. Die Dissertation zeigt, dass Wissenskalibrierung und KI-Aversion auf Alltagsebene, Routinisierungsschwellen im Arbeitskontext und rollenbezogene Spannungen auf organisationaler Ebene nicht isolierte Probleme darstellen. Vielmehr bilden sie miteinander verbundene Bedingungen eines mehrstufigen Verankerungsprozesses. Damit wird KI-Nutzung nicht nur als Frage individueller Akzeptanz und KI-Adoption nicht nur als Frage organisationaler Implementierung verstanden, sondern als Zusammenspiel von Wahrnehmung, Nutzungspraxis und organisationaler Einbettung.

Für die Forschung bedeutet dies einen Schritt weg von isolierten Erklärungen einzelner Nutzungskontexte hin zu einer stärker mehrstufigen und kontextsensitiven Perspektive auf KI-Nutzung und KI-Adoption. Für die Praxis legt die Arbeit nahe, dass erfolgreiche KI-Verankerung vor allem dann gelingen dürfte, wenn Kompetenzen, Nutzungssituationen, Rollenbeziehungen und organisationale Strukturen gemeinsam gestaltet werden. Für Organisationen bedeutet dies, private KI-Erfahrungen ihrer Mitarbeitenden ernst zu nehmen, ohne sie ungefiltert in den Arbeitskontext zu übertragen; individuelle Nutzung zu ermöglichen, ohne organisationale Verantwortung zu vernachlässigen; und Governance zu schaffen, ohne KI-Nutzung durch unklare Rollen, fehlende Freigaben oder übermäßige Unsicherheit zu blockieren.

Zusammenfassend macht die Dissertation sichtbar, dass KI nicht einfach eingeführt, akzeptiert oder skaliert wird. KI-Verankerung lässt sich vielmehr als Stabilisierung über verschiedene Ebenen hinweg verstehen, von der individuellen KI-Nutzung im Alltag über die Nutzung im Arbeitskontext bis hin zur organisationalen KI-Adoption. Nachhaltige KI-Verankerung scheint dort zu entstehen, wo subjektive Wahrnehmung, routinisierte Nutzungspraxis und organisationale Einbettung so zusammenwirken, dass aus ersten Erfahrungen tragfähige, legitime und verantwortbare Formen der KI-Nutzung entstehen können.

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Anhang A: Lebenslauf

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Berufserfahrung

KI-Vertriebsspezialist, Zentraleuropa
Hewlett Packard Enterprise, Frankfurt (Schwalbach)
Seit 11/2023

- Verantwortlich für Vertriebstätigkeiten im Bereich High-Performance Computing und Künstliche Intelligenz in Zentraleuropa
- Koordination bereichsübergreifender Teams zur Entwicklung und Umsetzung von KI-Geschäftsmöglichkeiten
- Betreuung und Weiterentwicklung von Kunden- und Marktaktivitäten im KI-Umfeld

KI-Experte im AI Startup Rising Programm
Hessisches Forschungszentrum für Künstliche Intelligenz, Darmstadt
10/2022 – 10/2023

- Evaluierung und Begleitung von KI-Start-ups
- Unterstützung bei der Einordnung und Weiterentwicklung von KI-Geschäftsmodellen
- Aufbau und Pflege von Kontakten zu Organisationen, Investoren und Politik- und Forschungsinstituten

Technischer Vertriebsspezialist, IBM Storage
IBM Deutschland GmbH, Frankfurt
02/2020 – 09/2022

- Technische und vertriebliche Unterstützung im Bereich Storage, Hybrid Multicloud, Big Data und AI
- Mitarbeit an Kundenprojekten und Lösungskonzepten

Auslandspraktikum im Vertrieb, Automotive Aftermarket
Robert Bosch (SEA) Pte Ltd, Singapur
10/2017 – 06/2018

- Marktanalysen für die Märkte Singapur, Myanmar, Kambodscha und Brunei
- Unterstützung vertrieblicher Aktivitäten im Automotive Aftermarket

Werkstudent im Projektmanagement
DB Netz AG, Frankfurt
12/2016 – 10/2017

- Mitarbeit im Projekt DIANA (Digitale Weichendiagnose)
- Unterstützung projektbezogener organisatorischer und inhaltlicher Aufgaben

Akademischer Werdegang

Berufsbegleitende Promotion (Dr. rer. nat.)
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Master of Science, Vertiefungen: Data Science, Software-Business 04/2017 – 03/2020
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Anhang B: Eidesstattliche Erklärung

Hiermit versichere ich,

– dass ich die vorgelegte Arbeit selbst angefertigt und alle benutzten Hilfsmittel in der Arbeit angegeben habe,
– dass ich diese Dissertation nicht schon als Prüfungsarbeit für eine staatliche oder andere wissenschaftliche Prüfung eingereicht habe, und
– dass weder die gleiche noch eine andere Abhandlung der Dissertation bei einer anderen Universität oder einem anderen Fachbereich der Rheinland-Pfälzischen Technischen Universität Kaiserslautern-Landau veröffentlicht wurde.

Kaiserslautern, den

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