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Unrealistic Optimism Regarding Artificial Intelligence Opportunities in Human Resource Management

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ABSTRACT

Artificial intelligence (AI) has many uses in domains like automotive and finance or business divisions like human resource management (HRM). This study presents a survey that was conducted among a German national sample (n = 79) of HRM personnel from small- and medium-sized enterprises regarding the expected impact of AI on their own and other companies. Indications for unrealistic optimism, i.e., assuming negative impacts are more likely for others than oneself, were identified. AI will play an increasingly important role, with cost reductions and efficiency gains serving as the highest motives and a lack of AI specialists representing the highest inhibitor. Participants assume that AI will reduce the number of employees in other companies, while it let the one in their own grow. They expect AI to take over more tasks in other companies and believe AI will more impact other companies' HRM, especially in administrative processing. Future research should include (repeated) investigations into other business divisions.

KEYWORDS

HRM Subareas, Impact of AI, Importance of AI, Optimism Bias, Small and Medium-Sized Enterprises, Survey

INTRODUCTION

Artificial intelligence (AI) is an essential technology of the 21st century (Buxmann & Schmidt, 2021; Jain et al., 2018). Both research and practice apply it to various domains, including automotive (Lorente et al., 2021) and finance (Goodell et al., 2021), or business divisions like human resource management (HRM) (Tambe et al., 2019). Modern information technology (IT) applications of AI include automated programming and interactive interpreters (Russell et al., 2016).

AI was first mentioned by McCarthy et al. (1955) nearly 70 years ago. However, AI prospers more than ever due to technological advancements (Rai et al., 2019). About 20 years ago, Kurzweil (2005) declared AI to be deeply integrated in all domains and business divisions. McLellan (2022) recently repeated the call for small- and medium-sized enterprises (SME) to focus on AI adoption. Through productivity-enhancing automation and job replacement, AI will change society by decreasing (Chelliah, 2017) or increasing (Daugherty et al., 2019) the number of employees.

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HRM deals with *human resources*, which play a prominent role within a company. As such, human resources represent a significant success factor for an organization (Noe et al., 2020). Combining the potential of AI technology with the essential role of HRM is, therefore, highly relevant for SME.

Organizations face several challenges in implementing AI. They must ensure that organizational prerequisites (i.e., AI strategy, AI knowledge, and employee qualification) are covered while obeying principles of ethics and privacy (Dahm & Dregger, 2020; Vrontis et al., 2022). Applications of AI in subareas of HRM include strategic planning, personnel search and acquisition (Channabasamma et al., 2021; Dahm & Dregger, 2019; Knobloch & Hustedt, 2019; Pandey & Bahukhandi, 2022; Vrontis et al., 2022), personnel selection (Vrontis et al., 2022), administrative processing of HRM activities (Dahm & Dregger, 2019; Knobloch & Hustedt, 2019; Strohmeier & Piazza, 2015; Vrontis et al., 2022), communication with (potential) employees (Dahm & Dregger, 2019; Iyer et al., 2020; Knobloch & Hustedt, 2019), development and implementation of training measures (Knobloch & Hustedt, 2019), employee evaluations (Vrontis et al., 2022), development of measures for employee retention (Atef et al., 2022), and evaluation of the potential of managers (Dahm & Dregger, 2019). Big data and digital transformation challenge SME by changing established market and communications processes. Therefore, SME must reinvent their business models, as AI's automated processes can lead to a growing demand for AI specialists (Neuburger et al., 2021).

As Tambe et al. (2019) note, AI faces four challenges when applied in HRM: (1) complex phenomena; (2) small data sets; (3) accountability questions; and (4) adverse employee reactions to AI-based management decisions. Zhu et al. (2021) highlight general employees' perceptions of AI in the implementation process, including degrees of technology optimism toward AI. Companies should use several strategies to adapt to perceptions surrounding AI's cognitive and operational capabilities (Zhu et al., 2021). Furthermore, there is research regarding the attitude toward AI (Sindermann et al., 2021; Schepman & Rodway, 2020; Fast & Horvitz, 2017), e.g., in recruiting (Pandey & Bahukhandi, 2022).

Sindermann et al. (2021) provide a short, reliable, and valid measure of the attitude toward AI, using a multinational sample (Germany, China, the United Kingdom) of university students. Schepman & Rodway (2020) validate another general attitude toward AI scale, dividing it into a positive and a negative subscale with a sample of workers from various occupations. Pandey & Bahukhandi (2022) focus on the applicants' perception toward the use of AI in the recruitment process. As early as 1995, Milne (1995) connected unrealistic optimism with neural networks without applying this to a specific business division like HRM. Fast & Horvitz (2017), in analyzing news text corpora, find discussions about AI to have been consistently more optimistic. Thus far, no study has examined the unrealistic optimism HRM personnel might have regarding AI in HRM when comparing their own company to other companies.

Unrealistic optimism refers to the assumption of negative impacts being more likely for others than for oneself or positive impacts being more likely for oneself than for others (Weinstein & Klein, 1996). This is sometimes referred to as optimism bias (Jefferson et al., 2017). This study adds such an investigation to the literature by providing a survey with a national sample of $n = 79$ interviewed HRM personnel. The study aims to answer the following question: How do HRM personnel perceive AI implementation, including motives and inhibitors in HRM (subareas) and AI impact in their company, as compared to other companies? The study will compare their perceptions about their own company and other companies to find evidence for potential instances of unrealistic optimism (Weinstein & Klein, 1996).

Regarding the well-known unified theory of acceptance and use of technology (UTAUT) by Venkatesh et al. (2003), unrealistic optimism can be linked to performance or effort expectancy. UTAUT defines performance expectancy as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447). Unrealistic optimism might lead to an overestimation of a system (e.g., AI's positive impact on one's job or company performance compared to other individuals or companies). Likewise, effort expectancy, "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450), may link to unrealistic optimism in terms of overestimating the ease of the system (e.g., AI use for one's own company compared to other individuals or companies). Thus, unrealistic optimism complements UTAUT's performance or effort expectancy as facets of user expectations prior to implementation as potential relevant predictors of functional and dysfunctional implementation.

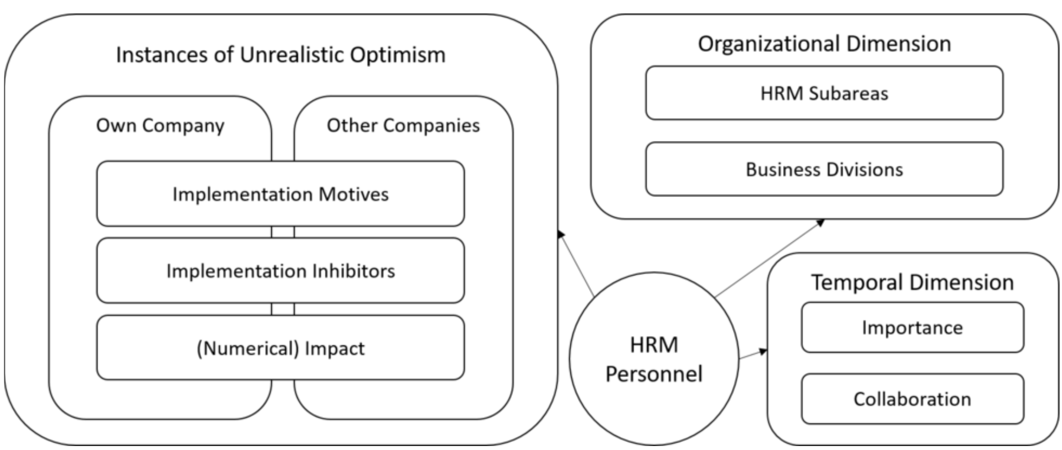
Figure 1 gives an overview of the study's nomological network. The inspected subjects are HRM personnel who reported their perceptions toward the implementation motives, inhibitors, and (numerical) impact of AI regarding their own company and other companies. Differences might be instances of unrealistic optimism. Next, in examining the organizational dimension, participants describe their perceptions regarding AI support in HRM subareas and business divisions. Upon reviewing the temporal dimension, the author sheds light on participants' expectations regarding the importance of AI to their company and the fruitfulness of the collaboration of humans and AI in recruiting for today, in five years, and ten years.

Following the introductory section, the article will present a theoretical background of AI in HRM. This will include selected scientific works that deal with unrealistic optimism. The author will explain the survey method, including the study design and statistical methods, sample description, and variable overview. The results section will present the survey's key findings, which correspond to the nomological network. It is grouped into instances of unrealistic optimism next to the organizational and temporal dimensions. The study will conclude by discussing the results, including theoretical and managerial implications, and outlining the limitations and avenues for future research.

THEORETICAL BACKGROUND: UNREALISTIC OPTIMISM AND AI IN HRM

Weinstein (1980) coined the term "unrealistic optimism" by presenting study participants with a list of positive and negative life events (e.g., owning a home or getting lung cancer). Participants estimated their likelihood to be above average for positive events and below average for negative events. Thus, they indicated unrealistic optimism (the assumption of negative impacts being more likely for others than for oneself and positive impacts being more likely for oneself than for others) without proper justification (e.g., relevant risk factors) for this assumption (Weinstein & Klein, 1996). Jefferson et al. (2017) referred to the concept as optimism bias, emphasizing the latter part of the definition. Further research applied the concept to the domains of mental health (Kleiman et al., 2020; Taylor & Brown, 1988), self-assessment (Dunning, 2011), behavioral finance (Hirshleifer, 2015; Barberis & Thaler, 2003; Odean, 1998), and climate change (Gifford, 2011).

Figure 1. Nomological network of the study



Recent research focuses on multiple ways of AI application in HRM (Dahm & Dregger, 2019; Fink, 2021; Knobloch & Hustedt, 2019; Leukert et al., 2019; Liebert & Talg, 2019; Lieske, 2022; Strohmeier & Piazza, 2015; Vrontis et al., 2022). Dahm & Dregger (2019) present three ways of AI support for HRM. Firstly, AI may support HRM personnel in formulating job descriptions. Archived job descriptions are analyzed semantically to avoid the use of formulations that attract one gender more than the other. Here, unrealistic optimism may lead to the expectation that AI is a better support for one's own company than for others by delivering less biased job descriptions. Additionally, chatbots can support the application process. The use of input factors, such as location and required abilities for a job description, allows AI to predict the length of a recruitment period. Thus, HRM personnel can begin to shorten the recruitment period. Finally, AI may predict applicants' personality traits by analyzing their voices and using linguistic features in an automated telephone interview to reduce turnover. Herein, a model trained with 5,000 people recording their voice and taking a traditional personality test backs the AI. This method earned critique regarding its precision (Schwertfeger, 2015).

Knobloch & Hustedt (2019) provide six examples of automation in HRM: (1) talent analytics; (2) active sourcing for candidates; (3) applicant screening by preselecting applications and machine learning-powered online interviews; (4) digital assessment centers; (5) employer branding and actively approaching applicants; and (6) staff development and career planning. Unrealistic optimism is evident if one expects this AI automation to work better for their own company and to face fewer inhibitors than for other companies.

In an IBM survey, Bokelberg et al. (2017) list several application scenarios for AI in HRM. Employees applying for vacation can receive information about a colleague's overlapping request, prompting the employee to resubmit a request approval. Newcomers can receive added support through intranet help pages. AI-based speech analysis can perform a sentiment analysis and recommend breaks. Herein, unrealistic optimism may lead to situations where HRM expects schedules or break suggestions to be better than those at other companies, potentially dismissing individual employees' needs. Team leaders can receive training suggestions tailored for their team members via AI. Through the implementation of AI, managers hiring new employees may learn that they need to invite more candidates.

Strohmeier & Piazza (2015) also establish six uses of AI applications in HRM: (1) turnover prediction with artificial neural networks (ANN); (2) candidate search with knowledge-based search engines (KBSE); (3) staff rostering with genetic algorithms (GA); (4) sentiment analysis with text mining; (5) résumé data acquisition with information extraction; and (6) employee self-service with interactive voice response.

1. Strohmeier & Piazza (2015) elaborate that turnover prediction with ANN focuses on employee turnover, i.e., the *voluntary* resignation of employees. This leads to short-term revenue losses and mid-term search costs for new employees, especially in the case of dysfunctional turnover. ANN now use input parameters like age, gender, wage, distance to work, and work time to find complex patterns that lead to (dysfunctional) turnover and the ability to identify the employees who will resign. This helps HRM focus on factors leading to turnover, the employees in question, and mitigating the consequences of anticipated turnover (Atef et al., 2022).
2. A candidate search with KBSE matches candidates to open positions. KBSE skip literal differences between search terms and derive conclusions from candidates' profiles (like having studied in France means being able to speak French). Thus, KBSE may automate searches and presort results. Compared to a manual search, AI provides increased efficiency and quality (Strohmeier et al., 2011; Strohmeier & Piazza, 2015). These two ways of AI application in HRM bear the potential for unrealistic optimism when companies expect AI to better predict turnover in their own company or search and find candidates for their own company compared to other companies.
3. Staff rostering with GA uses employee parameters, such as availability and abilities, to optimize their satisfaction and overall cost, e.g., for overtime. Employee availability and abilities determine valid staff rosters, while employee satisfaction and overtime costs are evaluation factors. GAs'

selection, crossover, and mutation deliver new (generations of) staff rosters that outperform manual scheduling (Strohmeier & Piazza, 2015).

4. Sentiment analysis with text mining uses texts written by employees to gain insights about their views on HRM-relevant topics like remuneration and working atmosphere. Sources of these texts include social networks and employer-rating websites. Texts must be preprocessed and classified to objectively process sentiments. This allows sentiment comparisons to other companies and the processing of large amounts of text (Liu & Zhang, 2012; Strohmeier et al., 2015; Strohmeier & Piazza, 2015).
5. Résumé data acquisition with information extraction supports HRM's application process by processing and extracting information from semi-structured text data like résumés (Athukorala et al., 2020; Cabrera-Diego et al., 2019; Sen et al., 2012; Strohmeier & Piazza, 2015). Résumés may also be sourced via the internet (Channabasamma et al., 2021). Automated processing outperforms manual screening in both speed and precision (Dahm & Dregger, 2019; Strohmeier & Piazza, 2015).
6. Similarly, AI can analyze employees' résumés to identify the skills of successful project managers. Applying project managers' résumés may be scanned for social skills to support the hiring of HRM personnel. This will improve and shorten the application process (Dahm & Dregger, 2019). Employee self-service with interactive voice response lets employees autonomously perform typical HRM tasks like updating personal data or choosing further training. Web applications like speech-based search and chatbots or automated phone agents assist employees in these tasks. The continual (24/7) availability of these technologies and savings in HRM personnel costs trump shortcomings like a necessary training period and acceptance problems (Iyer et al., 2020; Strohmeier & Piazza, 2015; Strohmeier & Kabst, 2014). Unrealistic optimism in this area may lead to expectations of AI-supported employee self-service to perform better in their own company than in other companies, possibly leading to misalignments in the number of HRM employees needed.

In their multidisciplinary, systematic review, Vrontis et al. (2022) present 22 articles that deal with AI in HRM, specifically in the subareas of job replacement, human-AI collaboration, training, decision making, and recruiting. The study distinguishes between job replacement by AI at a task level, followed by a job level. The change in the number of employees may reflect unrealistic optimism when employees systematically expect AI to reduce the number of employees differently in other companies than in their own company. Over- or underestimating the future number of employees may threaten the HRM division's efficiency in acquiring or releasing personnel. The same holds for human-AI collaboration and AI's share of tasks. Expecting AI to take over unequal shares in one's own company than in other companies may indicate unrealistic optimism, possibly leading to misalignment between the personnel that HRM recruits and the personnel a company needs regarding AI-related abilities and general professional knowledge.

METHOD

Study Design and Statistical Methods

The study incorporated a structured questionnaire that benefitted from focused, targeted, and insightful gathering of information (Yin, 2014). An attention check complemented the survey to improve its robustness (Meade & Craig, 2012). The questionnaire started with demographics, expectations, and knowledge of AI. It also considered the use of AI in one's own and others' companies. It continued with AI in the HRM division in both one's own company and others' companies, finishing with a brief question about the other divisions. The goal was to investigate how HRM personnel perceive AI implementation, including motives and inhibitors in HRM (subareas) and AI impact in their company compared to other companies, regarding unrealistic optimism (Weinstein & Klein, 1996). It took place online for forty days (September 19 to October 28, 2019). Password restriction was not applied. Participation was limited to one time. A hidden timer measured the duration that contestants spent answering the questionnaire. The author further processed the results via SPSS. These were examined to generate the figures and tables within the article.

Participants

The author contacted 3,419 HRM personnel from Germany. They were also asked to share the link with their HRM colleagues. Out of these 3,419 people, 813 followed the link, leading to an overall response rate of 23.8%. Of these 813 people, 189 finished the survey, leading to an overall response rate of 5.3%. Upon sanitizing the sample, the author excluded participants who failed the attention check and those who did not work in SME. This left a set of 89 participants. As research indicates, the speed of finishing a survey (whether too fast or too slow) can affect the results (Greszki et al., 2015; Tourangeau et al., 2000). Therefore, the author decided to extend the mean completion time (623.25 seconds) in both directions by one standard deviation (346.04 seconds). The study excluded participants ($n = 10$) outside of this interval [277.21;969.29]. Thus, the final sample contained 79 participants.

Table 1 presents descriptive statistics of the dataset of surveyed HRM personnel. Of the sample's 79 participants, 32 were male and 46 were female (see Footnote 1). The age ranged from 23 to 63

Table 1. Descriptive statistics of the dataset

Variable	N	Mean	Std. Dev.	Minimum	Maximum
Gender	79	1.61	0.517	1	3
Age	79	38.34	9.219	23	63
Education level	79	4.76	0.604	3	6
Company size	79	1.24	0.43	1	2
Management responsibility	79	2.01	0.776	1	3
Industry					
Banking/insurance	79	0.08	0.267	0	1
Education	79	0.04	0.192	0	1
Chemistry	79	0.04	0.192	0	1
Service	79	0.27	0.445	0	1
Electronics	79	0.05	0.221	0	1
Automobile	79	0.01	0.113	0	1
Healthcare	79	0.04	0.192	0	1
Retail	79	0.03	0.158	0	1
Information technology	79	0.37	0.485	0	1
Communications	79	0.01	0.113	0	1
Consumer goods	79	0.04	0.192	0	1
Engineering	79	0.04	0.192	0	1
Public sector	79	0	0	0	0
Logistics	79	0	0	0	0
Utilities	79	0	0	0	0
Construction	79	0.05	0.221	0	1
Consulting	79	0.09	0.286	0	1
Entertainment	79	0.06	0.245	0	1
Other	79	0.27	0.445	0	1

years, with mean participant age of 38. Regarding the education level, most participants ($n = 61$) had a university degree (coded 5), while only two reached the highest education level of a PhD (coded 6). When looking at company size, most of the sample ($n = 60$) worked for small companies (0-249 employees), while the rest ($n = 19$) worked at medium-sized enterprises (250-500 employees). Upon examining management responsibility, a third of the participants ($n = 24$) claimed to be part of upper management (coded 3), while the largest group ($n = 32$) belonged to lower or middle management (coded 2). A minority ($n = 23$) reported having no management responsibility (coded 1).

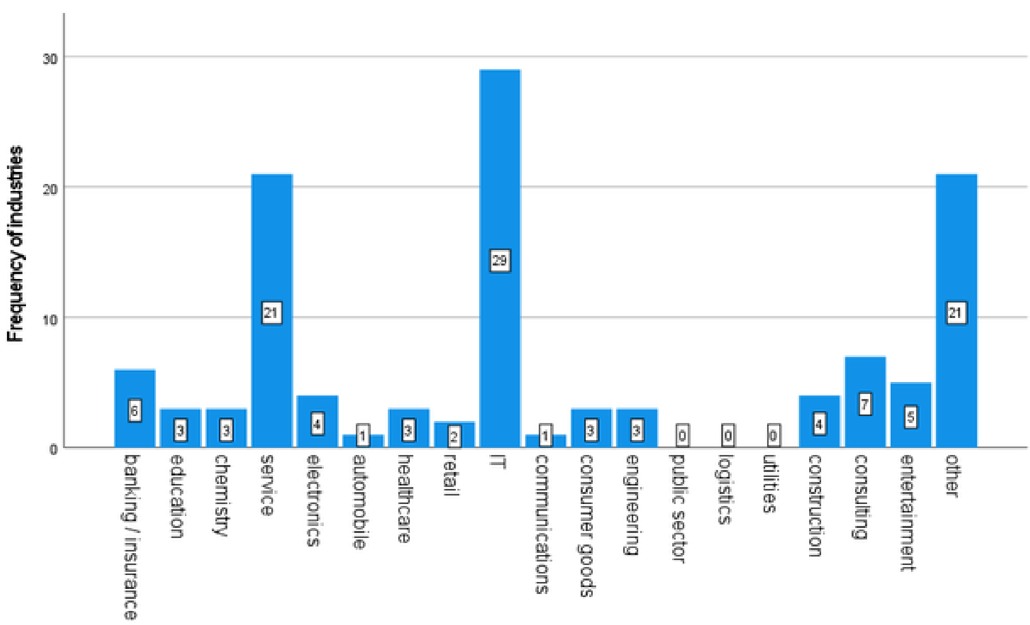
Figure 2 shows the frequency of industries reported by participants. Multiple selections were possible. When inspecting participants' industries, there were primarily IT ($n = 29$), while the service industry was runner-up ($n = 21$). The least number of participants reported working in automobile and communications ($n = 1$, each). No participants selected public sector, logistics, or utilities.

Measures

To capture instances of unrealistic optimism, participants rated motives of AI implementation for their own company and other companies on a five-point Likert scale, ranging from 1 (not a motive at all) to 5 (very important motive). Considered motives were cost reductions ($M_{own} = 3.24$, $M_{other} = 4.19$), efficiency gains ($M_{own} = 3.97$, $M_{other} = 4.48$), make better decisions ($M_{own} = 3.38$, $M_{other} = 3.54$), keeping up with the times ($M_{own} = 3.30$, $M_{other} = 3.78$), and new business models ($M_{own} = 3.38$, $M_{other} = 3.70$). Similarly, a five-point Likert scale, ranging from 1 (not an inhibitor at all) to 5 (very big inhibitor), measured inhibitors of AI implementation for their own company and other companies, including costs too high ($M_{own} = 3.23$, $M_{other} = 3.67$), fears of employees ($M_{own} = 2.86$, $M_{other} = 3.30$), excessive data protection requirements ($M_{own} = 3.42$, $M_{other} = 3.67$), lack of manpower (AI specialists) ($M_{own} = 3.71$, $M_{other} = 4.14$), lack of availability of algorithms ($M_{own} = 3.22$, $M_{other} = 3.54$), and lack of availability of data ($M_{own} = 3.24$, $M_{other} = 3.44$).

The study employed two approaches to measuring the expected AI impact. First, participants had to directly answer which impact they expect AI to have on HRM in their company and other companies on a five-point Likert scale, ranging from 1 (no impact) to 5 (very high impact) ($M_{own} =$

Figure 2. Frequency of industries (multiple selections possible)



2.38, M_{other} = 3.01). Second, they had to indirectly report their expected numerical impact via the expected change in the number of employees and share of tasks taken by AI within the next five years for their own company and other companies. For the report of the change in the number of employees, participants had to choose between values of -100% and +100% with steps of 20% and the option to report no estimate (M_{own} = 0.032, M_{other} = -0.085, n = 68). For the report of the change of share of tasks taken by AI, participants chose between values of 0% and 100% with steps of 10% and the option to report no estimate (M_{own} = 0.193, M_{other} = 0.282, n = 74). The last two questions regarding the indirect report of the expected numerical impact also occurred with the HRM division in focus: change in the number of employees (M_{own} = -0.074, M_{other} = -0.204, n = 57) and change of share of tasks taken by AI (M_{own} = 0.225, M_{other} = 0.309, n = 59).

Regarding the organizational dimension of the study, participants responded to AI as a good support in the following nine HRM subareas via a five-point Likert scale, ranging from 1 (do not agree at all) to 5 (fully agree). HRM subareas were strategic planning of HRM (M = 2.85), personnel search and acquisition (M = 3.71), personnel selection (M = 3.04), administrative processing of HRM activities (M = 3.94), communication with (potential) employees (M = 2.72), development and implementation of further training measures (M = 2.86), evaluation of employees (M = 2.23), development of measures for employee retention (M = 2.90), evaluation of the potential of managers (M = 2.65). Next to that, participants also reported on a five-point Likert scale ranging from 1 (not at all) to 5 (very strongly) how AI will influence the other business divisions IT (M = 4.16), administration (M = 3.84), finance/controlling (M = 3.94), marketing/sales (M = 3.30), and purchasing/production/logistics (M = 3.90).

Two questions were of focus upon the study's temporal dimension. On the one hand, participants reported their estimates of the importance of AI to their company for three points—today (M = 2.22), in five years (M = 3.14), and ten years (M = 3.91)—on a five-point Likert scale ranging from 1 (very low) to 5 (very high). On the other hand, participants evaluated the fruitfulness of the collaboration between humans and AI in the HRM subarea of recruiting for three points—today (M = 2.19), in five years (M = 3.03), and ten years (M = 3.42)—on a five-point Likert scale ranging from 1 (not fruitful at all) to 5 (very fruitful).

Dependent t-tests for mean value comparisons were carried out for two groups, presupposing a normal distribution as parametric tests. The normal distribution was assumed only for values made in percentages, as values from Likert scales tend to be not normally distributed (Norman, 2010). Non-parametric tests for dependent samples for two groups (Wilcoxon signed ranks-test) and for more than two groups (Friedman test) were carried out (Field, 2013).

RESULTS

Instances of Unrealistic Optimism

From Figure 3, one can conclude that for their own company, participants value efficiency gains (3.97) as the highest motive for AI implementation. They regard cost reductions (3.24) as the least important motive. Interestingly, the participants consider these two motives the highest for AI implementation for other companies. For every motive, the participants consider the motives to be of higher importance for other companies than for their own.

Figure 4 considers the inhibitors for AI implementation in their own company and in other companies mentioned by the survey participants. Participants see the highest inhibitor for their own company in a lack of manpower, especially AI specialists (3.71). For other companies, they value this inhibitor even higher (4.14). They consider the fears of employees (2.86) as the lowest inhibitor for their own company and other companies (3.30). Interestingly, they value every inhibitor more important for other companies than for their own company.

Figure 3. Motives for AI implementation in own and other companies

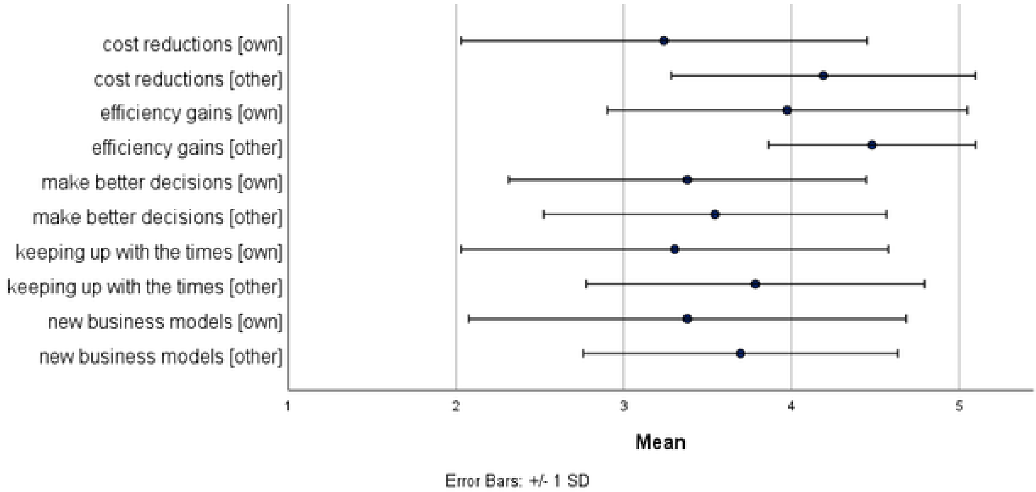
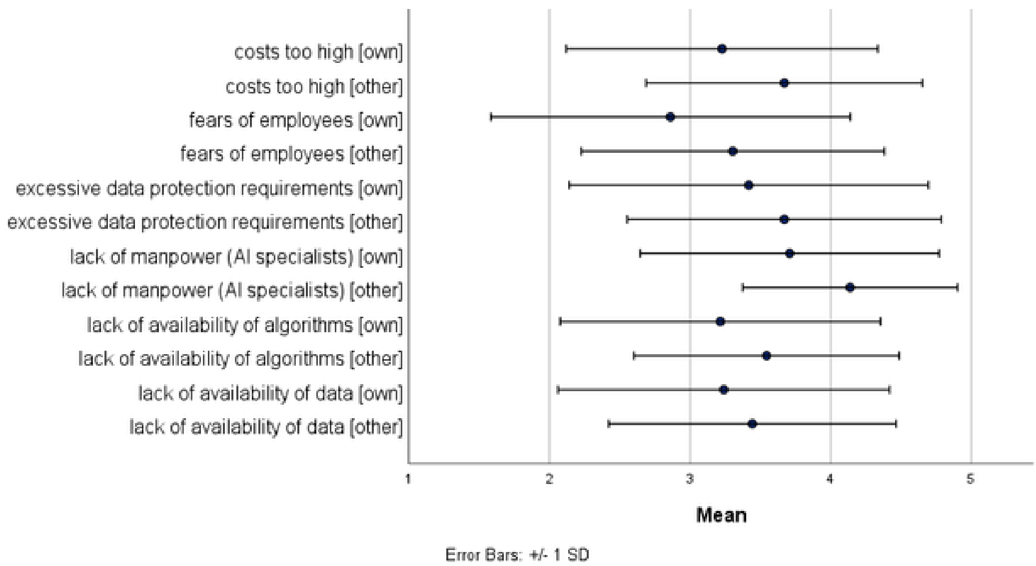


Figure 4. Inhibitors for AI implementation in own and other companies



From Figure 5, one may conclude the participants' evaluation of AI's impact on HRM in their own and other companies. More than one out of six respondents (17.7%) expect no impact from AI on their HRM division; virtually nobody (2.5%) thinks so for other companies' HRM divisions. Twice as many respondents see a high or very impact from AI for other companies (24.1%) than for their own company (12.7%). A Wilcoxon signed ranks test confirms these distributions to be statistically significantly different from each other (asymptotic significance < 0.001).

The following presents the expected numerical impact of AI on the participants' and other companies. Afterward, the perspective is put on HRM, in particular, with an additional view of an aggregated measure of AI impact.

Figure 5. AI impact on HRM in own and other companies

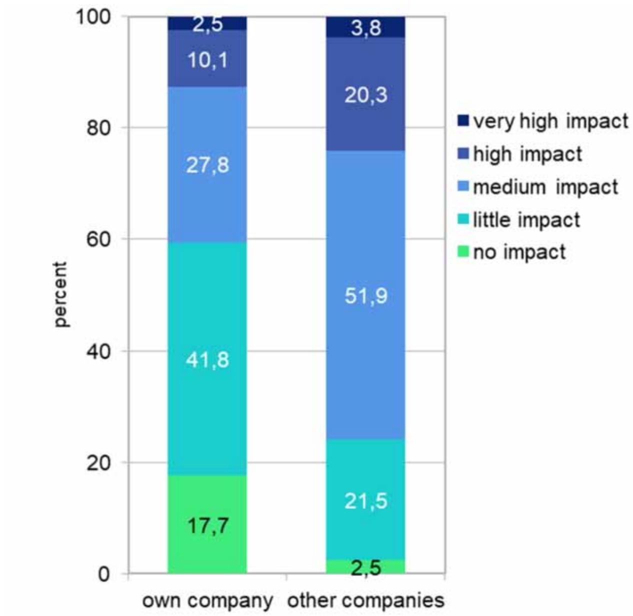


Table 2 shows the expected change in the number of employees and share of tasks taken by AI within the next five years for one's own company and other companies. Not all participants answered these questions ($n_{\#employees} = 68$, $n_{\%tasks} = 74$). While the survey respondents expect a slight increase (3.2%) in their number of employees through AI, they expect a decrease (8.5%) for other companies. Regarding the share of tasks that AI will cover within the next five years, participants estimate 19.3% for their own company and 28.2% for other companies on average. Paired samples t-tests confirm the statistical significance of these results ($p < 0.01$ and $p < 0.001$).

When looking at the evaluations regarding the HRM division in particular, the following evolutes. Like Table 2, the following Table 3 provides the expected change in the number of employees and share of tasks taken by AI within the next five years for one's own company and other companies in the HRM division. Not all participants answered these questions ($n_{\#employees} = 57$, $n_{\%tasks} = 59$). For the HRM division, the survey respondents expect a slight decrease (7.4%) in their number of employees

Table 2. Descriptive statistics of the dataset regarding the change in the number of employees and share of tasks taken by AI within the next five years for own and other companies, including test statistics

	Variable	Mean	N	Std. Dev.	Std. Error Mean	t	df	One-Sided p	Two-Sided p
Pair 1 (number of employees)	own company	0.032	68	0.2482	0.03010	3.059	67	0.002	0.003
	other companies	-0.085	68	0.2546	0.03088				
Pair 2 (share of tasks)	own company	0.193	74	0.1581	0.01839	-4.577	73	< 0.001	< 0.001
	other companies	0.282	74	0.1547	0.01798				

Table 3. Descriptive statistics of the dataset regarding the change in the number of employees and share of tasks taken by AI within the next five years for own and other companies in the HRM division, including test statistics

	Variable	Mean	N	Std. Dev.	Std. Error Mean	t	df	One-Sided p	Two-Sided p
Pair 1 (number of employees)	own company	-0.074	57	0.1587	0.02102	6.201	56	< 0.001	< 0.001
	other companies	-0.204	57	0.1668	0.0221				
Pair 2 (share of tasks)	own company	0.225	59	0.1384	0.01803	-5.291	58	< 0.001	< 0.001
	other companies	0.309	59	0.1329	0.01731				

through AI. They expect a more significant decrease of (20.4%) for other companies. Regarding the share of tasks that AI will cover within the next five years in the HRM division, participants estimate 22.5% for their own company and 30.9% for other companies on average. Paired samples t-tests confirm the significance of these results ($p < 0.001$ for both).

Organizational Dimension

In the overview of Figure 6, survey respondents rated nine HRM subareas regarding how well AI may support them within the next five years. For the subareas of administrative processing of HRM activities (3.94) and personnel search and acquisition (3.71), they show the highest rate of agreement, while they rate the evaluation of employees the lowest (2.23).

Figure 7 illustrates how the respondents value AI's influence on different business divisions from a very strong influence (5) to no influence at all (1). Respondents see the most substantial influence

Figure 6. Support via AI in HRM subareas

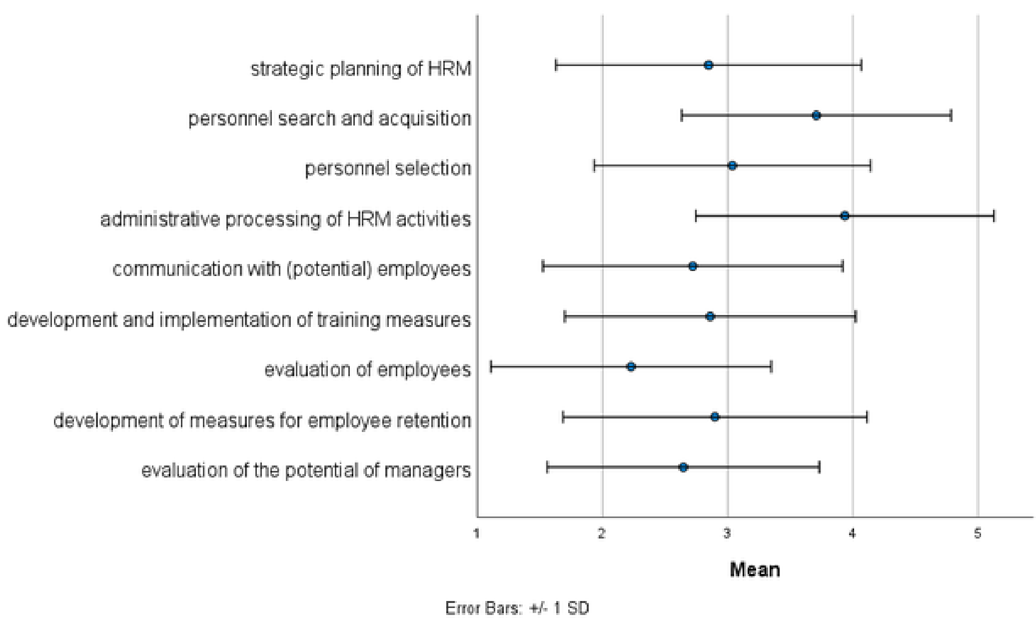
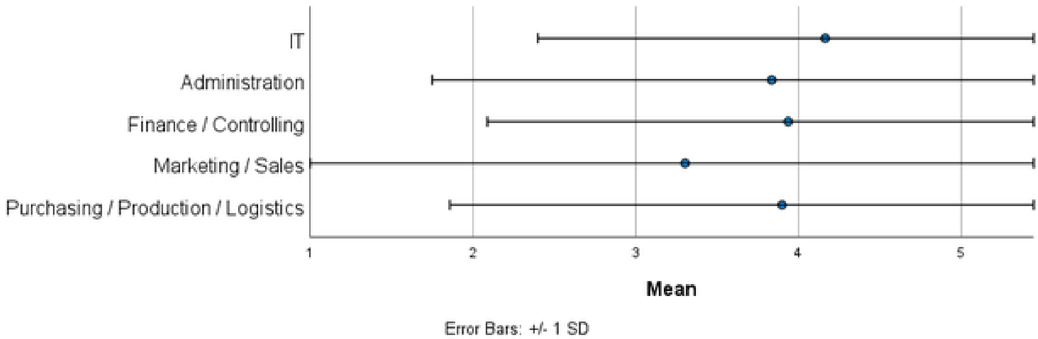


Figure 7. Impact of AI implementation on different business divisions



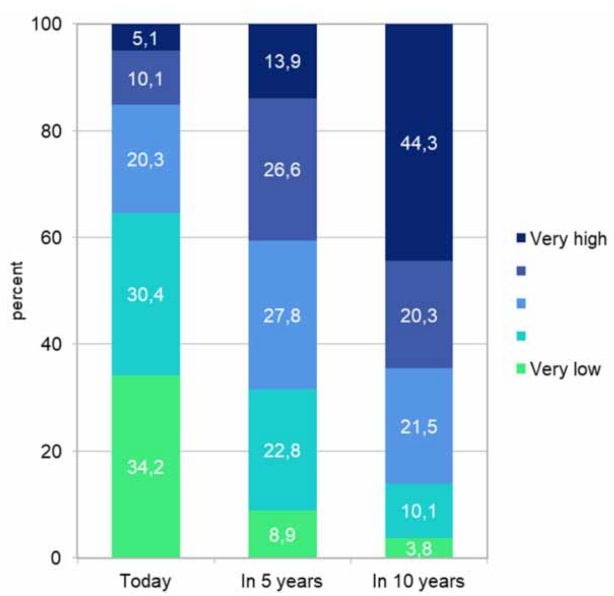
in IT (4.16). They see the lowest influence in the business division of marketing/sales (3.30). When performing related samples of Friedman's two-way analysis of variance by ranks, only marketing/sales, being lower than all other divisions, is statistically significant. The large error bars in Figure 7 indicate the participants' various estimates for this question.

Temporal Dimension

Figure 8 shows the participants' estimates of the importance of AI to their company for three points: today, in five years, and ten years. While a third concedes AI to be of very low importance in their company for today, only 3.8% do so regarding the estimate for ten years from now. Today, only one out of twenty participants regard AI to be of very high importance for their company, while ten years from now, almost half of the participants (44.3%) think so, indicating the expected growing importance of AI to participants' companies.

Looking at the state of current AI implementation in the participants' companies, roughly a quarter already implement AI (24.05%). Three out of ten companies have no ambitions to implement

Figure 8. Importance of AI for several points in time



AI in the near future (30.38%). The remainder will evaluate or plan for AI implementation in their company. Regarding the HRM division, only every fifth respondent explored AI in HRM (21.52%). Interestingly, nearly two-thirds of those had negative experiences (64.71%).

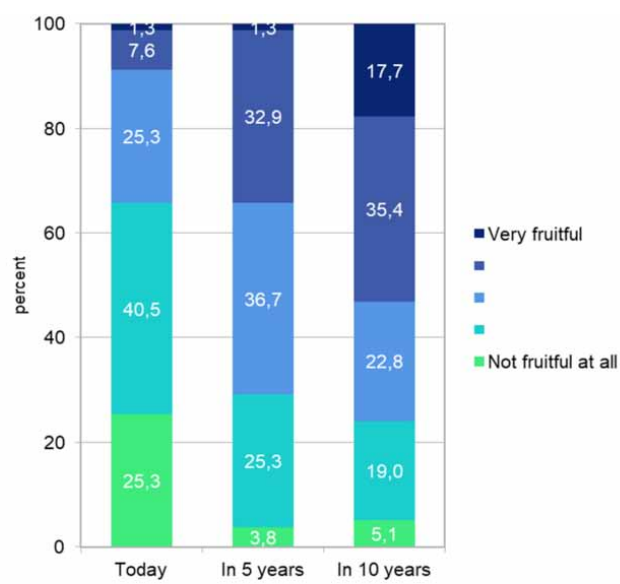
Focusing on the HRM division in particular, Figure 9 provides an overview of the participants' estimates regarding the fruitfulness of the collaboration between humans and AI in the specific HRM subarea of recruiting for today, in five years, and ten years. Upon inspecting the figure, one can see that a quarter (25.3%) evaluates the collaboration as not fruitful at all for today. In comparison, 17.7% consider the collaboration to be very fruitful ten years from now. This indicates a general trend toward more fruitful collaboration between humans and AI in the specific HRM subarea of recruiting.

CONCLUSION

In this study, the author investigated how HRM personnel perceive AI implementation, including motives and inhibitors in HRM (subareas) and AI impact in their company compared to other companies (concerning unrealistic optimism). To this end, the author conducted a structured questionnaire among a German national sample ($n = 79$) of HRM personnel from SME, unveiling instances of unrealistic optimism. The study also found insights regarding the organizational and temporal dimension of AI implementation in SME.

The theoretical and managerial contributions provided by this study are threefold. First, the study is the first, to the best of the author's knowledge, to investigate the unrealistic optimism of HRM personnel regarding AI in HRM when comparing their own company to other companies. Thus, it extends the research landscape and closes a gap, further highlighting the effects of AI in HRM (Budhwar et al., 2022). Participants expect AI to impact their company and HRM division unequally compared to other companies. Thus, HRM personnel do not only have different expectations regarding their business division (i.e., HRM), but for the level of the company. Herein, participants show no home bias for their own division. Regarding the motives and inhibitors for AI implementation, the survey participants rate every one of higher importance for other companies than for their own companies. Interestingly, the difference is most prominent for cost reductions, which participants rate as the

Figure 9. The fruitfulness of collaboration between humans and AI in recruiting for several points in time



second most important motive for other companies, but least important for their own company. This may manifest in participants attributing the cost leadership strategy to other companies more often than to their own (Porter, 1998). Participants expecting a higher impact from AI on HRM in other companies than in their own may show unrealistic optimism. This also corresponds to the motives and inhibitors for AI implementation being of higher relevance for other companies than for their own company, as participants assume other companies to be more impacted by AI, thus, getting more severely impacted by the benefits (motives) and dangers (inhibitors) of AI's advent.

Similarly, survey participants expected other companies' general employee numbers to decrease while they expected their own to increase through AI within the next five years. Obviously, this cannot occur for all companies, generating the interesting question: Which prediction will manifest? Academia researched both scenarios regarding the decrease (Chelliah, 2017) and increase (Daugherty et al., 2019) in the number of employees through the implementation of AI. For the HRM division in particular, participants expected a higher reduction in the number of employees for other companies than for their own company. Regarding the share of tasks taken over by AI for the whole company or the HRM division in particular within the next five years, respondents expected a higher share for other companies than for their own. These opinions indicate further instances of unrealistic optimism held by SME HRM personnel, as they rate their own company and HRM division as structurally different from other companies and their HRM division, in such a way that tasks may be taken over by AI more frequently in other companies. Thus, they assume other companies' tasks to be more suitable for AI, i.e., narrowly defined, data-rich, repeated tasks (Leprince-Ringuet, 2020), than their own.

Second, the author delivers preliminary insights into the anticipated imbalanced effects of AI on different HRM subareas and business divisions in SME. Thus, the author confirms the anticipated growing importance of AI. When examining the organizational dimension regarding the specific HRM areas, survey respondents see most AI support for administrative processing of HRM activities and personnel search. No clear conclusion can be made when focusing on AI's impact on business divisions other than HRM. Overall, the participants expect AI to substantially impact every business division, although slightly less in marketing/sales. This is in line with general expectations of AI as an essential technology of the 21st century (Buxmann & Schmidt, 2021). Upon inspecting the temporal dimension, study participants agree on the growing importance of AI over time and the rising degree of the fruitfulness of collaboration between humans and AI in recruiting over time.

Third, interested HRM practitioners from SME and beyond may also benefit from consulting this study. They could inspect which motives and inhibitors for AI implementation are ranked highest (lowest) by their peers to focus on those regarding their own AI implementation strategy. Additionally, HRM practitioners could compare the expected changes in the number of employees and share of tasks taken over by AI with their predictions to benchmark their estimates and adapt their AI implementation strategy.

LIMITATIONS AND FUTURE RESEARCH

Limitations of this study, leading to avenues for future research, include the selected division of HRM and the company intern perspective. First, researchers could inspect other divisions to broaden the picture of AI perception in SME. An investigation of the business division of marketing/sales would be promising, as the survey's participants expect a slightly lower impact of AI in this division. Focusing on HRM, possible extensions of this study may include switching the perspective from company intern to company extern. Like Dahm & Dregger (2019), one may focus on the applicants' perspective when surveying (Vrontis et al., 2022). In general, as Vrontis et al. (2022) note, research on AI in HRM is scarce and needs further examination. Variations of AI, such as explainable AI (XAI), could be of particular interest, as increased interpretability may add to user acceptance, alter user expectations about this technology, and reduce information asymmetry between the user and AI tool.

Second, the survey occurred at one point and featured a national sample from Germany. Follow-up studies could interview individuals at several points to uncover temporal changes in the AI in HRM perception in general and unrealistic optimism in particular. Including other languages and participants from other states could add further robustness to the presented results or shed light on cultural differences (Dahm & Dregger, 2019; Vrontis et al., 2022). Additionally, as several questions aimed at other companies in general, future research could distinguish between companies of similar industry and size and those with different attributes. Together, this would help get a clearer picture of specific expectations regarding SME compared to other companies.

Third and finally, participants' AI knowledge was heterogeneous. Information texts trying to mitigate differences and level participants' AI knowledge may have been longer. Future research could require respondents to approximate their technical knowledge or explicitly measure AI literacy by employing an objective measurement scale (Long & Magerko, 2020).

CONFLICT OF INTEREST

The author of this publication declares there is no conflict of interest.

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ENDNOTES

[1] Gender was coded with three options: male (coded 1); female (coded 2); and diverse (coded 3).

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