

Human-AI Collaboration in Risk Management: A Survey Study on Determinants of AI Acceptance in Germany, Austria, and Switzerland*

Ibrahim KAHYA and Peter MARKOVIC

University of Economics in Bratislava, Slovak Republic

Correspondence should be addressed to: Ibrahim KAHYA, Ibrahim.Kahya@euba.sk

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Abstract

Artificial intelligence (AI) is transforming professional risk management by enabling the processing of vast datasets and structuring complex decision-making environments. However, the successful integration of these systems depends heavily on how effectively human professionals and AI algorithms collaborate in corporate settings. While traditional technology adoption models focus on perceived usefulness and general trust, the specific interplay between user-related demographics, the demand for explainable AI (XAI), and the organizational barriers created by unmet transparency expectations remains insufficiently understood in specialized risk domains.

To address this gap, this study conducts a quantitative survey among $N = 71$ risk management professionals who are operating within the Finance/Insurance sector and the Chemical/Pharmaceutical industries across Germany, Austria, and Switzerland. Statistical analyses, including comparative diagnostics and multivariable linear regression modeling, were performed to isolate the key drivers of institutional AI acceptance.

The empirical results reveal that while AI is universally recognized as operationally helpful, but workplace efficiency alone does not automatically translate into institutional acceptance. In the multivariate model, user age was positively associated with AI acceptance with challenging common assumptions about digital familiarity. The transparency gap was negatively associated with AI acceptance, suggesting that unmet explainability expectations may reduce acceptance. No statistically significant differences in AI acceptance were found across the preferred collaboration mechanisms. Ultimately, the study highlights that fostering epistemic trust in human-AI interfaces requires organizations to implement robust, explainable frameworks that make automated outputs professionally defensible and compatible with regulatory requirements.

Keywords: Artificial Intelligence; Risk Management; AI Acceptance; Explainable AI; Human-AI Collaboration; Transparency

JEL-Classification: G32; D81; D91; M15; O33;

Introduction

Artificial intelligence (AI) is becoming increasingly important in risk management. AI-based systems can process large amounts of data, identify patterns, and support decision-making in complex and uncertain environments, creating new opportunities but also raising questions about their reliable and acceptable integration into professional decision processes.

In risk management, technical performance alone is not sufficient. AI-supported decisions must also be understandable, transparent, and compatible with accountability structures. For this reason, explainability, perceived transparency, and human oversight have become central to the discussion on effective human-AI collaboration.

Although previous research has extensively addressed trust, usefulness, and transparency in general technology adoption models, such as the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), the specific factors shaping AI acceptance in professional risk management remain insufficiently understood (Glikson and Woolley, 2020). In particular, the role of explainability, transparency perception, perceived operational relief, and demographic characteristics such as age and professional experience requires further empirical investigation.

Against this background, this study examines the determinants of AI acceptance in risk management. Based on a quantitative survey of professionals from the Finance and Insurance sector and the Chemical and Pharmaceutical industry in the German-speaking region, the article analyzes the conditions that support effective human--AI collaboration and the broader acceptance of AI-based systems.

Theoretical Background

Risk management is commonly understood as an organizational response to uncertainty rather than merely as a technical exercise in loss prevention. It involves the identification, assessment, treatment, and communication of risks that may affect organizational objectives (International Organization for Standardization, 2018; Aven and Renn, 2009). This perspective is particularly relevant in environments where decisions must be justified not only analytically, but also procedurally.

The increasing use of artificial intelligence altered this landscape considerably. AI systems can process large volumes of data, detect non-obvious patterns, and support predictive assessments in complex decision settings (Mesihovic and Nordström, 2021). However, their value in risk management depends not only on predictive capability, but also on whether outputs can be interpreted, challenged, and integrated into established decision routines (Aven and Renn, 2009; International Organization for Standardization, 2018). In corporate frameworks, this challenge is often exacerbated by systemic barriers in deploying automated analytics within legacy structures (Davenport and Ronanki, 2018; Dwivedi et al., 2021).

Transparency is therefore a central concern. Risk governance literature emphasizes that uncertainty management depends on communication, accountability, and openness regarding the basis of decisions (International Organization for Standardization, 2018). Klinke and Renn (2001) likewise argue that transparent and discursive approaches are especially important where risk-related decisions are shaped by ambiguity and legitimacy concerns. For AI-supported risk management, this suggests that acceptance is unlikely to emerge when system outputs remain detached from the interpretive frameworks of professional users.

Closely related to transparency is explainability. In risk-sensitive organizational settings, users must understand not only the final output, but also, at least broadly, why a recommendation appears plausible. Explainability enables users to connect system outputs with domain knowledge, professional judgment, and institutional responsibility, making it a practical condition for meaningful use rather than a purely technical feature (Mesihovic and Nordström, 2021). This aligns with the broader paradigm shift from opaque 'black box' systems to 'glass box' models, where interpretability serves as a foundational pillar for institutional trust (Rai, 2020; Shin, 2021).

Research on risk perception and decision-making under uncertainty supports this view. Risk is shaped not only by objective conditions, but also by subjective interpretation, communication, and psychological framing (Slovic, 1990; Vassie et al., 2005). Likewise, judgment under uncertainty is influenced by heuristics and biases, suggesting that AI may help structure information more consistently than unaided human judgment, while opaque systems may create new vulnerabilities if users defer to outputs they cannot critically assess (Tversky and Kahneman, 1974; Mesihovic and Nordström, 2021).

For this reason, human oversight remains central to human--AI collaboration in risk management. Final responsibility cannot be detached from human actors, since decisions often involve contextual interpretation, normative trade-offs, and organizational accountability (Aven and Renn, 2009; International Organization for Standardization, 2018). AI may improve analytical preparation, but evaluation and final judgment remain embedded in human roles and governance structures.

Acceptance is also unlikely to be uniform across users. Differences in perceptions of uncertainty, trust, control, and credibility suggest that age and professional experience may shape how AI systems are interpreted in practice (Slovic, 1990; Tversky and Kahneman, 1974). More experienced professionals may be better able to

position AI as a supportive tool within established decision routines, whereas less experienced users may perceive it more strongly through the lens of uncertainty, dependency, or loss of autonomy. Taken together, the literature suggests that AI acceptance in risk management is shaped by the interaction of transparency, explainability, human oversight, and user-related perceptions of reliability and control (Klinke and Renn, 2001; Mesihovic and Nordström, 2021).

Research Questions and Hypotheses

Building on the empirical focus of this study, the research investigates the determinants of effective human--AI collaboration in risk management, with particular emphasis on transparency, explainability, and user-related factors. Although prior research has highlighted trust and perceived usefulness in technology adoption, the interplay between explainability, transparency perception, and demographic influences in risk management remains insufficiently understood.

The first objective is to examine how transparency and explainability shape human acceptance of AI systems in risk management. This leads to the first research question:

- RQ1: How do transparency and explainability influence human acceptance of AI systems in risk management?

The second objective concerns organizational and procedural conditions of human--AI interaction, particularly workflow integration, feedback mechanisms, and interaction structures. This leads to the second research question:

- RQ2: What factors determine effective human--AI collaboration in risk management processes?

The third objective addresses individual differences among users, especially the role of age and professional experience in shaping trust, perception, and acceptance. This leads to the third research question:

- RQ3: How do age and professional experience influence the perception, acceptance, and trust in AI systems?

Based on these research questions, the following hypotheses were derived:

- H1: Higher perceived transparency of AI systems is positively associated with AI acceptance.
- H2: The perceived importance of explainable AI (XAI) is positively related to AI acceptance.
- H3: A larger gap between the importance of explainability and the perceived transparency of AI systems negatively affects AI acceptance.
- H4: The perceived operational relief provided by AI systems is positively associated with AI acceptance.
- H5: Age is positively associated with AI acceptance in risk management contexts.
- H6: Professional experience is positively associated with AI acceptance in risk management contexts.
- H7: The implementation of structured human-AI collaboration mechanisms positively influences AI acceptance.

Methodology

Research Design and Data Collection

This study employed a quantitative research design to investigate the factors enabling effective collaboration between human actors and artificial intelligence (AI) systems within the domain of risk management. Data were collected through a structured online survey focusing on user acceptance, perceived relief from routine tasks, and requirements for transparent and explainable decision-making processes. The survey was conducted in Q4 2025. Participants were recruited via LinkedIn and came from Germany, Austria, and Switzerland. Statistical analyses were performed using Jamovi.

Sample Description

The final sample consists of $N = 71$ professionals from the Finance and Insurance sector and the Chemical and Pharmaceutical industry. The calculation suggested that a sample of at least 34 participants each group was necessary to demonstrate a statistically medium effect of $\rho = 0.5$ with a high probability of 95%.

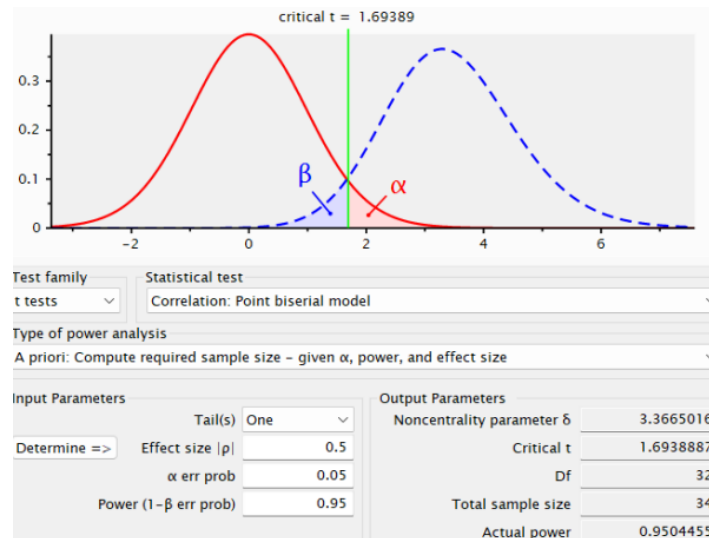


Figure 1: Required sample size; source: own illustration based on GPower

The sample exhibits the following characteristics:

- Industry Affiliation: Participants are nearly equally distributed between the Finance and Insurance sector ($n = 34$) and the Chemical and Pharmaceutical industry ($n = 37$).
- Internationality: A majority of the respondents ($n = 57$) operate in an international business context, while 14 professionals work in domestic environments.
- Age and Experience: The sample covers a broad demographic spectrum, ranging from early-career individuals under 30 years old to highly experienced professionals with over 40 years of experience.

Measurement Instruments and Variables

The survey utilized 5-point ordinal scales (Likert-type) for the primary quantitative variables, where higher values indicate higher levels of the respective attribute. The core variables measured include:

1. AI Acceptance: Measures general acceptance levels of AI systems within the respondent's industry.
2. AI Relieve: Assesses the perceived support and relief provided by AI in risk management tasks.
3. Explainable AI (XAI): Evaluates the importance of understanding AI decision-making foundations.
4. Transparency Feeling: Captures the current subjective perception of how transparent AI systems are within the work environment.

Furthermore, the variable 'Work Together' examined specific organizational measures for collaboration, offering four distinct options: transparent decision-making bases, regular performance reviews, integration into existing workflows, and clearly defined responsibilities. Qualitative insights were also gathered through open-ended questions regarding data quality, funding transparency, and model consistency.

Statistical Analysis

Data analysis was conducted using descriptive statistics, including means, medians, standard deviations (SD), and minimum/maximum values. To ensure statistical rigor, 95% confidence intervals (CI) were calculated for the means, assuming that sample means follow a t-distribution with $N - 1$ degrees of freedom. Comparative analyses were performed across demographic subgroups (age, industry, internationality, and professional experience) to identify significant patterns in AI acceptance and transparency needs.

Although the central variables were measured on 5-point Likert-type scales, they were treated as approximately interval-scaled for the purposes of descriptive analysis, correlation analysis, and linear regression, which is a common approach in empirical social research when scale categories are ordered and used consistently across respondents. Given the exploratory character of the study and the objective of identifying broader patterns of association, this analytical strategy was considered appropriate.

Empirical Results and Data Synthesis

Determinants of AI Acceptance and Collaboration

The analysis of 'AI Acceptance' reveals a moderate to high general willingness to integrate AI systems in professional risk management, with an overall mean score of 3.52.

Table 1: Variable 'AI Acceptance' general acceptance (Source: Own Illustration)

Descriptives	N	Missing	Mean	95% Confidence Interval		Median	SD	Minimum	Maximum
				Lower	Upper				
AI_acceptance	71	0	3.52	3.28	3.76	4	0.998	1	5

Note. The CI of the mean assumes sample means follow a t-distribution with N - 1 degrees of freedom

However, significant demographic variances emerged:

- The Age Paradox: Acceptance levels demonstrated a distinct positive correlation with age. Younger professionals (under 30) exhibited the lowest acceptance levels ($M = 2.20$). In contrast, acceptance increased markedly in older cohorts, peaking with professionals over 60 ($M = 4.17$). This suggests that older professionals may possess a higher degree of openness toward integrating AI tools into specialized risk management tasks.

Table 2: 'AI Acceptance' by Age (Source: Own Illustration)

Descriptives							
	Age classf.	N	Mean	Median	SD	Minimum	Maximum
AI_acceptance	< 30 years	5	2.20	2	0.837	1	3
	30 - 40 years	17	3.47	4	0.943	2	5
	40 - 50 years	22	3.64	4.00	0.902	2	5
	50 - 60 years	21	3.57	3	1.028	2	5
	> 60 years	6	4.17	4.00	0.753	3	5

- Experience-Based Nuances: Descriptive differences across experience groups were observed, but these patterns did not translate into a comparably robust inferential effect. Individuals with 10–20 years and 30–40 years of experience reported the highest acceptance ($M \sim 3.8$), whereas those with less than 10 years remained significantly more skeptical ($M = 3.11$).

Table 3: 'AI Acceptance' by Years of Profession (Source: Own Illustration)

Descriptives							
	Years of Profession class.	N	Mean	Median	SD	Minimum	Maximum
AI_acceptance	< 10 years	19	3.11	3	0.937	1	4
	10 - 20 years	22	3.82	4.00	1.053	2	5
	20 - 30 years	13	3.38	4	0.961	2	5
	30 - 40 years	12	3.83	4.00	1.030	2	5
	> 40 years	5	3.40	3	0.548	3	4

- Industry and Contextual Stability: Interestingly, acceptance remained consistent across organizational contexts. No statistically significant differences were observed between professionals in international versus domestic settings ($M \sim 3.5 - 3.6$). Similarly, industry-specific analysis showed nearly identical acceptance rates in the Finance/Insurance sector ($M = 3.56$) and the Chemical/Pharmaceutical industry ($M = 3.49$).

Table 4: 'AI Acceptance' by Industry (Source: Own Illustration)

Descriptives								
	Industry	N	Missing	Mean	Median	SD	Minimum	Maximum
AI_acceptance	Finance- / Insurance Industry	34	0	3.56	4.00	1.160	1	5
	Chemical- / Pharmaceutical Industry	37	0	3.49	3	0.837	2	5

Table 5: Correlation analysis 'AI Acceptance (Source: Own illustration)'**Correlation Analysis**

Korrelationsmatrix		AI_acceptance	Transparency_feeling	Explainable_AI	AI_relieve	Age	Years_Profession
AI_acceptance	Pearson's r	—					
	df	—					
	p-Wert	—					
Transparency_feeling	Pearson's r	0.173	—				
	df	69	—				
	p-Wert	0.150	—				
Explainable_AI	Pearson's r	-0.081	-0.080	—			
	df	69	69	—			
	p-Wert	0.503	0.508	—			
AI_relieve	Pearson's r	0.212	-0.026	0.257	—		
	df	69	69	69	—		
	p-Wert	0.076	0.829	0.031	—		
Age	Pearson's r	0.290	0.021	0.052	0.012	—	
	df	69	69	69	69	—	
	p-Wert	0.014	0.862	0.666	0.922	—	
Years_Profession	Pearson's r	0.123	-0.088	-0.083	-0.132	0.795	—
	df	69	69	69	69	69	—
	p-Wert	0.307	0.464	0.493	0.273	< .001	—

The correlation analysis revealed a significant positive relationship between age and AI acceptance ($r = 0.290$, $p < .05$), supporting H5. In contrast, no significant relationships were found between AI acceptance and perceived transparency ($r = 0.173$, $p = .150$) or the importance of explainable AI ($r = -0.081$, $p = .503$), leading to a rejection of H1 and H2.

Perceived AI relief showed a weak positive association with acceptance ($r = 0.212$, $p = .076$), indicating a potential but statistically non-significant trend. Interestingly, a significant relationship was found between perceived AI relief and the importance of explainable AI ($r = 0.257$, $p < .05$), suggesting that users who experience greater operational benefits also place higher value on explainability.

An additional correlation analysis was conducted (**Error! Reference source not found.**) to examine the relationship between the transparency gap and AI acceptance. To capture the potential mismatch between users' expectations and current system practice, a transparency gap variable was constructed as the numerical difference between the perceived importance of explainable AI and the currently perceived transparency of AI systems. Higher values indicate a larger discrepancy between the desired level of explainability and the level of transparency currently experienced by respondents. Conceptually, this variable reflects the extent to which organizations may fall short of users' interpretability expectations. The analysis showed a weak negative correlation between the transparency gap and AI acceptance. The observed relationship did not reach statistical significance.

Table 6: Correlation Transparency Gap (Source: Own illustration)

Correlation matrix

Korrelationsmatrix		Transparency_Gap	AI_acceptance
Transparency_Gap	Pearson's r	—	
	df	—	
	p-Wert	—	
AI_acceptance	Pearson's r	−0.180	—
	df	69	—
	p-Wert	0.133	—

$$\text{Calculation of Transparency_Gap} = \text{Explainable AI} - \text{Transparency feeling}$$

A linear regression model was estimated (**Error! Reference source not found.**) with AI acceptance as the dependent variable and age, perceived AI relief, and the transparency gap as predictors. The model accounted for 17.7% of the variance in AI acceptance . Age and AI relief were positively associated with AI acceptance, whereas the transparency gap showed a negative association .

Table 7: Linear regression 'AI Acceptance' (Source: Own illustration)

Model Fit Measures		
Model	R	R ²
1	0.421	0.177

Note. Models estimated using sample size of N=71

Model Coefficients - AI_acceptance				
Predictor	Estimate	SE	t	p
Intercept	1.2914	0.7393	1.75	0.085
Age	0.0275	0.0105	2.62	0.011
AI_relieve	0.2900	0.1323	2.19	0.032
Transparency_Gap	-0.1524	0.0760	-2.00	0.049

Collinearity diagnostics (**Error! Reference source not found.**) did not indicate problematic multicollinearity among the predictors, with VIF values ranging from 1.05 to 3.06 and tolerance values between 0.327 and 0.954.

Table 8: Collinearity diagnostics (Source: Own illustration)

Collinearity Statistics		
	VIF	Tolerance
Age	2.98	0.335
Years_Profession	3.06	0.327
AI_relieve	1.11	0.898
Transparency_feeling	1.05	0.954
Explainable_AI	1.11	0.899

To compare alternative model specifications, two linear regression models were estimated. Model A (**Error! Reference source not found.**) included age, years of professional experience, perceived AI relief, perceived transparency, and explainable AI.

Table 9: Linear regression Model A (Source: Own illustration)

Linear Regression: Model A

Model Fit Measures

Model	R	R ²	AIC	BIC
1	0.441	0.194	199	215

Note. Models estimated using sample size of N=71

Model Coefficients - AI_acceptance

Predictor	Estimate	SE	t	p
Intercept	1.3126	0.9208	1.43	0.159
Age	0.0448	0.0183	2.46	0.017
Years_Profession	-0.0197	0.0171	-1.15	0.252
AI_relieve	0.2641	0.1382	1.91	0.061
Transparency_feeling	0.1177	0.0994	1.19	0.240
Explainable_AI	-0.2023	0.1390	-1.45	0.151

Whereas Model B (**Error! Reference source not found.**) included age, perceived AI relief, and the transparency gap.

Table 10: Linear regression Model B (Source: Own illustration)

Linear Regression: Model B

Model Fit Measures

Model	R	R ²	AIC	BIC
1	0.421	0.177	196	208

Note. Models estimated using sample size of N=71

Model Coefficients - AI_acceptance

Predictor	Estimate	SE	t	p
Intercept	1.2914	0.7393	1.75	0.085
Age	0.0275	0.0105	2.62	0.011
AI_relieve	0.2900	0.1323	2.19	0.032
Transparency_Gap	-0.1524	0.0760	-2.00	0.049

Although Model A showed a slightly higher coefficient of determination than Model B, Model B demonstrated a more parsimonious structure and better model fit according to the information criteria compared to Model A. Moreover, all predictors in Model B reached statistical significance, whereas in Model A only age was significant. Model B therefore served as the preferred model for subsequent interpretation.

Perceived Efficiency and Relief (AI Relieve)

The variable 'AI Relieve' yielded a remarkably high mean score of 4.28, indicating that professionals perceive significant support from AI in risk management.

Table 11: 'AI Relieve' descriptives (Source: Own Illustration)

Descriptives

	N	Missing	Mean	95% Confidence Interval		Median	SD	Minimum	Maximum
				Lower	Upper				
AI_relieve	71	0	4.28	4.08	4.48	4	0.848	2	5

Note. The CI of the mean assumes sample means follow a t-distribution with N - 1 degrees of freedom

- **Inter-generational Perceptions:** While all age groups reported high relief, the youngest cohort (under 30) reported the highest perceived support (M = 4.80, Median = 5). This creates a notable contrast with their lower general acceptance scores. Professionals over 60 followed closely (M = 4.50), while the 40–50 age group reported the lowest, albeit still high, relief score (M = 4.00).

Table 12: 'AI Relieve' by Age (Source: Own Illustration)

Descriptives							
	Age classf.	N	Mean	Median	SD	Minimum	Maximum
AI_relieve	< 30 years	5	4.80	5	0.447	4	5
	30 - 40 years	17	4.29	4	0.772	3	5
	40 - 50 years	22	4.00	4.00	0.873	2	5
	50 - 60 years	21	4.38	5	0.973	2	5
	> 60 years	6	4.50	4.50	0.548	4	5

- Sectoral and Experience Trends: Professionals in the Finance and Insurance sector perceived higher relief ($M = 4.50$) compared to those in the Chemical and Pharmaceutical industries ($M = 4.08$).

Table 13: 'AI Relieve' by Industry (Source: Own Illustration)

Descriptives								
	Industry	N	Missing	Mean	Median	SD	Minimum	Maximum
AI_relieve	Finance- / Insurance Industry	34	0	4.50	5.00	0.663	2	5
	Chemical- / Pharmaceutical Industry	37	0	4.08	4	0.954	2	5

- Regarding experience, the highest relief was reported by those with 30–40 years in the field ($M = 4.50$), while the most experienced group (>40 years) reported the lowest mean ($M = 3.80$).

Table 14: 'AI Relieve' by Years of Profession (Source: Own Illustration)

Descriptives							
	Years of Profession class.	N	Mean	Median	SD	Minimum	Maximum
AI_relieve	< 10 years	19	4.37	4	0.684	3	5
	10 - 20 years	22	4.36	4.50	0.727	3	5
	20 - 30 years	13	4.00	4	1.225	2	5
	30 - 40 years	12	4.50	5.00	0.674	3	5
	> 40 years	5	3.80	4	1.095	2	5

Error! Reference source not found. presents the descriptive statistics of AI relief across age groups. To examine whether the observed differences between these groups were statistically significant, a one-way ANOVA was conducted.

Table 15: Group descriptives AI Relieve (Source: Own illustration)

Group Descriptives						
	Group	N	Mean	Median	SD	SE
AI_relieve	Finance- / Insurance Industry	34	4.50	5.00	0.663	0.114
	Chemical- / Pharmaceutical Industry	37	4.08	4.00	0.954	0.157

In order to evaluate whether age-related differences in perceived AI relief extend beyond descriptive variation, a one-way ANOVA was performed (**Error! Reference source not found.**).

Table 16: AI Relieve One-Way ANOVA (Source: Own illustration)

One-Way ANOVA (Welch's)					
	F	df1	df2	p	
AI_relieve	2.06	4	20.0	0.124	

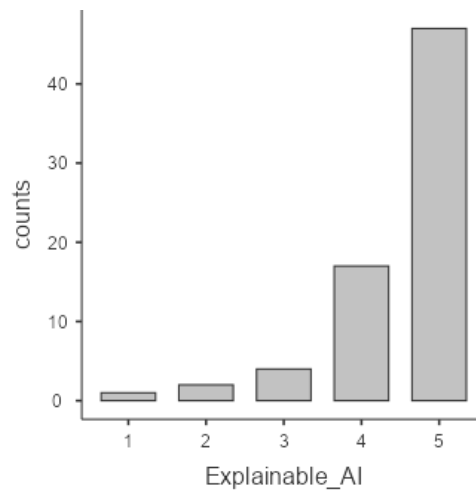
Group Descriptives					
	Age classf.	N	Mean	SD	SE
AI_relieve	< 30 years	5	4.80	0.447	0.200
	30 - 40 years	17	4.29	0.772	0.187
	40 - 50 years	22	4.00	0.873	0.186
	50 - 60 years	21	4.38	0.973	0.212
	> 60 years	6	4.50	0.548	0.224

Although younger respondents under 30 years reported the highest mean level of perceived AI relief ($M = 4.80$), the overall group differences did not reach statistical significance ($F = 2.06$, $p = .124$). Levene's test indicated that the assumption of homogeneity of variances was met ($p = .401$), and post hoc comparisons did not reveal any significant pairwise differences.

Mechanisms for Effective Human-AI Collaboration

Descriptive results suggest that transparent decision-making and workflow integration were among the most frequently prioritized conditions for effective human-AI collaboration.

Table 17: 'Explainable AI' (Source: Own Illustration)



- Preferred Collaborative Measures: Across demographics, professionals prioritized transparent decision-making bases and regular performance reviews.

Table 18: 'Explainable AI' by age (Source: Own Illustration)

Descriptives								
	Age classf.	N	Missing	Mean	Median	SD	Minimum	Maximum
Explainable_AI	< 30 years	5	0	4.80	5	0.447	4	5
	30 - 40 years	17	0	4.29	5	1.047	2	5
	40 - 50 years	22	0	4.64	5.00	0.658	3	5
	50 - 60 years	21	0	4.33	5	0.966	1	5
	> 60 years	6	0	5.00	5.00	0.000	5	5

- Career-Stage Preferences: Early-career individuals favoured regular performance evaluations of AI expenditures. Mid-to-late career professionals (30–40 years of experience) placed the highest emphasis on the integration of AI into existing processes and tools.

Table 19: 'Explainable AI' by work experience (Source: Own Illustration)

Descriptives						
	Years of Profession class.	N	Mean	Median	Minimum	Maximum
Explainable_AI	< 10 years	19	4.58	5	2	5
	10 - 20 years	22	4.45	5.00	2	5
	20 - 30 years	13	4.62	5	3	5
	30 - 40 years	12	4.50	5.00	3	5
	> 40 years	5	4.20	5	1	5

- Structural Oversight: Clearly defined responsibilities were consistently rated as less critical than transparency and procedural integration.

Table 20: 'Transparency Feeling' (Source: Own Illustration)

Descriptives									
	N	Missing	Mean	95% Confidence Interval		Median	SD	Minimum	Maximum
				Lower	Upper				
Transparency_feeling	71	0	2.79	2.52	3.06	3	1.15	1	5

Note. The CI of the mean assumes sample means follow a t-distribution with N - 1 degrees of freedom

To examine whether AI acceptance differs depending on which collaboration mechanism respondents considered most important for effective human–AI interaction, a one-way ANOVA was conducted (**Error! Reference source not found.**). The results indicated no statistically significant differences in AI acceptance between the four groups, both in the conventional ANOVA and in the more robust Welch test. Descriptively, respondents who prioritized the integration of AI into existing processes and tools reported the highest mean AI acceptance, whereas those emphasizing clearly defined responsibilities showed the lowest mean. Levene's test suggested that the homogeneity of variances assumption was met, while the Shapiro–Wilk test indicated a deviation from normality.

Table 21: ANOVA AI acceptance (Source: Own illustration)

One-Way ANOVA					
		F	df1	df2	p
AI_acceptance	Welch's	0.745	3	23.2	0.536
	Fisher's	0.644	3	67	0.590

Group Descriptives					
	Colaboration AI	N	Mean	SD	SE
AI_acceptance	1	25	3.44	1.044	0.209
	4	7	3.29	1.113	0.421
	2	23	3.48	1.039	0.217
	3	16	3.81	0.834	0.209

1: Transparent decision-making processes for AI

2: Regular performance reviews/evaluations of AI expenditures

3: Integration of AI into existing processes/tools

4: Clearly defined responsibilities

The Transparency Gap: Explainability vs. Current Perceptions

The results indicate a marked descriptive discrepancy between the perceived importance of explainable AI and the current level of perceived transparency within organizations.

- Universal Demand for XAI: 'Explainable AI' (XAI) was rated as critically important, achieving an overall mean of 4.51 and a median of 5. This demand was nearly universal, with the oldest group (>60) providing a perfect mean score of 5.00.

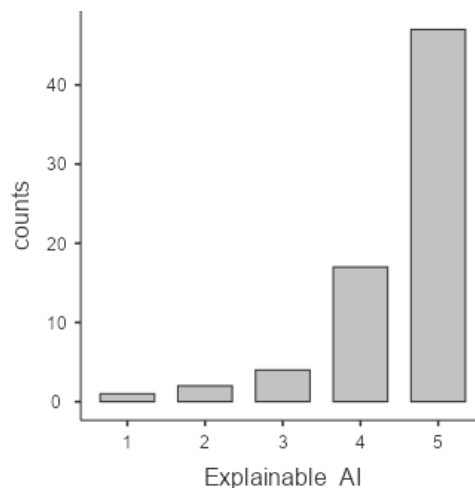


Figure 2: Rating of 'Explainable AI' (Source: Own illustration)

- Lower Current Perceived Transparency: In contrast, the 'Transparency Feeling' variable—measuring current perceived transparency—was lower at a moderate 2.79. The youngest professionals reported the lowest sense of current transparency (M = 2.40).

Table 22: 'Transparency Feeling' (Source: Own Illustration)

Descriptives	N	Missing	Mean	95% Confidence Interval		Median	SD	Minimum	Maximum
				Lower	Upper				
Transparency_feeling	71	0	2.79	2.52	3.06	3	1.15	1	5

Note. The CI of the mean assumes sample means follow a t-distribution with N - 1 degrees of freedom

- Strategic Transparency Measures: To address this perceived gap, participants most frequently prioritized explanatory reports on AI decisions, followed by standardized documentation processes and AI impact assessments.

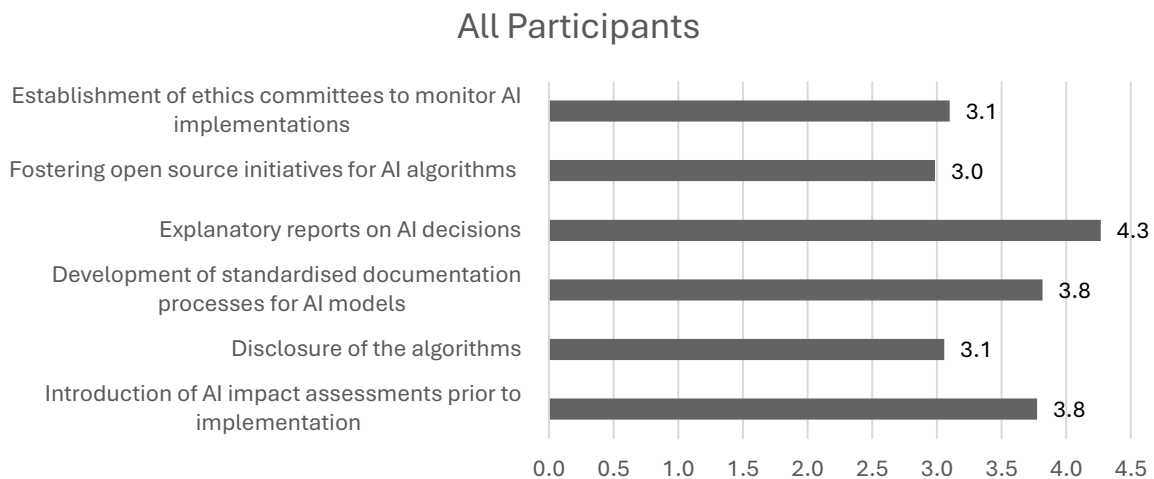


Figure 3: 'Transparency Measures' all participants (Source: Own Illustration)

Qualitative Dimensions of AI Reliability

Open-ended responses revealed three recurring themes regarding the conditions required for reliable AI-supported risk management: data integrity, domain-specific applicability, and financial as well as technical accountability.

- Data Integrity: Respondents emphasized the importance of high-quality, unbiased, and sufficiently validated data to reduce the risk of misleading or distorted AI-based outputs.
- Domain Specialization: Several participants stressed that AI systems should be trained and applied in a clearly delimited institutional or sector-specific context rather than as overly generic tools.
- Financial and Technical Accountability: Participants also highlighted the need for transparency regarding funding sources, model development, and the information basis used for AI-supported risk assessments.

Discussion: Deciphering the Human-AI Interplay

The findings of this study provide a differentiated picture of how AI is perceived in professional risk management settings. Overall, the results suggest that AI is widely regarded as operationally useful. Broader acceptance appears to be associated with contextual fit, perceived transparency, and user-related characteristics such as age and experience. Rather than pointing to a single dominant determinant, the findings indicate that effective human-AI collaboration seems to be shaped by the interplay of technical, organizational, and user-related conditions.

Age, Experience, and AI Acceptance

The empirical results show that age is positively associated with AI acceptance in the context of risk management. This finding is notable because it runs counter to the common assumption that younger professionals are generally more open to digital technologies. In this study, older respondents reported higher levels of acceptance, suggesting that AI may be perceived less as a disruptive innovation and more as a practical support tool in established professional routines. The hypothesis that age would positively influence AI acceptance is therefore supported.

The role of professional experience is less straightforward. While some descriptive patterns indicate higher acceptance among respondents with more years in the field, the effect does not appear as stable or as strong as the age effect. The results do not provide robust support for H6; any role of professional experience appears limited and context-dependent. This suggests that experience alone is not sufficient to explain acceptance, and that other factors such as role perception, accountability, and organizational context may be more relevant.

Utility Does Not Automatically Create Acceptance

A second important result concerns the relationship between perceived operational relief and AI acceptance. The data indicate that AI is widely seen as useful and supportive in everyday work. Respondents generally acknowledged that AI can reduce routine tasks and improve efficiency. However, this perceived relief did not translate automatically into stronger acceptance. The direct relationship was weak, which suggests that practical usefulness is necessary, but not sufficient, for broader acceptance.

This finding is important because it challenges a simplified utility-based view of technology adoption. In risk management, efficiency gains alone do not seem to outweigh concerns related to interpretability, accountability, and professional control. AI may therefore be appreciated as a supportive instrument, while still facing hesitation when it comes to broader institutional integration but this interpretation should remain cautious: the bivariate association did not reach conventional significance levels.

The Role of Transparency and Explainability

The hypotheses related to transparency and explainability require a more differentiated interpretation. On the one hand, the literature suggested that both perceived transparency and the importance of explainable AI should foster acceptance. On the other hand, the empirical findings do not show a clear direct effect for either variable. Neither perceived transparency nor the general importance attributed to explainable AI emerged as significant standalone predictors of AI acceptance.

This does not mean that transparency and explainability are irrelevant. Rather, the results suggest that these factors matter most when they are considered in relation to the actual gap between expected and perceived transparency. The transparency gap was negatively associated with acceptance in the multivariate model, indicating that acceptance decreases when users perceive a mismatch between what they expect and what the system currently provides. In this sense, transparency appears to function less as an isolated driver and more as a condition of credibility.

Accordingly, H1 and H2 were not supported, whereas H3 received support only in the multivariate specification.

Collaboration Mechanisms and Organizational Fit

The results also provide insight into the organizational dimension of human-AI collaboration. Respondents tended to prioritize transparent decision bases, regular performance reviews, and integration into existing workflows. Clear responsibility structures were mentioned less frequently. This suggests that participants value collaboration mechanisms that support interpretability and procedural embedding rather than rigid formalization alone.

At the same time, the inferential analysis did not show significant differences in AI acceptance across the preferred collaboration mechanisms. So H7 was not supported: the preferred mechanism does not appear to differentiate acceptance levels in this sample. This finding indicates that while such mechanisms are viewed as useful, they do not in themselves explain variations in acceptance. Their role may be more indirect, by creating conditions under which trust and usability can develop over time.

Reliability as a Qualitative Requirement

The open-ended responses strengthen the quantitative findings by showing that acceptance is closely tied to perceived reliability. Three themes appeared repeatedly: data integrity, domain-specific applicability, and financial or technical accountability. These responses suggest that respondents do not judge AI only by its output quality, but also by the credibility of its data basis, its relevance to the specific context, and the transparency of its development and funding structures.

This qualitative evidence helps explain why high perceived usefulness does not automatically result in high acceptance. Even when AI is seen as efficient, professionals may remain cautious if they have doubts about the reliability of the underlying data or the appropriateness of the model for their specific environment. Acceptance in this setting is therefore not only a question of performance, but also of epistemic confidence.

Research Contributions

To underscore the academic and practical value of this study, its core contributions can be delineated into theoretical advancements and actionable managerial implications:

Theoretical Contributions

- **Deconstructing Demographical Stereotypes:** Traditional technology acceptance models (e.g., TAM, UTAUT) often posit a linear negative relationship between age and digital tool adoption. The findings point to an age-related pattern that differs from common assumptions in general technology adoption research: older, highly experienced risk professionals exhibit significantly higher AI acceptance scores ($M = 4.17$) than younger cohorts ($M = 2.20$). The paper provides a new theoretical rationale: in expert domains, AI is evaluated less as a disruptive threat to professional identity and more as a pragmatic administrative tool.
- **The "Transparency Gap" as a Multivariable Construct:** While bivariate correlation analyses showed no isolated significant direct impact of transparency feelings ($r = 0.173$, $p = .150$) or XAI importance on acceptance ($r = -0.081$, $p = .503$), this research advances theoretical frameworks by introducing the "transparency gap" as a composite multivariable predictor. The regression results suggest that transparency expectations may matter most when considered jointly with other predictors ($\beta = -0.1524$, $p = .049$).
- **Empirical Boundary-Setting for the Utility-Acceptance Nexus:** The findings do not support a purely utility-based interpretation of AI acceptance. Despite an exceptionally high overall relief score ($M = 4.28$), the weak bivariate link to acceptance emphasizes that in accountability-driven governance contexts, perceived efficiency cannot compensate for a lack of interpretability and professional defensibility.

Managerial & Practical Contributions

- **Targeted Onboarding Frameworks:** For corporate risk management and implementation strategies, these findings demonstrate that change management should not target older generations with basic digital literacy training. Instead, deployment strategies must focus on mitigating the skepticism of early-career professionals who express high perceived relief ($SM = 4.80$) but remain fundamentally anxious about expert autonomy and systemic reliability.
- **Auditable System Architecture over Formal Oversight:** Pragmatically, organizational designers learn from this data that rigid formal structures (like predefined responsibility matrices, which scored lowest in user preference) are insufficient. To close the critical "transparency gap" and foster epistemic trust, organizations should consider investing in explanatory tools, documentation, and ongoing evaluation mechanisms.

Implications for Research and Practice

Taken together, the findings suggest that future research on Human - AI collaboration in risk management should move beyond one-dimensional adoption models. Acceptance seems to be shaped by an interplay of

demographic characteristics, perceived utility, transparency expectations, and organizational embedding. This implies that future studies may benefit from more explicit models that integrate technical, institutional, and user-related determinants rather than treating them as isolated predictors.

For practice, the results indicate that organizations should not focus exclusively on efficiency gains when implementing AI in risk management. Instead, adoption strategies should combine workflow integration, explainability-oriented communication, and transparent governance structures. AI outputs should become more understandable and auditable for professional users. Such an approach is especially important in high-stakes environments where legitimacy depends not only on correct outcomes, but also on the ability to justify how those outcomes were produced.

These implications should be interpreted in light of the study's exploratory design and sector-specific sample.

Limitations

The sample size of $N = 71$ participants, while statistically sufficient according to the a priori power analysis to detect medium effects, is relatively small for extensive generalizations. The small sample also limits the stability of subgroup comparisons and regression estimates. Furthermore, the recruitment was restricted to the DACH region (Germany, Austria, and Switzerland), which might reflect specific cultural and regulatory approaches to corporate risk management that do not apply globally.

- **Industry Biases:** The data collection focused exclusively on two highly regulated sectors: the Finance/Insurance industry and the Chemical/Pharmaceutical industry. While this allowed for a controlled comparison between risk-sensitive domains, the findings may not map seamlessly onto less regulated or highly agile environments, such as digital startups or the creative industries.
- **Methodological Scale Treatment:** Following common practices in exploratory social sciences, the 5-point Likert-type ordinal scales were treated as interval-scaled data for parametric testing (regression and ANOVA). Future studies could employ more robust non-parametric alternatives or structural equation modeling (SEM) with larger sample sizes to validate these directional paths.
- **Self-Report Biases:** The reliance on self-reported survey data via LinkedIn may introduce a self-selection bias, where professionals with an a priori interest or stronger opinions on artificial intelligence were more likely to participate. Longitudinal studies observing actual behavioral interactions between risk managers and AI systems in real-time workflows would offer a valuable validation of the subjective acceptance scores recorded here.

Conclusion

This study examined how transparency, explainability, perceived utility, demographic factors, and organizational conditions relate to AI acceptance in risk management. The results show that AI is generally perceived as helpful in operational terms. Practical usefulness on its own does not guarantee broader acceptance. Instead, acceptance appears to depend on a more complex interplay between age, perceived relief, and the extent to which explainability expectations are met.

The findings also indicate that transparency and explainability should not be understood as isolated determinants. Simple comparisons did not show a direct relationship between AI acceptance and either current transparency or the desire for explainability. But in a broader analysis, the 'transparency gap'—the distance between what users need and what they perceive—became statistically significant. This suggests that unmet expectations regarding interpretability may reduce acceptance particularly when combined with other contextual and user-related factors. However, this applies only to this multivariate model and should not be misinterpreted as a general direct effect.

A further contribution of the study lies in its organizational perspective. Respondents clearly valued transparent decision-making, performance evaluation, and workflow integration as relevant conditions for effective human–AI collaboration. However, the inferential results did not show significant acceptance differences across the four preferred collaboration mechanisms, meaning that H7 was not supported in the present analysis.

Finally, the qualitative findings underline that reliable AI-supported risk management requires more than technical functionality. Data integrity, contextual specialization, and financial as well as technical accountability emerged as central conditions for trust. Overall, the study suggests that a successful human–AI interface in risk management is more likely when operational usefulness is accompanied by interpretability and organizational accountability.

References

- Aven, T. and Renn, O. (2009) ‘On risk defined as an event where the outcome is uncertain’, *Journal of Risk Research*, 12(1), pp. 1–11.
- Davenport, T. and Ronanki, R. (2018) ‘Artificial intelligence for the real world’, *Harvard Business Review*, 96(1), pp. 108–116.
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Artis, G., Coombs, C. R., Crick, T., ... & Galanos, V. (2021) ‘Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy’, *International Journal of Information Management*, 57, p. 101994.
- Glikson, E. and Woolley, A. W. (2020) ‘Human trust in artificial intelligence: Review of empirical research’, *Academy of Management Annals*, 14(2), pp. 627–660.
- International Organization for Standardization (2018) ISO 31000:2018 Risk management — Guidelines. Available at: <https://www.iso.org/standard/65694.html> (Accessed: 7 January 2026).
- Klinke, A. and Renn, O. (2001) ‘Precautionary principle and discursive strategies: classifying and managing risks’, *Journal of Risk Research*, 4(2), pp. 159–173. <https://doi.org/10.1080/136698701750128105>.
- Mesihovic, S. and Nordström, H. (2021) Artificial Intelligence and Machine Learning usage in credit risk management - A study from the Swedish financial services industry. Available at: https://gupea.ub.gu.se/bitstream/2077/67844/1/gupea_2077_67844_1.pdf (Accessed: 16 June 2024).
- Rai, A. (2020) ‘Explainable AI: From black box to glass box’, *Journal of the Academy of Marketing Science*, 48(1), pp. 137–141.
- Shin, D. (2021) ‘The effects of explainability and causability on user trust’, *New Media & Society*, 23(3), pp. 500–519.
- Slovic, P. (1990) Perceptions of Risk - Reflections on the psychometric paradigm. Available at: https://scholarsbank.uoregon.edu/xmlui/bitstream/handle/1794/22510/slovic_289.pdf?sequence=1&isAllowed=y (Accessed: 16 June 2024).
- Tversky, A. and Kahneman, D. (1974) ‘Judgment under uncertainty - Heuristics and biases’, *Science*, 185, pp. 1124–1131. <https://doi.org/10.1126/science.185.4157.1124>.
- Vassie, L., Slovic, P., Fischhoff, B. and Lichtenstein, S. (2005) ‘Facts and fears: Understanding perceived risk’, *Policy and Practice in Health and Safety*, 3(sup1), pp. 65–102. <https://doi.org/10.1080/14774003.2005.11667668>.
- Venkatesh, V., Morris, M. G., Davis, G. B. and Davis, F. D. (2003) ‘User acceptance of information technology: Toward a unified view’, *MIS Quarterly*, 27(3), pp. 425–4