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To fear or not to fear – Human resource development professionals' positioning towards artificial intelligence with a focus on augmentation

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A B S T R A C T

Artificial intelligence (AI) has far-reaching implications for education. Within organizations, especially companies, human resource development (HRD) enables and supports learning processes among employees. In a similar way to teachers and lecturers, HRD professionals play an important role in implementing AI in HRD. However, there is a lack of quantitative empirical evidence about this process. The aim of this paper is to shed light on how HRD professionals position themselves with respect to AI. The concept of Davenport and Kirby's augmentation strategies, adapted to HRD, act as the theoretical background. The core idea of augmentation lies in human-AI collaboration. In our study, we empirically validate this concept of augmentation strategies and predict the extent to which HRD professionals pursue the five strategies: step in, step up, step forward, step aside, and step narrowly. The predictors are grouped into three areas: attitudes, competence beliefs, and goal orientation. HRD professionals (N = 330) from German-speaking countries act as the sample. Covariance based structural equation modeling (CB-SEM) and partial least squares structural equation modeling (PLS-SEM) act as the method for data analysis. The findings reveal the crucial impact of cognitive attitudes towards digitalization and AI anxiety when pursuing the augmentation strategies. AI competence beliefs are an important predictor for collaboration with AI. General digital competence beliefs can only indirectly predict the augmentation strategies. Implications for theory and practice are discussed.

"F-E-A-R has two meanings: 'Forget Everything And Run' or 'Face Everything And Rise.' The choice is yours." – Zig Ziglar (1926-2012).

1. Introduction

Digital transformation has far-reaching implications for education (Benvenuti et al., 2023; Harteis et al., 2020; Holmes et al., 2019; Ifenthaler & Seufert, 2022; Martin et al., 2024; OECD, 2021). Two waves can be distinguished in digital transformation (Wahlster, 2017; Seufert et al., 2021). In the first wave, data and processes are implemented in machine readable ways. Massive open online courses (MOOCs) are an example of the first wave of digitalization as learning takes place in a digital environment (Guggemos et al., 2022). The second wave of digitalization deals with the use of generated data relying on artificial intelligence (AI). AI can be described as a set of technologies that enable computers and machines to perform cognitive functions which usually require human intelligence (Haesevoets et al., 2021). For instance, the data generated through MOOC learning can be used for AI-powered prediction of learning achievement (Liu et al., 2022). Against this backdrop, the first wave of digitalization lays the ground for the second wave driven by AI. Not only schools (Martin et al., 2024) and higher education institutions (Crompton & Burke, 2023; Zawacki-Richter et al., 2019) are affected by AI, but also companies (Harteis et al., 2020; Ifenthaler & Seufert, 2022; Marsh et al., 2022; O'Neill et al., 2023). Within companies, human resource development (HRD) is responsible for enabling and supporting learning processes among employees. HRD can be defined as "any process or activity that, either initially or over the long term, has the potential to develop adults' work-based knowledge, expertise, productivity and satisfaction, whether for personal or group/team gain, or for the benefit of an organization, community, nation or, ultimately, the whole of humanity" (McLean & McLean, 2001, p. 322). AI yields several opportunities for HRD (Bhatt & Muduli, 2023; Ekuma, 2024; George & Thomas, 2019). These include the use of predictive analytics for talent development, personalized learning experiences, and automated evaluation of learning processes.

However, there is a lack of understanding about what drives the AI implementation process in HRD. Based on a review of the literature,

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Bhatt and Muduli (2023) claim that HRD professionals play an important role in successful AI integration, in particular their motivation to use AI. Moreover, the AI-related knowledge of HRD professionals has to be considered in AI integration (Ekuma, 2024). The important role of HRD professionals in the digital transformation of companies is analogous to the university and school context, where lecturers and teachers are the focus (Howard et al., 2021; Ng et al., 2023; Scherer et al., 2021).

When attempting to understand how the integration of AI into organizations occurs, the concept of the *augmentation strategies* of Davenport and Kirby (2016) has gained much attention in management research (Anthony et al., 2023; Krakowski et al., 2023; Raisch & Krakowski, 2021). Davenport and Kirby (2016) claim that knowledge workers, such as HRD professionals, can follow five mutually exclusive and collectively exhaustive strategies regarding AI. These strategies include *step narrowly* and *step forward*. If HRD professionals choose a *step narrowly* strategy, they would focus on tasks where AI cannot be used (in a profitable way), i.e., they would avoid AI use. An example could be top-management coaching where the use of AI may not be accepted. By choosing a *step forward* strategy, HRD professionals would participate in the development of (new) AI solutions in HRD, for instance, contributing to the development of an adaptive learning system.

Although the concept of augmentation strategies seems promising for HRD (Meier et al., 2021), there is a lack of quantitative empirical evidence about these strategies (Einola & Khoreva, 2023). An obvious reason may be that, to our knowledge, there is no measurement instrument available to capture the five augmentation strategies. Developing a measurement instrument, therefore, might be the first step towards quantitatively investigating the concept of augmentation strategies. It would also help to understand the relationship between the five augmentation strategies. Our first research question (RQ) is.

RQ1: How can the five augmentation strategies of Davenport and Kirby (2016) be measured in a reliable and valid way in the context of HRD?

To gain an understanding about concepts such as augmentation strategies, it is important to investigate what variables can predict them (Newman et al., 2007). Our second research question is.

RQ2: What are the individual level predictors of the extent to which HRD professionals pursue the five augmentation strategies?

To answer RQ2, we develop a conceptual model (Tondeur et al., 2021) of predictors. As we are focusing on the individual level, context factors such as the line of business or the country are not considered. In doing so, we aim to contribute to a better understanding regarding the implementation process of AI in HRD, specifically, and in education, in general.

The study at hand contributes to research on AI implementation in three ways. Firstly, it focuses on human-AI collaboration, rather than the substitution of humans (teachers, HRD professionals) by AI, which may be suitable for education (Brusilovsky, 2024; Molenaar, 2021). Secondly, it introduces the concept of augmentation strategies from management research and presents an instrument to capture these five strategies. Finally, it contributes to a better understanding of AI implementation in education by presenting a conceptual model that can predict the five augmentation strategies.

2. Review of the literature and conceptual framework

2.1. Human-AI collaboration

There is broad evidence that AI surpasses humans in many domains (Haesevoets et al., 2021). This is not only the case for complex games, such as AlphaGo, but also for real-life applications. For instance, Blohm et al. (2022) showed that AI, on average, achieves a higher investment performance when compared to the performance of business angels. However, the superiority of AI in some areas does not imply that AI will take over jobs on a large scale. This may also be the case for HRD (George & Thomas, 2019). Rather than focusing on substituting (HRD) professionals with AI, it may be worthwhile to investigate how humans and AI can collaborate (Joksimovic et al., 2023; Saghafian & Idan, 2024; Siemens et al., 2022; Wesche et al., 2022; Zirar et al., 2023). Such collaboration is associated with superior performance when compared to substitution (Daugherty & Wilson, 2018; Joksimovic et al., 2023; Raisch & Krakowski, 2021; Saghafian & Idan, 2024). Hybrid intelligence can act as the conceptual basis for this notion of human-AI collaboration (Dellermann et al., 2019; Knoth et al., 2024). Hybrid intelligence involves the combination of human intelligence and AI in complex problem solving in order to achieve superior results that neither could accomplish alone. In hybrid intelligence, humans act as teachers who train AI systems, and the AI systems can also learn from human input to improve their performance over time. This collaborative approach aims to overcome the current limitations of AI by leveraging the strengths of both human and machine intelligence. The complementary strengths of humans are flexibility, creativity, empathy, and intuition (Dellermann et al., 2019; Jarrahi, 2018; Krakowski et al., 2023). The complementary strengths of AI are pattern recognition, probabilistic reasoning, consistency, and the speed of machine intelligence (Dellermann et al., 2019; Jarrahi, 2018; Krakowski et al., 2023).

Empirical evidence lends support to the benefits of human-AI collaboration (Krakowski et al., 2023). Based on data from centaur chess tournaments (human players collaborate with AI to improve their gameplay), it showed that the driver for success in the game is the collaboration of human and AI. Successful centaur chess players rely on complementary capabilities to enhance the AI performance. For instance, they prompt the AI to deeply analyze specific positions. In centaur chess, the chess-playing ability of humans is no longer a valuable resource in terms of performance because it is inferior to AI. Leading players in centaur chess are frequently computer engineers with moderate chess skills.

Besides the benefits of human-AI collaboration from a conceptual and empirical point of view, it may also be in line with standards on the ethical use of AI. For the European Union, the Independent High-Level Expert Group on Artificial Intelligence (2019) presented ethics guidelines for trustworthy AI. These guidelines have been adapted to education (European Commission, 2022), which includes HRD. The standards stress the concept of human oversight as a mechanism to prevent AI from undermining human autonomy. In light of this, AI in education that acts in an entirely autonomous way might not be in line with ethical standards. Rather, a human-AI collaboration may be conducive to meet these standards (Adams et al., 2023).

2.2. Augmentation strategies

Augmentation, as described by Davenport and Kirby (2015, 2016), represents a concept that specifies human-AI collaboration. The proposed five augmentation strategies are designed to be mutually exclusive and collectively exhaustive. Against this backdrop, the five strategies yield a more nuanced picture about AI integration in comparison to binary concepts of AI use (yes/no). Table 1 presents these five augmentation strategies adapted to the context of HRD. As Davenport and Kirby (2016) concede, the *step narrowly* strategy is a special case because AI is avoided. *Step up* is conceived as a management strategy that may not focus on the personal use of AI or collaboration with it. Rather, the focus is on the bigger picture, i.e., how AI can be integrated into the strategy of the organization. Following a *step aside* strategy, knowledge workers might rely on AI but use it as a tool rather than as a partner. *Step in* and *step forward* address active collaboration with AI. *Step in*, therefore, may be at the core of augmentation (Davenport & Kirby, 2016). *Step forward*, as the name implies, goes even further as it deals with bringing the field of AI in HRD forward.

Table 1
The augmentation strategies of Davenport and Kirby (2016) adapted to HRD (Meier et al., 2021).

Augmentation strategy: basic idea	Description	Example in HRD
Step in: Collaborate with AI	■ Be knowledgeable about specific AI (and their limitations) ■ Work productively with specific AI (and perhaps also train algorithms) ■ Provide feedback to developers for further improvement	Develop deep expertise in learning analytics and recommendation algorithms for improved recommendation system for digital learning content
Step up: Evaluate and manage AI	■ Evaluate AI and the results they achieve ■ Decide where to employ which AI and in what way (and where not to) ■ Manage business processes involving AI	Orchestrate decisions on the ethical use of personalized user data in order to improve intelligent learning systems
Step forward: Develop AI	■ Participate in the development of AI and their application to new domains	Contribute technical expertise to the development of new intelligent tools, e.g., chatbots helping to compile an individual development plan
Step aside: Apply specific human capabilities (possibly building on the output of AI)	■ Focus on tasks that go beyond information processing and that require specific human competencies, such as demonstrating empathy, motivating others, or creative problem solving	Provide coaching for workplace learning supported by appropriate digital tools and personalized, intelligent (learning) systems
Step narrowly: Specialize and avoid AI	■ Focus on and specialize in a niche where the use of AI is not possible (in a profitable way)	Facilitate design thinking sessions on solutions for a culture of learning and innovation

2.3. Predictors of augmentation strategies

2.3.1. Conceptual model

From an individual's point of view, the augmentation strategies can be regarded as (intended) behavior. Therefore, the theory of planned behavior (Ajzen, 1991) can be useful as a conceptual basis for predicting them. As the background of technology acceptance models, it has contributed to the understanding of technology integration within education (Scherer et al., 2019). In the context at hand, the theory of planned behavior would imply that attitudes, the subjective norm, and perceived behavioral control can predict the extent to which HRD professionals pursue the augmentation strategies. Concerning attitudes, both cognitive and affective elements can be distinguished (Ajzen, 2001; Suseno et al., 2022).

A further model that predicts technology implementation in education is the Will Skill Tool (WST) model (Knezek & Christensen, 2016; Tondeur et al., 2021). *Will* can be defined as "a positive attitude toward the use of technology in instruction", *skill* as "the ability to use and experience technology", and *tool* as "availability, accessibility and extent of use of technology" (Knezek & Christensen, 2016, p. 311). Rubach et al. (2023) argue, based on motivation theory, that goal orientation, competence beliefs, and subjective task values can predict technology integration. Since the tool component of the WST model may lack the individual control of HRD professionals, we do not consider it in our conceptual model. This is also the case for the social norm component of the theory of planned behavior.

In summary, we hypothesize from the individual HRD professional's perspective that attitudes (will, task value), competence beliefs (skill, perceived behavioral control), and goal orientation predict the pursuit of the augmentation strategies.

Based on this conceptual model, we develop hypotheses. By nature, the five augmentation strategies vary in the way in which they implement AI, ranging from *step narrowly* to *step forward*. Against this backdrop, we develop undirected hypotheses.

2.3.2. Cognitive attitudes towards digitalization

The cognitive component of attitudes can be defined as "an individual's thoughts, beliefs, ideas or perceptual responses about an object or subject" (Suseno et al., 2022, p. 1213). In our case, the object of interest is digital transformation. As pointed out, AI is part of a digitalization process.[1] *Cognitive attitudes* may be particularly important in an innovative business environment. Drawing from entrepreneurship research, a trade-off between advantages and disadvantages may be an important facet (Liñán & Chen, 2009). Concerning entrepreneurial intentions, personal attitudes are the best predictor for intended behavior (Liñán & Chen, 2009). The important role of attitude is acknowledged in technology acceptance research (Scherer & Teo, 2019). This is also the case for AI acceptance among teachers (Al Darayseh, 2023; Ayanwale et al., 2022) and human resource managers (Suseno et al., 2022). We hypothesize.

H1. Cognitive attitudes towards digitalization predict the extent to which HRD professionals pursue the five augmentation strategies.

2.3.3. Anxiety towards AI

Research into technology anxiety has come a long way (Wilson et al., 2023). Recently, several studies have addressed AI anxiety as a specific form of technology anxiety. AI anxiety can be defined as the fear, worry, or unease experienced by individuals in response to AI, its capabilities, and potential implications (Li & Huang, 2020). In light of this, it may address the affective component of attitudes. AI in the realm of companies is particularly associated with negative consequences, such as AI replacing jobs (Makarius et al., 2020; Zirar et al., 2023). Moreover, the rapid advancements in AI technology and the need to continuously learn new skills to keep up with AI developments can lead to anxiety among individuals (Brougham & Haar, 2018; Li & Huang, 2020). Overall, anxiety can act as a major force in creating apprehension and distress, which may influence the intention to implement AI (Suseno et al., 2022). However, anxiety may also have positive effects. Employees with higher levels of AI anxiety may exhibit greater motivation and persistence in learning new professional skills. Therefore, AI anxiety may contribute to positive outcomes in terms of professional skill development and adaptation to changing job requirements (Wang & Wang, 2022). Overall, we hypothesize.

H2. AI anxiety predicts the extent to which HRD professionals pursue the five augmentation strategies.

2.3.4. Competence beliefs

This section discusses the kind of competence beliefs that may predict the extent to which HRD professionals pursue the five augmentation strategies.

The DigComp framework of the European Union (Vuorikari et al., 2022) defines digital competence as "confident, critical and responsible use of, and engagement with, digital technologies for learning, at work, and for participation in society" (European Commission, 2019, p. 10). The DigComp framework comprises five components that constitute digital competence: information and data literacy, communication and collaboration, digital content creation, safety, and problem solving. An overarching factor of these five components can be regarded as *general basic information and communication technology competence beliefs* (Rubach et al., 2023). Drawing from the TPACK framework, such

[1] A pragmatic reason for considering digitalization, in general, instead of specifically in AI was also due to the fact that in a pretest, it was not possible to empirically separate the two constructs.

generic digital competence beliefs may be associated with technology knowledge (TK) (Koehler et al., 2013), i.e., they are not geared towards a specific domain such as HRD.

In the *swiss competence centre for innovations in learning* (scil) innovation circle (Meier et al., 2021), HRD experts discussed relevant AI applications in their field. Examples are the (semi) automated creation of learning content with AI-based tools, intelligent tutors, analytics for evaluation and quality development, and dialogue-based tutorial systems (chatbots for learning). These applications are well in line with current literature reviews (in HRD) (Bhatt & Muduli, 2023; Ekuma, 2024; Martin et al., 2024). Analogous to digital competence beliefs, we aim to capture AI competence beliefs with an overarching factor, i.e., the extent to which HRD professionals believe they are knowledgeable in representative AI applications in HRD. Referring to the TPACK framework, this kind of competence belief might correspond with TPACK (Celik, 2023): it addresses HRD (content) AI applications (technology) in the realm of education (pedagogy).

Competence beliefs in the area of the first wave of digitalization, i.e., digital competence beliefs, may be the prerequisite for competence beliefs in the realm of the second wave of digitalization (Benvenuti et al., 2023), i.e., AI competence beliefs. For instance, low competence beliefs in the area of digital content creation may be associated with even lower competence beliefs in the more advanced use of AI for content creation (in HRD). In line with TPACK research (Guggemos & Seufert, 2021), we hypothesize that digital competence beliefs indirectly predict the augmentation strategies mediated by AI competence beliefs. Overall, we hypothesize.

H3. AI competence beliefs predict the extent to which HRD professionals pursue the five augmentation strategies.

H4. Digital competence beliefs indirectly (mediated by AI competence beliefs) predict the extent to which HRD professionals pursue the five augmentation strategies.

2.3.5. Goal orientation

Other than teachers who might primarily pursue educational goals such as the personal growth of students, HRD professionals have also to consider the business perspective. The relationship between educational and financial goals is complex and multifaceted (Alagaraja, 2013; Short & Harris, 2010; van Rooij & Merkebu, 2015). Based on her review of the literature, Alagaraja (2013) concluded that HRD is important for the performance of an organization. Hence, the joint pursuit of educational and financial goals may not be contradictory. Following Harteis (2004), however, it may be necessary to distinguish between short- and long-term financial goal orientation. Assuming that AI yields benefits for HRD (Bhatt & Muduli, 2023; Ekuma, 2024; George & Thomas, 2019), a short-term financial goal orientation may be detrimental to achieving educational and long-term financial goals. If organizations introduce AI, substantial resources, e.g., time and money, are necessary at the beginning of the process (Raisch & Krakowski, 2021). This outflow of resources (investment) leads, with an unknown probability, to a return in the future, e.g., better trained employees or increased financial performance. A purely short-term financial goal orientation, i.e., a timeframe of less than one financial year, would prevent investment in AI because the potential benefits occur beyond this period of time. The benefits may be realized in the long run and contribute to long-term financial goals (>5 years [Ma & Tayles, 2009]). Overall, the goal orientation seems to play a crucial role in understanding AI implementation. For a successful AI integration, a long-term orientation may be conducive (Jarrahi, 2018).

From an individual perspective, goal setting has been shown to be effective for behavior change (Epton et al., 2017). Moreover, short-term goal orientation may lead individuals to prioritize immediate gratification over long-term success. This can result in a lack of persistence in pursuing more challenging, but ultimately more rewarding, long-term goals (Wang & Ford, 2020). Overall, we hypothesize.

H5. The pursuit of educational goals predicts the extent to which HRD professionals follow the five augmentation strategies.

H6. The pursuit of short-term financial goals predicts the extent to which HRD professionals follow the five augmentation strategies.

H7. Long-term financial goal orientation predicts the extent to which HRD professionals pursue the five augmentation strategies.

2.3.6. Summary

Fig. 1 summarizes our conceptual model for predicting the five augmentation strategies and the hypotheses grouped according to three areas: attitudes, competence beliefs, and goal orientation.

3. Method

3.1. Measurement instruments

All items can be found in Appendix.

Concerning the five augmentation strategies, members of the scil innovation circle (see section 2.3.4) developed self-assessment items. This may ensure content validity. Since the concept of augmentation strategies is fairly new, the items were preceded by an explanation and overview of the strategies. This comprises the content of Table 1 (in German).

The items on cognitive attitudes and AI anxiety are taken from Seufert et al. (2019) in the context of teachers and adapted to HRD. The development process was informed by the recommendations for the theory of planned behavior questionnaires (Ajzen, 2006). Concerning AI anxiety, we focus on the primarily job-related facets that are of concern for the individual HRD professional. Therefore, we do not consider aspects such as fear about negative societal impact or about human extinction by AI (Li & Huang, 2020). This approach is in line with Ayanwale et al. (2022).

To capture HRD professionals' digital competences beliefs, we use the instrument of Seufert et al. (2019) from the context of teachers and adapted it to HRD. The conceptual basis is the DigComp framework (Vuorikari et al., 2022). Concerning AI competence beliefs, we relied on the work of the scil innovation circle that discussed relevant AI applications in HRD. We specify both measurement instruments (digital competence beliefs and AI competence beliefs) as reflective. Hence, we assume that we draw representative and interchangeable items from, in principle, an infinite pool of possible items.

The items on educational goal orientation are based on the work of Harteis (2004), who claims that orientation towards educational goals manifests in the holistic development of employees, as well as supporting and enabling competence development among employees. To operationalize goal orientation, we rely on single item measures because we clearly define a short-term financial goal orientation with a timeframe of less than one financial year and a long-term orientation with a timeframe of more than five years (Ma & Tayles, 2009).

3.2. Data analysis

To answer RQ1, we utilize confirmatory factor analysis because the concept of *augmentation strategies* implies a five-dimensional factor structure. We use a robust maximum likelihood estimator (MLR). The following values serve as cut-off values (van de Schoot et al., 2012): acceptable fit: CFI and TLI >0.90, RMSEA <0.08, SRMR <0.10; good fit: CFI and TLI >0.95, RMSEA <0.05, SRMR <0.06.

To check for substantial local model misspecifications, we also evaluate the expected parameter change in combination with the modification index (Saris et al., 2009). Based on this, we compare our hypothesized model with reasonable competing models using the information criteria SPBIC and HBIC (Lin et al., 2017). We utilize R 4.4.0 (R Core Team, 2023), namely, the lavaan package 0.6–17 (Rosseel, 2012).

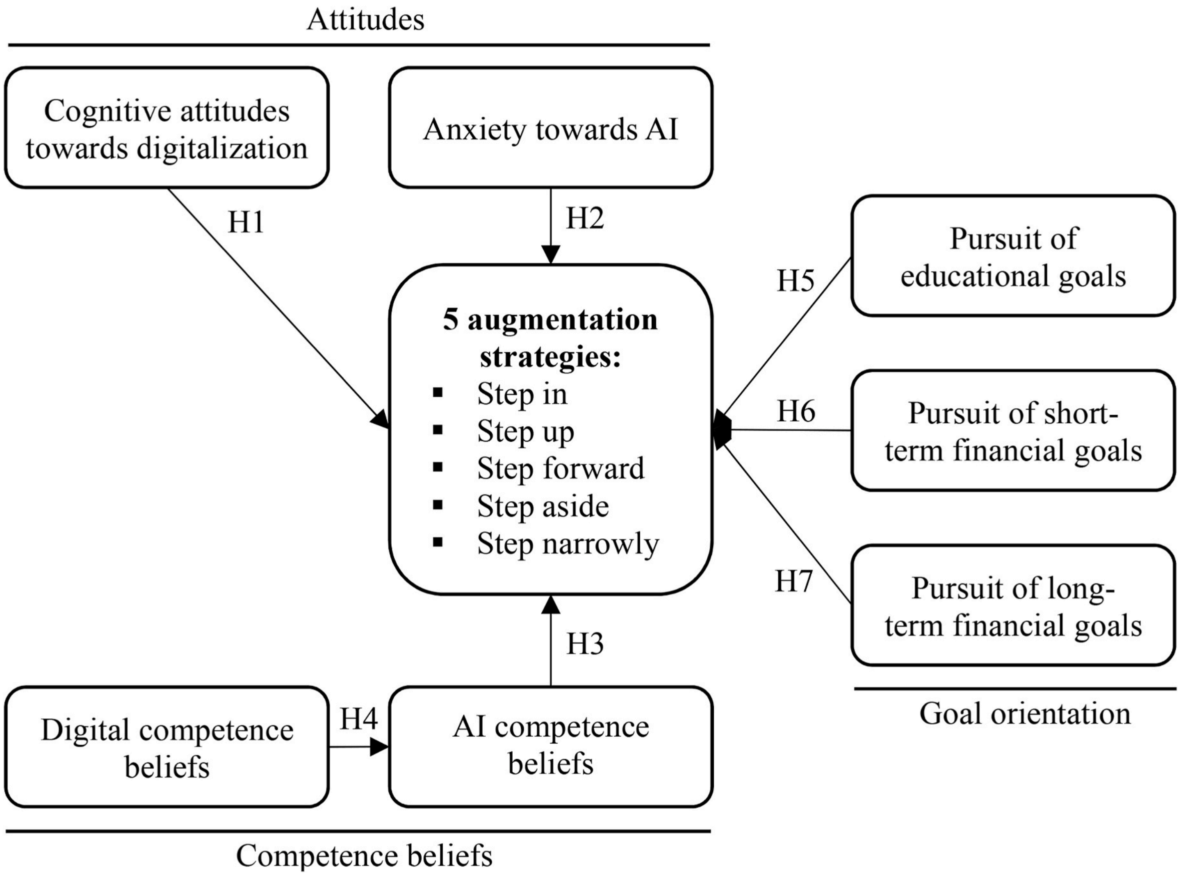

Fig. 1. Conceptual model for predicting the five augmentation strategies.

To answer RQ2, we use partial least squares structural equation modeling (PLS-SEM) by means of SMART-PLS 4.1.0.1 (Ringle et al., 2024). PLS-SEM is a suitable method for prediction-oriented HRD research (Legate et al., 2023). In particular, we prefer the use of PLS-SEM to covariance based structural equation modeling (CB-SEM) for answering RQ2 based on the following reasons. Although we specify competence beliefs as a reflective measurement instrument (e.g., Rubach & Lazarides, 2021), this construct may also be regarded as formative (Stadler et al., 2021). Indeed, a confirmatory tetrad analysis (Gudergan et al., 2008) indicates that the items are not entirely interchangeable. However, Sarstedt et al. (2016) showed that PLS-SEM, rather than CB-SEM, is fairly robust in specifying a formative instrument as a reflective one. The aim of RQ2 is prediction; PLS-SEM is a causal-predictive technique, i.e., the model is expected to show high predictive accuracy, while at the same time being grounded in hypotheses about causal relationships (Chin et al., 2020).

The quality of PLS-SEM is evaluated in two steps. First, the measurement instruments are evaluated, followed by the structural model. In this regard, our evaluation procedure follows Sarstedt et al. (2023). First, we assess our (solely reflective) measurement models as follows: internal consistency reliability is evaluated using ρA, which may be a good compromise between Cronbach's alpha (too conservative) and composite reliability (too liberal). It should be higher than 0.70 and lower than 0.95. All factor loadings should be above 0.708. Convergent validity may be ensured if the average variance extracted (AVE) is higher than 0.50; discriminant validity may be established if the heterotrait–monotrait ratio (HTMT) is smaller than 0.85. Concerning the structural model, the variance inflation factor (VIF) for all paths should be lower than three. Moreover, the in-sample model fit and the out-of-sample predictive power have to be assessed. The coefficient of determination R^2 is suitable for assessing the in-sample explanatory power. PLSpredict can be used to assess the out-of-sample predictive power, i.e., it could be evaluated if our conceptual model is able to predict the augmentation strategies beyond our sample. To this end, training and holdout samples are formed. The parameter estimates from the training sample are used to predict the values for the cases from the holdout sample. First, it is checked whether Q^2predict is larger than zero for all indicators. This would imply a more accurate prediction of our model in comparison to simply taking the means from the training sample. Afterwards, we focus on the target construct of our model, i.e., the five augmentation strategies, and check if the root mean square error of the PLS-SEM prediction is smaller than a prediction by a linear regression model. If this is the case for six (ten) out of the ten augmentation strategy items, this would imply a medium (high) out-of-sample predictive power. The cross-validated predictive ability test (CVPAT) offers a significance test for this procedure. It calculates the model's prediction error, which determines the average loss value. As a conservative benchmark, we compare the average loss value of a linear model prediction with that of our PLS prediction for all five augmentation strategies.

3.3. Sample

The data collection complies with the ethical standards of the University of St.Gallen. We collected data in collaboration with the German Association for Human Resource Management, which advertised our survey in its newsletters to its members. This approach yielded a sample of 330 participants from German-speaking countries. Based on Mahalanobis distances and an inspection of the data, we decided not to exclude any participants as outliers. The data contain 4.4% of missing values. We use regression imputation (mice package 3.16.0 [van Buuren & Groothuis-Oudshoorn, 2011]) with n = 10 imputations. Regression imputation has been shown as superior to all other methods, e.g., mean replacement, in the PLS-SEM context (Amusa & Hossana, 2024). Table 2 reports the characteristics of our sample. Compared with available data for Germany, the characteristics are, in general, well in line with the distribution in HRD, e.g., in terms of gender distribution (Bach et al., 2022). Companies with more than 999 employees (67.2%), however, are overrepresented in our sample. The reason for this may be our method of data collection. Employees from large companies may be more likely to be members of professional associations such as the German Association for Human Resource Management, and, therefore, such companies may be disproportionately high in our sample.

4. Results

4.1. Assessment of the measurement instrument

4.1.1. Augmentation strategies (RQ1)

The fit of our measurement model for the five augmentation strategies is decent: SB-$\chi^2(26) = 52.9$, $p = 0.001$, CFI = 0.969, TLI = 0.947, RMSEA = 0.063, SRMR = 0.030, SPBIC = 8464, HBIC = 8397. Besides this, convergent and discriminant validity as well as internal consistency reliability is ensured: AVE >0.571, HTMT <0.688, and McDonalds Omega total >0.727. Modification indices indicate that there may be a slight overlap of the *step in* and *step forward* strategies. However, combining these two strategies to make one factor decreased the fit of the model in such a way that it does not compensate for the reduced model complexity: $\Delta\chi^2(4)= 39.9$, $p < 0.001$, SPBIC = 8527, HBIC = 8469. Overall, we can positively answer RQ1: it is possible to measure the five augmentation strategies in a valid and reliable way in HRD.

Table 2
Characteristics of the sample (N = 330).

Criterion	Manifestation	Frequency	%
Gender	Female	219	66.4
	Male	110	33.3
	other	1	0.3
Age	≤27 years	18	5.4
	>27 and ≤ 35 years	64	19.4
	>35 and ≤ 44 years	87	26.4
	>44 and ≤ 52 years	90	27.3
	>52 years	71	21.5
Degree	Below Bachelor	38	11.5
	Bachelor	49	14.8
	Master	222	67.3
	PhD	21	6.4
Position	Clerk	181	54.8
	Manager	149	45.2
Company size	≤50 employees	17	5.2
	>50 and ≤ 499 employees	57	17.3
	>499 and ≤ 999 employees	34	10.3
	>999 and ≤ 4999 employees	92	27.9
	>4999 and ≤ 9999 employees	34	10.3
	>9999 and ≤ 49,999 employees	57	17.3
	>49,999 employees	39	11.7
Location of headquarters	Germany	246	74.5
	Austria	8	2.5
	Switzerland	64	19.4
	others	12	3.6
Business model	Business to business (B2B)	140	42.4
	Business to customer (B2C)	101	30.6
	B2B and B2C	89	27.0
Line of business (with a share >5%)	Manufacturing	67	20.3
	Finance and Insurance	44	13.3
	Administration	39	11.8
	Provision of other services	34	10.3
	Health and social services	24	7.3
	Provision of other business services	20	6.1
	Transport and warehousing	20	6.1

4.1.2. All measurement instruments

Table 3 summarizes the evaluation of all measurement instruments (including the five augmentation strategies) using the PLS-SEM approach. As can be seen from Table 3, the measurement instrument is sound: ρa >0.734, AVE >0.550, HTMT <0.688 (95%-CI [0.552, 0809]). The factor loadings (see Table in the Appendix) are in general above 0.708. The exceptions are two items pertaining to digital competence beliefs with standardized factor loadings of 0.678 (item 8) and 0.632 (item 9). Since convergent validity is ensured (AVE = 0.550) and the items are based on the DigComp framework, we decided to proceed with a single factor for digital competence beliefs. However, we will come back to this in the section on robustness checks.

4.2. Structural model (RQ2)

All variance inflation factors (VIF) are below 1.270. Therefore, collinearity is not an issue. Q^2-predict is larger than zero for all items of the augmentation strategies. Moreover, the PLS-SEM root mean square error is smaller than that of the linear regression model in seven out of ten augmentation strategy items. This indicates a medium out-of-sample predictive power. For *step up* and *step narrowly*, CVPAT indicates that the PLS prediction loss value is not significantly lower than that of a linear regression model: $p = 0.099$ and $p = 0.073$, respectively. For all other augmentation strategies, the PLS prediction is significantly better than that of a linear model at the 1% level. Overall, our PLS model beats a linear regression model in terms of out-of-sample predictive power ($p < 0.001$). In summary, our conceptual model may be useful for predicting augmentation strategies beyond our sample. Table 4 reports the paths of the structural model.

5. Post hoc power analysis and robustness checks

Concerning RQ1, we are able to detect a misspecified model (RMSEA >0.08) with a probability of 81.8% at the 5% significance level (package semPower: Moshagen & Bader, 2023). In terms of RQ2, as suggested by Sarstedt (2023), we used the inverted square root method to determine the achieved power (Kock & Hadaya, 2018). We are able to detect a standardized path coefficient of 0.137 with a power of 80% at the 5% significance level. The power of our study may be high enough to detect practically meaningful paths (Kock & Hadaya, 2018).

Vaithilingam et al. (2024) suggest the following robustness checks to demonstrate the soundness of PLS-SEM findings: evaluation of data normality, as well as addressing endogeneity, unobserved heterogeneity, and nonlinearity.

As can be seen from the Appendix, our data are not normally distributed. Although PLS-SEM is fairly robust against violations of normality, our data may exceed the acceptable levels for kurtosis (Vaithilingam et al., 2024). To check the robustness of our results, we extracted the PLS-SEM latent variable scores and used them in outlier robust linear regression models (SMDM estimation: Koller & Stahel, 2011). As expected, multivariate outliers may not be the reason for the, in parts, high kurtosis. The robust regression models, however, confirmed our findings based on PLS-SEM. Hence, non-normality of the data may not bias our reported results.

To check for unobserved heterogeneity, we performed a predicted oriented segmentation and a finite mixture segmentation. The former segmentation did not converge and the latter yielded inconclusive results. As suggested, we relied on the information criteria AIC3 and CAIC, complemented with BIC, to select the optimal model (Sarstedt et al., 2011). For the one-class solution we found AIC3 = 5308, CAIC = 5449, and BIC = 5412; for the two-class solution AIC3 = 5216, CAIC = 5501, and BIC = 5426; for the three-class solution AIC3 = 5161, CAIC = 5590, and BIC = 5477. All other multi-class solutions yielded higher information criteria (for AIC3). Except for AIC3, the one-class solution seems to be the best trade-off between precision and parsimony. Besides this, we checked to see if multiple-class solutions could be meaningful from a

Table 3
Reliability and validity assessment of the measurement instrument as well as correlation among constructs (N = 330).

	Construct	ρa	AVE	Correlation among constructs above diagonal, HTMT below diagonal											
				(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Cognitive attitudes towards digitalization	0.842	0.737	1	**−0.257**	**0.381**	**0.552**	0.129	0.116	0.100	**0.323**	**0.288**	**0.264**	**0.221**	−0.090
(2)	Anxiety towards AI	0.796	0.750	0.307	1	−0.052	**−0.139**	**−0.125**	0.005	−0.103	0.026	0.006	0.016	−0.017	**0.152**
(3)	AI competence beliefs	0.914	0.659	0.436	0.073	1	**0.515**	**0.139**	0.075	**0.174**	**0.311**	**0.222**	**0.323**	0.110	−0.057
(4)	Digital competence beliefs	0.839	0.550	0.654	0.177	0.584	1	0.136	0.040	**0.178**	**0.225**	**0.205**	**0.287**	0.090	−0.023
(5)	Pursuit of educational goals	0.789	0.823	0.157	0.180	0.166	0.188	1	0.081	**0.349**	**0.196**	**0.132**	**0.151**	**0.463**	0.024
(6)	Pursuit of short-term financial goals	–	–	0.135	0.016	0.079	0.092	0.089	1	**0.156**	0.100	0.038	0.010	**0.158**	**0.234**
(7)	Pursuit of long-term financial goals	–	–	0.113	0.133	0.183	0.191	0.395	0.156	1	**0.231**	**0.147**	**0.283**	**0.187**	**0.138**
(8)	Step in	0.735	0.787	0.418	0.041	0.379	0.287	0.261	0.119	0.270	1	**0.534**	**0.538**	**0.278**	−0.030
(9)	Step up	0.893	0.903	0.332	0.021	0.244	0.238	0.159	0.039	0.155	0.664	1	**0.521**	**0.335**	0.046
(10)	Step forward	0.841	0.863	0.313	0.025	0.367	0.343	0.187	0.051	0.309	0.687	0.601	1	**0.277**	0.038
(11)	Step aside	0.734	0.782	0.294	0.047	0.155	0.208	0.608	0.182	0.224	0.394	0.424	0.361	1	0.015
(12)	Step narrowly	0.779	0.818	0.113	0.201	0.077	0.060	0.057	0.265	0.155	0.066	0.055	0.053	0.048	1

Note. Figures in bold indicate significant correlations at the 5% level (2-sided). Standard errors based on percentile bootstrapping (n = 10,000). ρa = measure for internal consistency reliability, AVE = average variance extracted, HTMT = heterotrait–monotrait ratio.

Table 4
Standardized path coefficients and coefficient of determination (N = 330).

Independent variables	Dependent variables – augmentation strategies				
	In	Up	Forward	Aside	Narrowly
Cognitive attitudes towards digitalization	**0.258** [0.134, 0.381]	**0.257** [0.125, 0.381]	**0.189** [0.052, 0.316]	**0.183** [0.061, 0.305]	−0.068 [-0.194, 0.046]
Anxiety towards AI	**0.129** [0.016, 0.230]	0.095 [-0.025, 0.199]	0.105 [-0.007, 0.205]	0.085 [-0.039, 0.191]	**0.144** [0.025, 0.253]
AI competence beliefs	**0.178** [0.062, 0.295]	0.105 [-0.008, 0.217]	**0.215** [0.104, 0.327]	−0.026 [-0.130, 0.081]	−0.063 [-0.177, 0.052]
Digital competence beliefs → AI competence beliefs → augmentation strategies (indirect effect)	**0.091** [0.031, 0.158]	0.054 [-0.004, 0.117]	**0.111** [0.052, 0.177]	−0.013 [-0.070, 0.042]	−0.033 [-0.093, 0.027]
Pursuit of educational goals	0.100 [-0.041, 0.237]	0.065 [-0.081, 0.207]	0.032 [-0.107, 0.173]	**0.441** [0.285, 0.579]	−0.007 [-0.127, 0.115]
Pursuit of short-term financial goals	0.025 [-0.093, 0.145]	−0.020 [-0.125, 0.088]	−0.068 [-0.162, 0.033]	**0.101** [0.016, 0.189]	**0.225** [0.114, 0.333]
Pursuit of long-term financial goals	**0.149** [0.027, 0.273]	0.094 [-0.039, 0.223]	**0.237** [0.116, 0.351]	0.013 [-0.093, 0.123]	**0.138** [0.015, 0.253]
R^2	21.9%	14.0%	21.2%	27.5%	12.2%
R^2 adjusted	20.4%	12.4%	19.7%	26.2%	10.6%

Note. 95%-confidence intervals based on percentile bootstrapping (n = 10,000) in brackets.

conceptual point of view. To this end, we used χ^2-tests to investigate the association of class assignments of multiple-class solutions with the characteristics reported in Table 2, e.g., gender. We did not find significant associations ($p > 0.131$ [for role: clerk vs. manager, when comparing the two-class solution with the one-class solution]). Hence, a one-class solution may describe the data reasonably well.

A further issue regarding the validity of our results may be bias due to endogeneity caused by omitted variables. Following the guidelines of Hult et al. (2018), we used the Gauss copula approach to check for endogeneity. Inserting Gauss copulas showed that only the association of educational goal pursuit and step aside may suffer from endogeneity ($p = 0.033$). However, although the path coefficient goes up when considering a Gauss copula, the interpretation remains unchanged ($\beta = 0.642$, $p < 0.001$ vs. $\beta = 0.441$, $p < 0.001$). Overall, omitted variables may not bias our findings.

We also checked for non-linear relationships by including quadratic terms for all paths. No quadratic term was significant at the 5% level ($p > 0.152$).

As suggested by Sarstedt et al. (2023), we compared two further reasonable models with our initially hypothesized conceptual model. First, we split up the digital competence belief factor into two factors: hard skills (items 6–8) and soft skills (items 9–11). However, there is virtually no difference in the overall out-of-sample predictive power between the two models ($p = 0.770$). Hence, the model with one digital competence belief factor may be preferable as it is more parsimonious. The only factor in our model that indirectly predicts the augmentation strategies is digital competence beliefs. The question arises: does considering this construct increase the out-of-sample predictive power? This is not the case ($p = 0.277$). If the construct digital competence beliefs is removed, the PLS-SEM root mean square error is smaller than that of the linear regression model for all ten augmentation strategy items indicating a high out-of-sample predictive power.

To check the conceptual soundness of the mediation in our model (digital competence beliefs → AI competence beliefs → augmentation strategies), we relied on the framework of Zhao et al. (2010). Significant indirect associations in combination with insignificant direct associations would indicate a conceptually sound model. Since all direct paths from digital competence beliefs to the five augmentation strategies are statistically insignificant ($p > 0.400$), we conclude we have a sound mediation model.

Overall, our robustness checks demonstrate the soundness of our hypothesized model and the reported results.

6. Discussion

6.1. Findings

Concerning our conceptual model, the explanatory power, as indicated by the coefficient of determination R^2, is medium to low. The highest proportion of variance can be explained for *step aside* (27.5%), and the lowest proportion for *step narrowly* (12.2%). This amount of explained variance may be low but it is sufficiently high (>10%: Chin et al., 2020). It comes as no surprise that the explained proportion of variance is lower in comparison to technology acceptance studies (Scherer et al., 2019). These studies in general address specific technology use, e.g., tablet PCs, with predictors exactly geared towards this behavior. In comparison to this, the augmentation strategies are a more distal outcome. The proportion of explained variance can be increased when considering control variables. One particular noteworthy finding in this regard is controlling for company position (manager vs. clerk), which can explain a substantial proportion of variance of *step up* (8.4%, $p < 0.001$). This seems reasonable as a manager's duty may be to make decisions about AI implementation in their organization (Leyer & Schneider, 2021). However, in line with our robustness checks, the inclusion of control variables does not influence the finding on the individual level, which is the scope of our conceptual model. The out-of-sample predictive power of our model is medium to high. This indicates that our model is able to predict the five augmentation strategies beyond our sample reasonably well, and lends support to the generalizability of the results.

Concerning the predictors, cognitive attitudes towards digitalization are the best regarding the pursuit of the five augmentation strategies. These attitudes can predict all five augmentation strategies, with the exception of *step narrowly*. Since *step narrowly* implies the avoidance of AI, this highlights the important role of attitude for predicting technology integration in HRD and education in general (Scherer et al., 2019; Suseno et al., 2022).

Concerning AI anxiety, prior research yielded inconclusive results for an association between AI anxiety and behavioral intention. By referring to the augmentation strategies, we are able to provide a nuanced picture. Anxiety towards AI positively predicts *step narrowly*, i.e., avoiding AI, which is in line with Suseno et al. (2022). However, anxiety towards AI also positively predicts *step in*, i.e., collaborating with AI. From the perspective of HRD professionals there may be two ways to cope with their anxiety. This is compliant with the notion of Zig Ziglar: "F-E-A-R has two meanings: 'Forget Everything And Run' or 'Face Everything And Rise.' The choice is yours." Our results show the different implications of anxiety towards AI: either to avoid it or to collaborate with it (Suseno et al., 2022; Wang & Wang, 2022).

AI competence beliefs positively predict *step in* and *step forward*. These are the strategies where HRD professionals collaborate with AI. No association is found with *step narrowly*, which might be regarded as reasonable. Interestingly, there is also no association with *step aside* and *step up*. Concerning *step aside*, HRD professionals may focus on a specific human strength, such as empathy, instead of specific AI-related knowledge. An example could be coaching where AI can support human coaches (Graβmann & Schermuly, 2021). No specific AI competence (beliefs) may be necessary for stepping aside. Rather, in our example, for HRD professionals it may be sufficient to understand and use the output of the AI coaching system and rely on their social competence to ensure successful coaching processes. *Step up* is conceptualized as a management strategy. It is about deciding if and how AI may be used in an organization. Frameworks about the (ethical) integration of AI in organizations (Bankins, 2021; Brynjolfsson & Mitchell, 2017) show that AI competence (beliefs) may not be the most crucial aspect in this endeavor. Rather, other competencies, such as evaluating the ethical implication of AI use or knowledge about general AI capabilities, may be more important (Jarrahi, 2018). This kind of competence may be referred to as AI literacy (Long & Magerko, 2020). As hypothesized, digital competence beliefs only indirectly predict the augmentation strategies, namely, *step in* and *step forward*. They cannot directly predict any of the five augmentation strategies. This lends support to findings from TPACK research (Guggemos & Seufert, 2021). However, it leads to the question whether digital competence beliefs should remain in our conceptual model for predicting the augmentation strategies. If the sole purpose was to predict the extent of the augmentation strategies, digital competence beliefs could be removed. However, in order to understand how AI competence beliefs can be increased, retaining digital competence beliefs in the model is useful.

In terms of goal orientation, educational goal orientation can only predict *step aside*. The association is substantial ($\beta = 0.441$, $p < 0.001$) and is even higher if endogeneity is controlled for by means of a Gauss copula ($\beta = 0.642$, $p < 0.001$). The reason is an omitted variable that is positively (negatively) associated with educational goal pursuit and negatively (positively) associated with *step aside*. Social desirability may be such a variable (Harteis, 2004). The assertion that educational goals can primarily be achieved by pursuing *step aside* may not be necessarily true. Collaborating with AI and contributing to its development in HRD (*step in* and *step forward*) may, in the long run, be even more successful in achieving educational goals. *Step in*, in particular, contributes to harnessing the complementary strengths of humans and AI (Davenport & Kirby, 2016). The importance of considering time orientation (short vs. long term) may be in line with the finding of a positive association between short-term goal pursuit and *step aside*. In the short term, *step aside* may be the most suitable strategy for pursuing educational goals because other strategies might require substantial investment. The positive correlation of educational goal pursuit and long-term financial goal pursuit ($r = 0.349$, $p < 0.001$) is in line with research about a positive association between HRD activities and organizational performance (Alagaraja, 2013). Long-term financial goal pursuit positively predicts *step in*, *step forward*, and *step narrowly*. The first two associations are well in line with our hypothesis of necessary investment for stepping in and stepping forward. However, the positive association of long-term financial goal pursuit and *step narrowly* may be surprising. One explanation could be due to the fact that if HRD professionals did not expect the implementation of AI to yield financial benefits, resources invested in implementing AI would be wasted. Hence, saving these resources would be beneficial from a financial perspective in the short and long run.

Overall, we were able to confirm our hypotheses as all variables were able to predict at least one augmentation strategy. This lends support to our conceptual model (see Fig. 1).

6.2. Limitations

Our study is not without limitations. We discuss them in line with Cachero et al. (2020), by addressing internal, external, construct, and conclusion validity.

Compared to randomized field experiments, which are the gold standard (Antonakis et al., 2010), internal validity is suboptimal when answering RQ2. We rely on cross-sectional data. However, by using the Gauss copula approach (Hult et al., 2018), we can, at least, control for omitted variable bias. Nevertheless, cross-sectional data are, in general, problematic for making causal claims.

A threat to external validity could be our sample. It is narrow in scope as it comprises only HRD professionals from German-speaking countries. Small companies (<1000 employees) are underrepresented in our sample. Moreover, we recruited participants via the newsletters of the German Association for Human Resource Management. Being a member of such an HRD-related organization implies a certain amount of professionalization; these professionals may be different from HRD professionals in general. Furthermore, by referring to the DigComp framework (Vuorikari et al., 2022) and ethical standards within the European Union (European Commission, 2022), the scope of our research may be restricted to a European context.

Concerning construct validity, our reliance on self-assessment instruments may raise concerns about common method bias (Conway & Lance, 2010). However, the constructs in our conceptual model address beliefs and intentions that may naturally be captured with self-assessment instruments. Moreover, we relied, in parts, on relatively few items to operationalize the constructs (see Appendix): based on past experience regarding willingness to participate in surveys, the German Association for Human Resource Management restricted the length of the survey. Nevertheless, our measurement instruments are robust and meet generally accepted standards for validity and reliability.

Conclusion validity may be impaired as we focused on the individual level. However, the HRD professionals are embedded in organizations. Considering this multi-level structure could provide further insight into the pursuit of the augmentation strategies. Nevertheless, the reported associations at the individual level are sound as the robustness checks have indicated.

6.3. Implications

6.3.1. Theoretical implications

Understanding AI integration in education. In theory development, the trade-off between comprehensiveness and parsimony is paramount (Whetten, 1989). As we have shown, AI implementation in educational contexts such as HRD is more complex than currently reflected in available studies. Besides addressing to what extent AI is intended to be used, it may also be important to understand how and in what way AI might be implemented. In this regard, our work based on the concept of augmentation strategies complements studies about AI integration (Al Darayseh, 2023; Ayanwale et al., 2022; Suseno et al., 2022). The five augmentation strategies are designed to be mutually exclusive and collectively exhaustive (Davenport & Kirby, 2016). We checked to see if a more parsimonious model would be possible by combining strategies such as *step in* and *step forward*. Based on information criteria, this may not be the case; the five augmentation strategies may, indeed, be mutually exclusive. Moreover, the variables that can predict each of the augmentation strategies vary considerably, which points to their different nature.

Prediction of AI integration in education. We have demonstrated that goal orientation is an important factor in predicting the augmentation strategies. Goal orientation has, to our knowledge, been largely neglected in conceptual models that deal with technology integration (Tondeur et al., 2021). However, motivation theory points to the importance of goal orientation for predicting behavior (Kaplan & Maehr, 2007). Hence, adding goal orientation to a conceptual model for predicting technology integration may be desirable when trading off comprehensiveness and parsimony. This may be particularly the case in a business context, where educational and financial goals are present (Harteis, 2004). Our research shows that it may be important to consider the entire process of digitalization in order to understand AI integration. As pointed out, digital processes are necessary for effective AI integration (Wahlster, 2017). In our study, we considered the DigComp framework (Vuorikari et al., 2022), which may be a common denominator in Europe. This ensures a link to the (higher) education system. However, as we have shown, it may not be enough to only consider these digital competence beliefs as they can only indirectly predict *step in* and *step forward* strategies. Rather, specific AI competence beliefs may be considered in a conceptual model of AI integration. This is in line with TPACK research (Guggemos & Seufert, 2021).

Measurement instrument development. We are, to our knowledge, the first to present a measurement instrument that operationalizes the five augmentation strategies in a reliable, as well as convergent and discriminant valid, way. This can contribute to further, more nuanced research about AI integration in education. Furthermore, we have successfully validated an instrument to capture AI competence beliefs in the area of HRD. This may be beneficial because generic digital competence beliefs cannot directly predict technology integration. Both instruments were developed by HRD experts. Hence, the content validity of these measurement instruments may be ensured.

6.3.2. Practical implications

The most interesting question of all may be: Which of the five augmentation strategies should HRD professionals pursue? This, of course, depends on the perspective and position of the person, e.g., clerk vs. manager. If (individual) competitive advantages are to be realized, *step in* or *step forward* strategies seem to be the most advantageous (Krakowski et al., 2023). However, the HRD professionals in our sample primarily follow a *step aside* strategy. In HRD, which is a people business, this may be promising as human strengths such as social skills are decisive. In the short term, it may be tempting to focus on the *step aside* strategy. This is consistent with the found positive association of *step aside* with short-term financial goal orientation and the insignificant association with long-term goal pursuit. However, in order to be successful in the long run, HRD professionals may also consider using the *step in*, or even the *step forward*, strategy to a higher degree than is currently the case.

To elevate *step in* and *step forward* pursuit, HRD professionals may first focus on digital competence as set out by the DigComp framework. These may be the basis for more advanced and specific AI competence. As we have shown, the association of digital competence beliefs with the augmentation strategies is mediated by AI competence beliefs. Addressing such beliefs could be particularly promising because they are currently at a rather low level, i.e., there is much room for improvement (Ringle & Sarstedt, 2016). Boosting these competence beliefs could be achieved by professional development programs, which, in general, have shown to increase competence beliefs (Bray-Clark & Bates, 2003).

Moreover, anxiety towards AI may not necessarily be negative. It positively predicts *step in*. The awareness of negative personal consequences if the capabilities of AI are not harnessed may force HRD professionals to face their anxiety and overcome it by stepping in. This may be in line with the assertion of Baldwin (2023): "It's not AI that is going to take your job, but someone who knows how to use AI might."

7. Conclusion and outlook

Our research presents a measurement instrument for Davenport and Kirby's (2016) concept of augmentation strategies. This concept looks at the complementary strengths of humans and AI. In the future, collaboration with AI may become even more important with the increased spread of generative AI, such as ChatGPT (Fui-Hoon Nah et al., 2023). The concept of augmentation strategies may help to understand AI implementation in higher education institutions and schools. Future research may adapt our instrument for use in these areas. We presented a conceptual model to predict the extent to which HRD professionals pursue the augmentation strategies. This model is sound but could be extended in order to increase the proportion of explained variance. AI literacy (Knoth et al., 2024; Laupichler et al., 2023; Ng et al., 2021) may be a promising concept to consider because it is important for realizing the complementary strengths of humans and AI (Fui-Hoon Nah et al., 2023). Considering AI literacy would cover further important aspects, such as knowledge about the ethical implications of AI use and the capabilities of AI. Using a performance test to measure AI literacy (Hornberger et al., 2023) may be promising in order to alleviate concerns about common method bias. Besides this, our research has shown the importance of considering goal orientation for predicting AI implementation. This may also be the case in schools or higher education institutions. Further research might investigate the role of goal orientation in these settings.

CRediT authorship contribution statement

Josef Guggemos: Writing, Visualization, Validation, Project administration, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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During the preparation of this work the author used deepl.com in order to translate the items (see Appendix). After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Informed consent was obtained from all participants involved in the study.

Appendix

Used items, their mean, standard deviation, skewness, excess kurtosis, and standardized factor loadings.

Construct/Item stem	No.	Item	M	SD	Skew	Ex_{Kurt}	λ
Cognitive attitudes/How strongly do you agree with the following statements?	1	I like to deal with digitalization related topics in the context of HRD.	5.74	1.20	−1.16	2.04	0.900
	2	Digitalization brings more advantages than disadvantages for HRD.	5.69	1.21	−1.20	1.98	0.752
	3	I like acquiring knowledge in the field of digitalization.	5.88	1.10	−1.39	3.56	0.915
AI anxiety/How strongly do you agree with the following statements?	4	I'm afraid that the advancing digitalization will overwhelm me.	2.54	1.49	0.83	−0.15	0.929
	5	I fear that AI and intelligent machines will make me redundant.	1.77	1.13	1.77	3.19	0.798
Digital competence beliefs/Please rate your knowledge.	6	Sharing content through digital technologies	5.69	1.21	−1.67	4.12	0.800
	7	Collaborating with others using digital technology	5.71	1.16	−1.70	4.51	0.812
	8	Taking netiquette into account	5.50	1.56	−1.52	1.94	0.678
	9	Programming	2.59	1.65	0.62	−0.97	0.632
	10	Protecting digital devices	4.36	4.36	1.57	−0.38	0.773
	11	Solving technical problems with digital devices	4.21	4.21	1.66	−0.69	0.739
AI competence beliefs/Please rate your HRD-related knowledge.	12	Online diagnosis of employee competences	4.20	1.81	−0.60	−0.81	0.730
	13	(Semi) automated creation of learning content with AI-based tools	3.16	1.70	0.07	−1.27	0.822
	14	Algorithm-controlled curation/filtering of (open) learning content	2.71	1.61	0.36	−1.26	0.847
	15	Adaptive learning systems/intelligent tutorial systems	3.19	1.70	0.00	−1.35	0.878
	16	Analytics for evaluation and quality development	3.53	1.85	−0.07	−1.25	0.816
	17	Learning experience platforms	3.93	1.79	−0.38	−1.07	0.806
	18	Dialogue-based tutorial systems (chatbots for learning)	3.07	1.78	0.19	−1.34	0.774
Educational goal orientation/What principles guide your decisions in HRD?	19	Holistic development of employees	6.10	0.99	−1.85	6.20	0.915
	20	Supporting and enabling competence development among employees	5.78	1.27	−1.49	2.81	0.899
Short-term financial goal orientation/What principles guide your decisions in HRD?	21	Short-term (<1 year) financial goal orientation	5.21	1.49	−1.11	0.99	1
Long-term financial goal orientation/What principles guide your decisions in HRD?	22	Long-term (>5 years) financial goal orientation	5.18	1.40	−1.16	1.40	1
Step in/My role in HRD is …	23	to use AI-based solutions productively for my tasks.	4.82	1.40	−0.62	0.31	0.915
	24	to train AI-based solutions and to pass on guidance for further development to the developers.	4.00	1.56	−0.26	−0.67	0.899
Step up/My role in HRD is …	25	to explore possible applications for currently available AI systems.	4.67	1.49	−0.87	0.56	0.948
	26	to evaluate AI systems and help decide which systems are used for what, where and how.	4.77	1.44	−0.92	0.75	0.952
Step forward/My role in HRD is …	27	to contribute to the development of AI systems.	4.07	1.52	−0.45	−0.52	0.875
	28	to discover future fields of application for AI systems.	4.58	1.40	−0.81	−0.54	0.899
Step aside/My role in HRD is …	29	to design and implement development programs based on in-depth knowledge of target groups and context.	5.52	1.41	−1.34	1.92	0.866
	30	to accompany and advise employees on their development paths.	5.97	1.18	−1.71	4.08	0.902
Step narrowly/My role in HRD is …	31	to focus on tasks where no AI systems are used.	3.59	1.67	0.12	−0.92	0.898
	32	to cover tasks where the use of AI systems is not economically feasible.	4.36	1.71	−0.44	−0.75	0.910

Note. Items translated from German to English by the first author and refined by a professional copy editor. All items measured on a 7-point rating scale: For items 1 to 5 and items 19 to 32 ranging from entire disagreement to entire agreement. For items 6 to 18 ranging from not available to very high. Minimum = 1 and maximum = 7 for all items. Skew = Skewness, Ex_{Kurt} = Excess kurtosis, λ = standardized factor loading.

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