Human-AI Co-Evolution in Industrial Organizations: A Comparative Analysis of AI Adoption in Manufacturing and Business Functions in the Trinational Upper Rhine Region

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Abstract. This study examines organizational and human drivers of AI adoption and perceived organizational value in industrial organizations in the Trinational Upper Rhine Region, focusing on AI leadership, AI competencies, trust in AI, AI readiness, digital maturity, and explainable AI (XAI). Following a literature review and conceptual model development, a multilingual survey was conducted among professionals in the Trinational Upper Rhine Region. The proposed relationships were examined using Partial Least Squares Structural Equation Modeling (PLS-SEM), complemented by Measurement Invariance of Composite Models (MICOM) and Multi-Group Analysis (MGA). AI leadership positively influences AI competencies ($\beta = .291$, $p < .001$) and trust in AI ($\beta = .335$, $p < .001$), which subsequently enhance AI adoption. AI readiness ($\beta = .285$, $p < .001$) and digital maturity ($\beta = .189$, $p = .002$) further drive adoption. Most notably, AI adoption strongly contributes to perceived organizational value ($\beta = .564$, $p < .001$), whereas XAI shows no significant direct effect. The study integrates leadership, human capabilities, and organizational conditions within a unified AI adoption framework, providing cross-border empirical evidence on how organizations translate AI adoption into organizational value.

Keywords: artificial intelligence (AI); AI adoption; AI leadership; AI competence; trust in AI; organizational value; Trinational Upper Rhine Region.

1 Introduction

Artificial intelligence (AI) is transforming industrial organizations through automation, process optimization, and data-driven decision-making. However, successful AI adoption depends not only on technology but also on organizational and human capabilities [1;2;3;4]. In particular, AI leadership can foster employee competence and trust, while AI readiness, digital maturity, and explainability shape the organizational context for effective AI use [5, 6, 7]. Yet, integrated empirical evidence on these factors remains limited, particularly in the Trinational Upper Rhine Region spanning Germany, France, and Switzerland [8]. This study therefore examines how AI leadership, competence, trust, readiness, digital maturity, and explainability contribute to AI adoption and, ultimately, perceived organizational value [5, 6].

2 Theoretical Framing

This study adopts a sociotechnical perspective [2], integrating Human–AI Collaboration Theory [3], the Technology–Organization–Environment (TOE) framework [9], Dynamic Capabilities Theory [10], and Human-Centered AI [11]. Together, these perspectives conceptualize AI adoption as the interaction of leadership, human capabilities (AI competence and trust), and organizational and technological conditions (AI readiness, digital maturity, and XAI). Accordingly, AI capabilities represent combinations of technical, human, and organizational resources that enable organizational outcomes [12]. The model therefore proposes that AI

leadership strengthens competence and trust, facilitating AI adoption and ultimately perceived organizational value. Despite growing research on AI adoption, limited empirical evidence explains how AI leadership translates into adoption through human-centered mechanisms such as AI competence and trust in AI [13]. Moreover, organizational and technological factors such as AI readiness, digital maturity, and XAI are rarely examined jointly within an integrated model. This study addresses these gaps by testing a sociotechnical model of AI adoption and organizational value, with particular attention to the Trinational Upper Rhine Region.

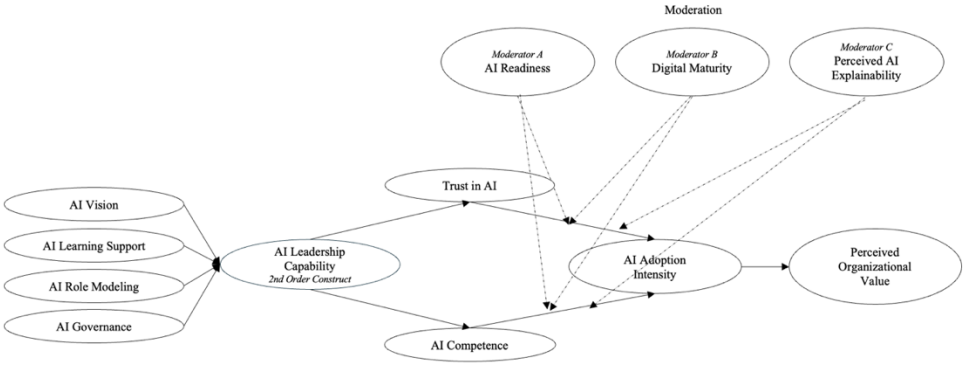


Fig. 1. Human-Centered AI Adoption and Value Creation Framework (HAIV Framework)
Source(s): Authors‘ work

AI leadership capability is conceptualized as a higher-order construct comprising AI vision, learning support, role modeling, and governance, reflecting the multidimensional nature of AI leadership [14]. This perspective is particularly relevant in the cross-border Upper Rhine region, where organizations operate across Germany, France, and Switzerland and face increasing requirements for responsible AI governance [15]. The model positions AI leadership as an organizational capability fostering AI competencies and trust, which facilitate AI adoption and ultimately perceived organizational value. AI readiness, digital maturity, and explainability complement this socio-technical perspective on organizational AI transformation.

Table 1. Constructs and Measurement Sources

Construct	Adapted from
AI Vision (AIV)	[12]
AI Learning Support (AILS)	[2; 13; 18]
AI Governance (AIG)	[19]
AI Role Modeling (AIRM)	[20; 21]
AI Leadership Capability (AILC)	[22]
AI Competencies (AIC)	[23]
Trust in AI (TAI)	[24; 25]
AI Adoption (AIA)	[26; 25]
Perceived Organizational Value (POV)	[27]
AI Readiness (AIR)	[28]
Digital Maturity (DM)	[28]
Perceived AI Explainability (XAI)	[29]

The conceptual model proposes that AI leadership capability fosters trust in AI and AI competence, which subsequently facilitate AI adoption intensity and perceived organizational value. AI readiness, digital maturity, and XAI are further examined as contextual factors influencing AI adoption. Based on these relationships, the following hypotheses are proposed.

AI Leadership Capability
H1a: AI vision has a positive effect on employees' trust in AI.
H1b: AI vision has a positive effect on employees' AI competence.
H2a: AI learning support has a positive effect on employees' trust in AI.
H2b: AI learning support has a positive effect on employees' AI competence.
H3a: AI role modeling has a positive effect on employees' trust in AI.
H3b: AI role modeling has a positive effect on employees' AI competence.
H4a: AI governance has a positive effect on employees' trust in AI.
H4b: AI governance has a positive effect on employees' AI competence.

AI Adoption Intensity
H5a: Trust in AI has a positive effect on AI adoption intensity.
H5b: AI competence has a positive effect on AI adoption intensity.

Perceived Organizational Value
H6: AI adoption intensity has a positive effect on perceived organizational value.

Moderating Effect of AI Readiness
H7a: AI readiness positively moderates the relationship between trust in AI and AI adoption intensity, such that the positive relationship is stronger at higher levels of AI readiness.
H7b: AI readiness positively moderates the relationship between AI competence and AI adoption intensity, such that the positive relationship is stronger at higher levels of AI readiness.

Moderating Effect of Digital Maturity
H9a: Digital maturity positively moderates the relationship between trust in AI and AI adoption intensity, such that the positive relationship is stronger at higher levels of digital maturity.
H9b: Digital maturity positively moderates the relationship between AI competence and AI adoption intensity, such that the positive relationship is stronger at higher levels of digital maturity.

Moderating Effect of Perceived AI Explainability
H10a: Perceived AI explainability positively moderates the relationship between trust in AI and AI adoption intensity, such that the positive relationship is stronger at higher levels of perceived AI explainability.
H10b: Perceived AI explainability positively moderates the relationship between AI competence and AI adoption intensity, such that the positive relationship is stronger at higher levels of perceived AI explainability.

3 Methodology

The study followed a structured, multi-stage quantitative research design. First, a literature review was conducted to identify the theoretical foundations and key determinants of organizational AI adoption. Based on the literature synthesis, a conceptual research model was developed, and the corresponding constructs and measurement items were derived and adapted from established literature. Subsequently, the survey instrument was designed, translated, and pre-tested before the sampling and data-collection process was initiated. Following data screening, descriptive statistics were used to characterize the final sample. The empirical model was then evaluated using PLS-SEM, beginning with an assessment of the measurement model

and subsequently examining the structural model and hypothesized relationships. Finally, the MICOM procedure was applied to establish measurement invariance across the regional groups, followed by MGA to investigate potential differences in structural relationships between respondents from the Upper Rhine region and the remaining sample. To ensure accessibility across the trinational research context, the questionnaire was administered in German, French, and English. A purposive, non-probability sampling approach was employed to recruit respondents with relevant organizational and AI-related experience. Participants were recruited through two complementary channels. First, the survey was distributed through existing networks, including companies collaborating with the university as dual partners, while students were also actively approached to support access to relevant organizational respondents. Second, professionals and experts were selectively contacted via the networking platform LinkedIn, with particular emphasis on individuals and organizations located in the trinational Upper Rhine region. This combined recruitment strategy aimed to reach respondents across different organizational functions, industries, and levels of AI experience while ensuring targeted representation of the regional research context.

4 Empirical Results

The demographic profile of the analytical sample was assessed in terms of gender, age, educational attainment, and professional experience. The final analytical sample comprised 221 respondents, drawn from an original dataset of 452 responses. Gender information was available for 219 respondents (99.1%), of whom 156 (71.2%) identified as male and 63 (28.8%) as female. Age information was likewise available for 219 respondents (99.1%), with the largest proportion belonging to the 25-34 years of age category (30.6%, n = 67), followed by 35-44 years (21.0%, n = 46) and 45-54 years (19.2%, n = 42). Regarding educational attainment, 44.3% (n = 97) held a master's degree, 21.0% (n = 46) a bachelor's degree, and 16.0% (n = 35) a doctoral degree, indicating that 81.3% of respondents held at least a bachelor's degree. In terms of professional experience, the largest group reported more than 20 years of work experience (30.1%, n = 66), while respondents were relatively evenly distributed across the remaining experience categories (15.1–18.7%). Following data screening, 221 of 452 responses were retained for analysis, of which 40.1% were from the Upper Rhine region. The sample covered diverse organizational sizes, functions, and industries, with engineering and R&D representing the largest functional areas (14.7% each) and manufacturing accounting for 13.8% of industry affiliations. AI exposure was high: 87.1% reported organizational AI use, while 71.6% indicated frequent or very frequent professional AI use. Overall, the heterogeneous sample enables the examination of AI adoption across organizational contexts and regional groups.

The measurement model demonstrated satisfactory reliability and convergent validity. Cronbach's alpha ranged from .819 to .940 and ρA from .831 to .955, exceeding the recommended threshold of .70 across all constructs. Composite reliability (ρC) ranged from .880 to .954, indicating high internal consistency, although AIRM (.954) and AIV (.953) marginally exceeded the recommended upper guideline of .95. AVE values ranged from .600 to .873 and therefore exceeded the .50 threshold for all constructs, supporting convergent validity. Overall, the results provide evidence of adequate construct reliability and convergent validity.

Table 2. Indicator Reliability & Convergent Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AIA	.819	.831	.880	.649
AIC	.890	.929	.913	.636
AIG	.897	.930	.935	.828
AILS	.924	.933	.952	.868
AIR	.907	.917	.928	.684
AIRM	.928	.955	.954	.873
AIV	.940	.942	.953	.771
DM	.865	.877	.899	.600
POV	.892	.895	.917	.649
TAI	.884	.928	.913	.678
XAI	.860	.872	.899	.642

Note: α ≥ .70; ρA ≥ .70; ρC = .70–.95; AVE ≥ .50.

Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT). With the exception of the relationship between AI Vision and AI Learning Support (HTMT = 0.904), all HTMT values were below the recommended threshold of 0.90, providing overall support for discriminant validity while indicating a marginal discriminant validity concern for these two conceptually related AI leadership dimensions. Discriminant validity was further assessed using the Fornell–Larcker criterion, according to which the square root of each construct's average variance extracted (AVE) should exceed its correlations with all other constructs. This criterion was satisfied for all constructs, providing additional support for discriminant validity in the measurement model [17].

The structural model results indicate several significant relationships among the investigated constructs. AI Leadership was positively associated with AI Competencies (β = .291, t = 4.820, p < .001) and Trust in AI (β = .335, t = 4.968, p < .001). In turn, AI Competencies (β = .208, t = 3.286, p = .001), Trust in AI (β = .180, t = 2.485, p = .006), AI Readiness (β = .285, t = 3.932, p < .001), and Digital Maturity (β = .189, t = 2.814, p = .002) were positively associated with AI Adoption. AI Adoption, in turn, showed a strong positive relationship with Perceived Organizational Value (β = .564, t = 12.050, p < .001). Explainable AI did not exhibit a significant direct relationship with AI Adoption (β = .062, t = 0.876, p = .190). Most moderation effects were also non-significant; however, Digital Maturity significantly moderated the relationship between Trust in AI and AI Adoption (β = −.137, t = 1.740, p = .041), indicating that the positive association between trust and adoption weakens as digital maturity increases.

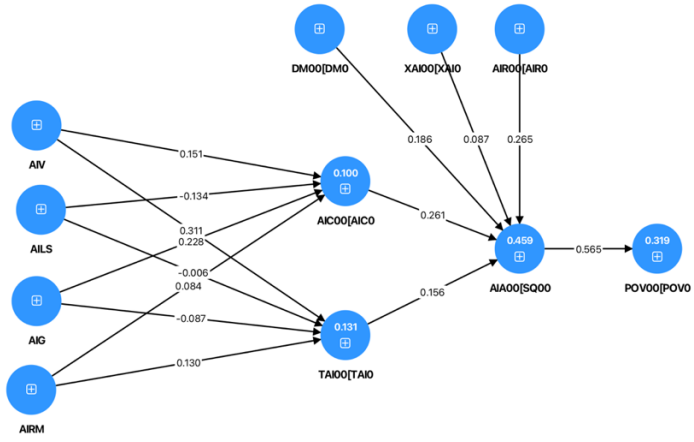


Fig. 2. Structural Model with Standardized Path Coefficients (β) and Coefficients of Determination (R^2)
Source(s): Authors' work

Table 3. Structural Model Assessment and Path Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AIA > POV	.564	.569	.047	12.050	.000
AIC > AIA	.208	.217	.063	3.286	.001
AIL > AIC	.291	.297	.060	4.820	.000
AIL > TAI	.335	.341	.067	4.968	.000
AIR > AIA	.285	.286	.072	3.932	.000
AIR x AIC > AIA	-.153	-.125	.099	1.538	.062
AIR x TAI > AIA	.046	.027	.080	0.579	.281
DM > AIA	.189	.183	.067	2.814	.002
DM x AIC > AIA	.092	.068	.095	0.968	.167
DM x TAI> AIA	-.137	-.115	.079	1.740	.041
TAI> AIA	.180	.176	.072	2.485	.006
XAI > AIA	.062	.068	.071	0.876	.190
XAI x AIC > AIA	-.065	-.078	.082	0.798	.213
XAI x TAI > AIA	.032	.034	.068	0.473	.318

Prior to the multi-group analysis, measurement invariance between respondents from the Upper Rhine region and the rest of the sample was assessed using the MICOM procedure. Compositional invariance was established for all constructs, as the original correlations exceeded the respective 5% quantiles of the permutation distributions and all permutation p-values were above .05. However, equality of composite means was not established, indicating systematic differences in construct levels between the two groups. Thus, partial measurement invariance was established, providing the prerequisite for comparing structural path coefficients across groups using PLS-MGA.

Table 4. Compositional Invariance Assessment

	Original correlation	Correlation permutation mean	5.0%	Permutation p value
AIA	.997	.998	.994	.183
AIC	.996	.992	.976	.632
AIL	.997	.998	.994	.159
AIR	.998	.998	.994	.359
DM	.993	.994	.985	.349
POV	.999	.998	.995	.614
TAI	.992	.996	.991	.069
XAI	.993	.995	.987	.269

Table 5. Equality of Composite Means Assessment

	Original difference	Permutation mean difference	5.0%	95.0%	Permutation p value
AIA	-.598	.005	-.220	.251	.000
AIC	-.284	-.000	-.225	.227	.020
AIL	-.437	-.002	-.230	.226	.002
AIR	-.330	-.003	-.224	.216	.009
DM	-.409	-.000	-.220	.226	.002
POV	-.517	.002	-.225	.228	.000
TAI	-.323	.001	-.227	.255	.012
XAI	-.386	.002	-.236	.252	.001

A MGA was conducted to examine whether the structural relationships differed between respondents from the Upper Rhine region and those from the rest of the sample. The analysis revealed no statistically significant differences between the two groups across the examined structural paths (all two-tailed $p > .05$). Thus, the results provide no evidence of systematic regional differences in the hypothesized relationships within the structural model.

Table 6. Multi-Group Analysis Upper Rhine Region vs. Remaining Sample

	Difference (YES - NO)	1-tailed (YES vs NO) p value	2-tailed (YES vs NO) p value
AIA > POV	.080	.217	.217
AIC > AIA	-.060	.659	.341
AIL > AIC	.182	.074	.074
AIL > TAI	.111	.184	.184
AIR > AIA	.264	.058	.058
AIR x AIC > AIA	.097	.314	.314
AIR x TAI > AIA	-.181	.839	.161
DM > AIA	-.202	.912	.088
DM x AIC > AIA	-.162	.799	.201
DM x TAI > AIA	.120	.263	.263
TAI > AIA	-.021	.550	.450
XAI > AIA	-.010	.521	.479
XAI x AIC > AIA	-.022	.548	.452
XAI x TAI > AIA	.144	.173	.173

5 Discussion

The findings support a multidimensional and human-centered perspective on organizational AI adoption. AI leadership was positively associated with AI competencies (β = .291) and trust (β = .335), highlighting leadership as an important enabler of the capabilities and perceptions required for AI transformation. In turn, AI competencies, trust, AI readiness, and digital maturity were significantly associated with AI adoption, with AI readiness showing the strongest direct antecedent relationship (β = .285). These results indicate that successful AI adoption depends on both organizational preparedness and human capabilities rather than technological conditions alone. Most importantly, AI adoption showed a strong relationship with perceived organizational value (β = .564), suggesting that adoption represents an important pathway through which organizational AI capabilities translate into value. In contrast, XAI had no significant direct effect, indicating that explainability may be more relevant in specific high-risk or regulated contexts than as a universal adoption driver. Digital maturity negatively moderated the trust–adoption relationship, suggesting that established digital structures may reduce reliance on individual trust. Finally, the multi-group analysis revealed no significant differences, providing preliminary evidence that the identified mechanisms are relatively stable across the investigated groups.

6 Conclusion

This study examined organizational and human factors shaping AI adoption and perceived organizational value based on a sample of 221 respondents. The PLS-SEM results show that AI leadership positively relates to AI competencies and trust, while AI competencies, trust, AI readiness, and digital maturity are positively associated with AI adoption. Most importantly, AI adoption shows a strong positive relationship with perceived organizational value. Digital maturity further exhibited a negative moderating effect on the trust–adoption relationship, suggesting that trust is particularly relevant at lower levels of digital maturity. In contrast, explainable AI and most hypothesized moderation effects were not significant. MICOM established partial measurement invariance, while the MGA revealed no significant structural differences between the Upper Rhine region and the comparison group. Overall, the findings highlight AI adoption as a multidimensional organizational process shaped by leadership, competencies, readiness, trust, and digital maturity. Future research should validate these relationships using larger, more balanced samples and longitudinal designs.

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