Appendix

A. List of AI skills and competencies (Alekseeva et al., 2021)

AI skills and competencies	
AI ChatBot	MLPACK
AI KIBIT	Mlpy
ANTLR	Modular Audio Recognition Framework
Apertium	MoSes
Artificial Intelligence	MXNet
Automatic Speech Recognition	Natural Language Processing
Caffe Deep Learning Framework	Natural Language Toolkit
Chatbot	ND4J
Computational Linguistics	Nearest Neighbor Algorithm
Computer Vision	Neural Networks
Decision Trees	Object Recognition
Deep Learning	Object Tracking
Deeplearning4j	OpenCV
Distinguo	OpenNLP
Google Cloud Machine Learning Platform	Pattern Recognition
Gradient boosting	Pybrain
H2O	Random Forests
IBM Watson	Recommender Systems
Image Processing	Semantic Driven Subtractive Clustering Method
Image Recognition	Semi-Supervised Learning
IPSoft Amelia	Sentiment Analysis
Ithink	Sentiment Classification
Keras	Speech Recognition
Latent Dirichlet Allocation	Supervised Learning
Latent Semantic Analysis	Support Vector Machines
Lexalytics	TensorFlow
Lexical Acquisition	Text Mining
Lexical Semantics	Text to Speech
Libsvm	Tokenization
Machine Learning	Torch
Machine Translation	Unsupervised Learning
Machine Vision	Virtual Agents
Madlib	Vowpal
Mahout	Wabbit
Microsoft Cognitive Toolkit	Word2Vec
	Xgboost

Table 5. List of AI skills and competencies

B. Robustness checks

We ran several robustness checks to ensure the validity of our findings: AI distinctiveness of principal variables (B.1), alternative operationalization of principal variables (B.2), sample selection bias (B.3), analyses segmented by firm type (B.4), and reverse causality regarding AI orientation (B.5). Additional checks were made as stated below, and Tables 5, 6 and 7 summarize the robustness findings.

B.1 Distinctiveness of AI orientation and HR-related AI implementation ability

We tested whether AI orientation and HR-related AI implementation ability are distinct from their general IT counterparts (IT orientation and HR-related IT implementation ability). Prior IS research found that TMTs usually do not discuss general IT-related matters in greater detail (Huff et al., 2008). Whereas TMTs seem to normally trust general IT and perceive it as less of a risk, they consider AI from a different perspective (Li et al., 2021). Hence, we argue that the orientation of a firm towards AI or IT and the subsequently demanded HR-related implementation ability are qualitatively distinct.

To test that AI orientation and HR-related AI implementation ability are distinct, we used two regression models where we replaced them as dependent variables with their general IT counterparts. We find that TMT AI literacy is neither associated with IT orientation (Table 6, model 8: $\beta = .015$, $p > .05$) nor HR-related IT implementation ability (Table 6, model 9: $\beta = -.050$, $p > .05$). Additionally, one can observe that IT orientation is uncorrelated with AI orientation and HR-related AI implementation ability (Table 1). In summary, we conclude that the robustness of our analysis is supported by the distinctiveness of AI (vs. general IT).

B.2 Alternative operationalization of AI orientation and HR-related AI implementation ability

Our main analysis argues that the frequency of AI terms within a firm's strategic communication indicates the degree of its AI orientation. Thus, we operationalize AI orientation as a continuous variable. While we account for industry effects with control variables, one could argue that even within a specific industry, multiple business models exist that differ in their applicability of AI (Dellermann et al., 2018). While a strong strategic direction toward AI might be most purposeful for some, others can use AI only in specific niche cases. To increase the robustness of our analysis, we construct a binary AI orientation variable (see section 4.2). The binary variable measures whether AI is discussed in a firm's strategy at all and not how much it is discussed. Hence, it accounts for further differences in business models within a given industry. We find that TMT AI literacy also significantly affects binary AI orientation (Table 6, model 10: $\beta = 1.053$, $p < .001$).

Based on the same logic, one could also argue that a firm's share of AI skills within its workforce depends on the business model. More AI skills might not necessarily be better (see section 4.2). We constructed a binary variable of HR-related AI implementation ability (HAIIA-binary), measuring whether a firm considers AI skills at all. In model 11 (Table 6), we find that both TMT AI literacy ($\beta = .349$, $p < .05$) and AI orientation ($\beta = .390$, $p < .05$) significantly affect this alternative operationalization of HAIIA-binary, as in our original model 2. Furthermore, one could argue that not only the share of AI skills in the workforce matters but also the AI skill breadth (see section 4.2). In model 12 (Table 6), we tested how TMT AI literacy ($\beta = 1.212$, $p < .001$) and AI orientation ($\beta = 1.826$, $p < .001$) affect "HAIIA-breadth." Both coefficients are significant and in the same direction as in our original model 2. In summary, we conclude that the alternative operationalizations of AI orientation and HR-related AI implementation ability support the robustness of our analysis.

B.3 Sample selection bias

We used the world's largest professional social network (LinkedIn.com) for data collection to ensure that we included a firm's breadth of job postings as comprehensively as possible, ultimately describing its HR-related AI implementation ability. However, using only one source of job postings could lead to sample selection bias since firms might post their open positions with a different focus on different platforms. Therefore, we additionally collected the firms' job postings from Indeed.com, another sizeable online job market (>250 million unique visitors per month (Indeed.com, 2023)). Of the 645 firms in our data set, 605 also advertised job postings on Indeed.com. We collected and processed the firm's job postings from Indeed.com with the same approach used for LinkedIn.com. In model 13 (Table 6), we ran model 2 (dependent variable: HR-related AI implementation ability) with an alternative dependent variable based on the data retrieved via Indeed.com instead of LinkedIn.com (dependent variable: HAIIA-Indeed). We found that the effects of TMT AI literacy and AI orientation on HAIIA-Indeed are also significant. Therefore, we conclude that the robustness check reduces concerns that our sample retrieved via Linked.com suffers from sample selection bias.

B.4 Analysis by firm type

While public firms (like our sample of incumbent firms) must disclose specific financial data, private firms (like our sample of startup firms) are not subject to such obligations. To further support the robustness of our analysis, we conducted analyses segmented by firm type, allowing us to control for the relevant financial data within the subsample of incumbent firms (Li et al., 2021). In models 14-16 (Table 7), we replicated the main models 1-3 only for incumbent firms, including the introduced financial variables. In models 17-19 (Table 7), we replicated the main models 1-3 only for startup firms. In both segmentations (models 14-16 and 17-19), the significant effects of the principal variables identified in models 1-3 hold (i.e., between TMT AI literacy, AI orientation, and HR-related AI implementation ability). We conclude that replicating the main effects in a "firm-type segmentation" supports the robustness of our main analysis. Furthermore, the analysis for incumbent firms only shows that the effects hold, even when including the financial control variables ownership concentration, net income, cost of goods sold, overhead costs, and leverage (Table 7, models 14-16). Descriptive statistics and correlations of the incumbent firm segment analysis, including financial control variables, are available in Appendix D (Table 8).

B.5 Reverse causality regarding AI orientation

Prior research has shown that CIO presence affects AI orientation and has provided corresponding robustness checks regarding reverse causality (Li et al., 2021). Thus, our analysis assumes that TMT AI literacy as a character trait of executives on a firm's TMT also predicts AI orientation. However, one could argue that a firm with a higher AI orientation attracts AI-literate executives. To support our causal ordering and to diminish concerns regarding reverse causality of AI-literate executives and AI orientation, we also collected data on the incumbent firms' AI orientation from an earlier point in time, extending our data set to a panel. We follow Li et al. (2021) to construct our panel. Therefore, we obtained the 10-k statements, which include the MD&As (and thus also AI orientation) of each incumbent firm three years before their 2022 10-k statement using the same methodology. Furthermore, we collected each executive's tenure, which is available in their online profile (the average tenure of an executive was 4.97 years). Subsequently, we tested for a significant difference in the share of AI-literate executives who newly joined a firm's TMT within the last three years for firms that increased their AI orientation compared to firms that did not increase their AI orientation during the period. We found no significant difference in the share of AI-literate executives who joined the TMTs of firms with increased AI orientation compared to firms without increased AI orientation (two-sided t-test: $p > 0.05$). Thus, we conclude that the robustness check diminishes concerns that AI orientation affects TMT AI literacy rather than TMT AI literacy affecting AI orientation.

C.1 Results of robustness checks (1/2)

Variable \ DV (Model ID)	IIO[1] (8) β	IIO[1] (8) s.e.	HITIA[2] (9) β	HITIA[2] (9) s.e.	AIO-binary[3] (10) β	AIO-binary[3] (10) s.e.	HAIIA-binary[4] (11) β	HAIIA-binary[4] (11) s.e.	HAIIA-breadth[5] (12) β	HAIIA-breadth[5] (12) s.e.	HAIIA-Indeed (13) β	HAIIA-Indeed (13) s.e.
Constant	.032	.036	(.005)	.041	.008	.157	.033	.174	.035	.129	.001	.002
TMT AI literacy (TMTAIL)	**.015**	**.025**	**(.050)**	**.029**	**1.053*** **	**.110**	**.349***	**.141**	**1.212*** **	**.104**	**.021*** **	.002
Mediator												
AI orientation (AIO)							**.390***	**.167**	**1.826*** **	**.124**	**.030*** **	.002
Controls												
CIO presence	(.007)	.008	.007	.009	(.052)	.036	(.033)	.040	(.004)	.030	<.001	.001
CTO presence	.004	.007	(.005)	.009	.062	.033	.051	.037	(.029)	.027	-.001	<.001
TMT size	<.001	.001	.001	.001	.002	.003	.005	.004	<.001	.003	<.001	<.001
Firm age	<.001	<.001	<.001	<.001	(.001**)	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Firm size	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Number of job postings	<.001	<.001	<.001	<.001	<.001	<.001	.001***	<.001	<.001	<.001	<.001	<.001
IT Orientation			.307***	.046	.097	.175	(.116)	.196	.141	.145	.001	.002
Industry controls												
Agriculture[6]	(.037)	.055	.020	.063	(.038)	.241	.585*	.268	(.017)	.199	-.001	.003
Construction	(.035)	.049	.093	.056	.167	.215	.435	.240	(.037)	.177	-.001	.003
Finance and insurance	(.030)	.036	.022	.042	.160	.159	.461**	.177	(.029)	.131	-.001	.002
Health care[7]	(.012)	.039	.062	.044	.293	.169	.441*	.188	(.024)	.139	<.001	.002
Information	(.033)	.048	.006	.055	(.074)	.209	.140	.232	(.018)	.172	<.001	.003
Manufacturing	(.013)	.035	.059	.041	.131	.155	.472**	.173	.028	.128	<.001	.002
Mining[8]	(.034)	.039	.060	.045	.094	.173	.245	.193	(.033)	.143	<.001	.002
PST services[9]	(.011)	.036	.038	.041	.309	.158	.345*	.176	.038	.130	.001	.002
Real estate[10]	(.021)	.039	.113*	.044	(.002)	.170	.142	.189	(.014)	.140	<.001	.002
Retail trade	(.010)	.039	.006	.045	.066	.171	.213	.190	(.027)	.141	<.001	.002
Transportation[11]	(.021)	.038	.040	.044	.293	.167	.490**	.186	.085	.137	.003	.002
Utilities	(.034)	.043	.030	.049	.013	.188	.518*	.209	.027	.154	<.001	.003
Wholesale trade	(.028)	.043	.063	.049	.240	.187	.352	.209	(.070)	.154	-.001	.003
R^2	.014		.127		.325		.218		.576		.544	
Adjusted R^2	(.017)		.097		.303		.190		.561		.527	
P-value of f-statistic	.981		<.001		<.001		<.001		<.001		<0.001	
n	645		645		645		645		645		605	

Notes: 1. IT orientation; 2. HR-related IT implementation ability; 3. AI orientation binary; 4. HR-related AI implementation ability binary; 5. HR-related AI implementation ability breadth; 6. Agriculture, forestry, fishing, and hunting; 7. Health care and social assistance; 8. Mining, quarrying, and oil and gas extraction; 9. Professional, scientific, and technical services; 10. Real estate and rental and leasing; 111. Transportation and warehousing; Significance levels: * = p < .05, ** = p < .01, *** = p < .001

Table 6. Results of robustness checks (1/2)

C.2 Results of robustness checks (2/2)

Variable \ DV (Model ID)	AIO[1] (14) β	s.e.	HAIIA[2] (15) β	s.e.	HAIIA (16) β	s.e.	AIO (17) β	s.e.	HAIIA (18) β	s.e.	HAIIA (19) β	s.e.
Constant	<.001	.035	.028	.050	.027	.052	(.073)	.063	(.233*)	.116	(.029)	.129
TMT AI Literacy (TMTAIL)	**.573*****	**.058**	**.438*****	**.093**			**.393*****	**.057**	**.850*****	**.121**		
Mediator												
AI Orientation (AIO)			**.556*****	**.069**	**.693*****	**.064**			**.696*****	**.148**	**1.199*****	**.149**
Controls												
CIO presence	(.016*)	.007	(.004)	.011	<.001	.011	(.037)	.057	(.037)	.106	(.005)	.122
CTO presence	(.008)	.008	.004	.011	.012	.012	(.016)	.028	(.110*)	.051	(.086)	.058
TMT size	.001	.001	.001	.001	.001	.001	.005	.005	.016	.008	.011	.010
Firm age	<.001	<.001	<.001*	<.001	<.001*	<.001	<.001	.005	.008	.010	.004	.011
Firm size	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Number of job postings	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
IT Orientation	(.038)	.041	.202***	.059	.229***	.060	(.162)	.139	(.403)	.258	(.311)	.295
Financial controls												
Ownership concentration	.011	.128	(.118)	.187	(.126)	.191						
Net income	<.001	<.001	<.001	<.001	.000*	<.001						
Cost of goods sold	<.001	<.001	<.001	<.001	<.001	<.001						
Overhead costs	<.001	<.001	<.001	<.001	<.001	<.001						
Leverage	(.015)	.014	(.005)	.020	(.007)	.021						
Industry controls												
Agriculture[3]	(.019)	.048	.013	.069	.030	.071						
Construction	(.006)	.043	(.003)	.062	.008	.063						
Finance and insurance	(.007)	.032	.022	.047	.033	.048						
Health care[4]	(.005)	.044	(.022)	.064	(.013)	.065	.013	.047	.094	.087	.072	.100
Information	(.014)	.042	(.017)	.060	(.011)	.062						
Manufacturing	.006	.031	.029	.045	.038	.046	.036	.057	.174	.106	.291*	.120
Mining[5]	.004	.034	.005	.050	.014	.051						
PST services[6]	(.018)	.032	.028	.047	.047	.048	.044	.038	.099	.071	.142	.081
Real estate[7]	.002	.035	(.001)	.050	.002	.052						
Retail trade	(.002)	.034	(.017)	.049	(.012)	.050						
Transportation[8]	(.014)	.037	.053	.054	.066	.055	(.003)	.049	.186*	.091	.213*	.104
Utilities	.006	.038	.026	.055	.026	.056						
Wholesale trade	.053	.038	(.008)	.055	(.010)	.057						
R^2	.229		.331		.298		.285		.521		.368	
Adjusted R^2	.184		.291		.258		.230		.481		.319	
P-value of f-statistic	<.001		<.001		<.001		<.001		<.001		<.001	
n	477		477		477		168		168		168	

Notes: 1. AI Orientation; 2. HR-related AI implementation ability; 3. Agriculture, forestry, fishing, and hunting; 4. Health care and social assistance; 5. Mining, quarrying, and oil and gas extraction; 6. Professional, scientific, and technical services; 7. Real estate and rental and leasing; 8. Transportation and warehousing; Significance levels: * = p < .05, ** = p < .01, *** = p < .001

Table 7. Results of robustness checks (2/2)

D. Descriptive statistics and correlations for incumbent firms only

Variable	Unit	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Top management team AI Literacy (1)	%	.032	.063	1														
AI Orientation (2)	%	.017	.080	.432***	1													
HR-related AI implementation ability (3)	%	.051	.125	.428***	.467***	1												
CIO presence (4)	%	.365	.482	.015	(.071)	(.059)	1											
CTO presence (5)	%	.298	.458	.202***	.049	.107*	(.093)*	1										
TMT size (6)	# Executives	11.0	5.1	.108*	.048	.063	.268***	.179***	1									
Firm age (7)	Years	73.5	61.5	(.111)*	(.051)	(.117)*	.116*	(.038)	.092*	1								
Firm size (8)	# Employees	57409	148997	.125**	.092*	.045	(.021)	.066	.07	.003	1							
Number of job postings (9)	# Job postings	396	364	.12**	.135**	.042	.051	.032	.043	.06	.312***	1						
IT Orientation (10)	%	.019	.084	.102*	.006	.165***	(.039)	.056	(.018)	.031	(.015	0	1					
Ownership concentration (11)	%	.103	.030	(.096)*	(.066)	(.093)*	.05	(.133)**	(.063)	(.04)	(.217)***	(.203)***	(.014)	1				
Net income (12)	k USD	3357.9	7549	.191***	.117*	.148**	(.046)	.085	(.043)	.041	.309***	.301***	.042	(.221)***	1			
Cost of goods sold (13)	k USD	16379.2	39188	.059	.076	.008	(.008)	.019	(.019)	.014	.67***	.21***	(.05)	(.196)***		1		
Overhead costs (14)	k USD	5180.47	10733	.085	.093*	.051	(.016)	.073	(.014)	.085	.822***	.369***	(.013)	(.251)***	.553***	.614***	1	
Leverage (15)	%	.671	.263	(.064)	(.045)	(.076)	.049	.034	.113*	.101*	.068	.184***	(.039)	(.022)	.022	.067	.106*	1

Table 8. Robustness: Descriptive statistics and correlations for incumbent firms only (including financial control variables, n = 477)

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