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Exploring the individual adoption of human resource analytics: Behavioural beliefs and the role of machine learning characteristics

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ABSTRACT

The technological capabilities of Human Resource Analytics (HRA), enhanced by recent innovations in Machine Learning (ML), offer exciting opportunities. However, organisations often fail to realise these potentials because of a limited understanding of why individuals choose to adopt or disregard respective tools. Prior research on innovation adoption offers preliminary insights but fails to aggregate the determinants of individual adoption into actionable suggestions for decisions in the ML adoption process. Our study applies focused interviews to examine non-ML experts' reasoning for using a specific tool tailored to a public sector organisation, which corresponds to the usual end-user perspective of ML-based HRA adoption. By drawing from the HRA adoption framework, provided by Vargas et al. (2018), we contribute to the literature by identifying relevant beliefs and experiences influencing one's intention to adopt ML-based HRA and by qualitatively linking these beliefs to ML characteristics such as transparency, automation and fairness. For practitioners, we provide actionable guidance emphasising the need to ensure fairness proactively, as interviewees do not consider this aspect when deciding to adopt ML-based HRA.

1. Introduction

The diffusion of analytics into Human Resources Management (HRM) processes, including talent management, performance evaluation and workforce planning, presents a promising opportunity. Human Resources Analytics (HRA), as it is referred to in this context, is classified as diffusing innovation and describes “a practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to Human Resources (HR) processes, human capital, organisational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making” (Marler and Boudreau, 2017, p. 15). Modern-day technological advances help HR professionals asserting their value when defending against possible displacement by finance or data science departments (Angrave et al., 2016), and they provide support for a wide range of different HR functions (Prikshat et al., 2023a). In recruitment, for example, HRA can be used to streamline processes and achieve greater speed and efficiency (Hunkenschroer and Luetge, 2022), whilst in HR development, it helps to identify the link between employee engagement and performance metrics – and thus positively influences them (Davenport et al., 2010). Although traditional HRA encompasses several statistical approaches and methodologies, Machine Learning (ML), such as deep-learning algorithms and Artificial Intelligence, is expected to drive the greatest change in HRM practice. For example, online work platforms such as Uber, Upwork and Deliveroo automate extensive core business processes, ranging from HRM decision-making to execution in the form of selection, compensation and task assignment – all of which is done through ML (Meijerink et al., 2021). In addition, ML-based HRA tools for predicting voluntary employee turnover allow companies to derive retention strategies that not only reduce costly replacements in the short term, but also retain expertise within the organisation, thereby securing a competitive advantage (Chowdhury et al., 2022).

Prior research identifies individual resistance to ML-based HRA which could hinder its success in corporate practice. In contrast to other HRA technologies, sophisticated ML algorithms, for instance, have the disadvantage of being too complex to interpret easily, which subsequently leads to opacity (Kellogg et al., 2020; Langer and König, 2021). As more data and multifaceted algorithms become available, a computer learns more complex patterns and “consequently builds its own representation of a classification decision, [which it does] without regard for

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human comprehension“ (Burrell, 2016, p. 10). Therefore, algorithms exceed human abilities to understand the system and can generate severe trust issues (Arrieta et al., 2020). Furthermore, prior research observes attempts to manipulate and exploit these advanced ML-based systems, known as “algoactivism” (Kellogg et al., 2020; Meijerink and Bondarouk, 2023), and a more general aversion to advanced algorithms, called “algorithm aversion” (Mahmud and Islam, 2022). Consequently, the successful leverage of the described potential of ML-based HRA critically depends on the ability to convince the individuals of an organisation to use these systems (Vaio, 2022).

However, as most academic HR literature aims to understand the factors determining the adoption of HRA on an organisation-wide level (e.g., Margherita, 2022), and irrespective of the specific tool (e.g., Vargas et al., 2018), there is very little knowledge on the successful individual adoption of HRA – and especially ML-based HRA. Coming from the apparent need for a better understanding of the individual adoption process for ML-based HRA, as well as the ambiguous effect of ML characteristics, we ask the following two research questions:

RQ1: What beliefs and experiences influence the individual's intention to adopt ML-based HRA?

RQ2: How do the characteristics of ML engender these behavioural beliefs?

To answer these research questions, we examine the individual opinions and thoughts of employees of a public sector organisation about a specific ML-based HRA tool for predicting voluntary turnover, the implementation of which the organisation is currently evaluating. Drawing from the focused interviews method provided by Merton and Kendall (1946), we discuss the performance of the predictive HRA tool, as well as several explanatory figures, with employees in interviews and analyse their personal perspectives, experiences and spontaneous reactions to these different approaches. Following Vargas et al. (2018), we then interpret our empirical results with the help of a conceptual framework derived from the *Theory of Planned Behaviour* (TPB) by Ajzen (1991). On the one hand, our results show that the perceived (self-) efficacy of interviewees also highly depends on the design of the HRA tool and the entered dataset, in addition to perceived skills and competencies. On the other hand, the attitude of the interviewed employees is not only formed by their personal enjoyment or concerns in terms of working with the tool, but also by the way in which they perceive it assists them in their daily work. We additionally identify that several ML characteristics (perceived self-learning capabilities, degree of automation, transparency and trialability) influence behavioural beliefs and in turn effect the adoption of the tool in HRM processes.

Our study makes three main contributions to the literature. First, it contributes to the ongoing debate about the relevant factors driving the decision to adopt HRA (Coolen et al., 2023). By examining this decision from an individual instead of an organisation-wide perspective, we provide deeper insights into the different behavioural beliefs determining the decision to adopt ML-based HRA. Based on our findings, we propose several ML-related extensions and adjustments to the more general adoption framework of Vargas et al. (2018). Second, our study contributes to the current literature on ML design approaches and their effect on HRA adoption (Marler and Boudreau, 2017; Langer and König, 2021; Haque et al., 2023), and third, it contributes to research on ML transparency, suggesting that appropriate visualisation influences end-user adoption (Haque et al., 2023). However, in contrast with Haque et al., 2023, our results demonstrate a lack of ethical reflection, as fairness plays no role in individual decisions to adopt ML-based HRA, albeit protected group differences were made apparent in the interviews.

The paper is organised as follows. The second section reviews the literature on the (individual) adoption of HRA, highlights the related limitations and derives the conceptual framework of our study. The third section summarises the research method, empirical environment as well as the research object and data analysis process. The fourth section presents the results. A refined model at the end of this section summarises the factors that influence individual intentions to adopt ML-based HRA and the impact of ML characteristics. Finally, in the fifth section, the results are discussed and propositions made before a conclusion is drawn.

2. Related research and theoretical framework

In the following section, a conceptual framework for the present study is derived by summarising and discussing the state of knowledge on the (individual) adoption of HRA.

2.1. Prior research regarding the adoption of HR analytics

The factors that drive or hinder the adoption of HRA have been almost exclusively explored from an organisation-wide perspective (e.g., Margherita, 2022; Böhmer and Schinnenburg, 2023; Coolen et al., 2023). Prior research draws from the TOE framework (e.g., Pumplun et al., 2019; Chatterjee et al., 2021; Neumann et al., 2022), with the underlying idea that the adoption of HRA from an organisation-wide perspective is mainly driven by technological, organisational and environmental contexts. Technological contexts include, for example, the existing IT infrastructure of an organisation (Neumann et al., 2022), while the environmental contexts can be, for example, competitive pressure or customer readiness (Neumann et al., 2022). The organisational context includes cultural aspects (such as the culture of innovation or change management) as well as resources (e.g., budgets or human capital) (Neumann et al., 2022). Prior research concludes that the employees themselves – aligned with their skills and knowledge – play a major role in the adoption of HRA in corporations (Coolen et al., 2023; Vaio, 2022). Furthermore, work ethics (Basu et al., 2023) or supervisor support (Prikshat et al., 2023b) have been identified as additional major drivers for organisation-wide adoption.

To the best of the authors' knowledge, only Vargas et al. (2018) have examined the individual adoption of HRA and proposed a comprehensive framework in this regard. Drawing from the *Theory of Planned Behaviour* by Ajzen (1991) and the *Innovation Diffusion Theory* posited by Rogers (2003), the authors explain the actual level of adoption of HRA through an individual's perceived self-efficacy, attitude and social influence regarding its use as well as trialability. Self-efficacy represents an individual's beliefs about their abilities to reach a behavioural goal (Bandura, 1977), which translates to their evaluation of the technological and quantitative skills they deem necessary to adopt HRA. One's attitude towards a specific behaviour is derived from the expected consequences of this behaviour (Fishbein and Ajzen, 2010). As the perceived consequences of using HRA partly depend on an individual's self-efficacy regarding the use HRA, the latter will influence their attitude, among several other beliefs for the given context. Social influence represents the perceived norms in favour of or against HRA, and trialability encompasses beliefs about the degree to which HRA can be tested before adoption. Vargas et al. (2018) distinguish the three different decision-making steps of knowledge-gathering, persuasion and decision, whereby perceived self-efficacy is formed during the knowledge-gathering step, and attitude, social influence and trialability are derived during the persuasion step. The conducted survey empirically supports the proposed causal relationships as well as the effect of technology self-efficacy.

2.2. Limitations of the HR analytics conceptual framework

While the derived conceptual framework provided by Vargas et al. (2018) extends the fundamental understanding of individual HRA adoption, it does have some limitations. First, it only includes trialability as a potential technological factor to distinguish between different HRA technologies. The proliferation of ML questions the reality, as the framework does not distinguish between the different characteristics of the HRA tool. Furthermore, as HRA includes many different algorithms, systems and methods (Meijerink et al., 2021), and prior research in information systems finds significant effects of an IT systems's design on its subsequent use (Haque et al., 2023), there is clearly the need to further characterise and differentiate the proposed model from this perspective. Especially in the context of ML, research has emerged in the HR (Langer and König, 2021), management (Glikson and Woolley, 2020) and information systems (Arrieta et al., 2020) literature arguing that transparency must be another fundamental determinant of individual ML adoption. In contrast to traditional statistical methods in HRA, transparency is not always present in ML, because (a) predictors are not understandable, (b) relationships between predictors and predictions are hidden and (c) no explanation for a specific prediction is given (Arrieta et al., 2020; Burrell, 2016; Langer and König, 2021). This is problematic, because a prediction without clear explanations, or at least justification for the rationale behind the prediction, can lead to trust issues (Glikson and Woolley, 2020; Langer and König, 2021). Park et al. (2021), for instance, illustrate that only with sufficient transparency can various user burdens (emotional, mental, biases, etc.) be overcome during ML adoption. Transparency is also closely related to another fundamental determinant of HRA adoption, namely fairness (e.g., no discrimination against minorities), which can only be tested when professionals use their expertise and experience to determine the level of fairness of individual ML predictions through intuitive thinking (Chowdhury et al., 2022). To achieve sufficient ML transparency, Explainable Artificial Intelligence (XAI) offers a rapidly evolving interdisciplinary research area with multiple technical solutions (Arrieta et al., 2020). Finally, the ability to automate decisions fully is an ML characteristic that represents a major shift for traditional HRA technologies (Meijerink et al., 2021). When algorithms are used for automated scenarios, they must also be accountable for the decisions they make (Busuioc, 2021). In summary, and in line with Lee and Cha (2023), we suggest that transparency, fairness and accountability (in terms of automated use) determine the adoption of ML-based HRA. Besides technical ML characteristics, decisions made during roll-out also affect the adoption of ML. In this regard, some studies have found that the ability to try (=trialability) has a positive impact on adoption (Omrani et al., 2022). However, research is still inconclusive in terms of exactly how these ML characteristics influence an individual's adoption of HRA.

Second, the notion of self-efficacy and attitude in the proposed framework of Vargas et al. (2018) is relatively narrow, and it might exclude potentially relevant beliefs. Compared to assumed self-efficacy, the perceived behavioural control (PBC) factor from the original TPB is a wider concept that includes beliefs about factors beyond one's individual control (Ajzen, 1991). It can be defined as the perceived ease or difficulty of performing a behaviour (Ajzen, 2002). For instance, the individual adoption of an HRA tool likely depends on the tool's suitability for a task and not only on one's perceived skills to use it. Furthermore, Vargas et al. (2018) examine self-efficacy regarding technology and mathematics in general, which are sufficient to estimate the average intention to adopt HRA but fall short when comparing the adoption of different HRA systems. However, the TPB is built upon the principle of compatibility, which states that the underlying factors must always refer to the underlying behaviour (Fishbein and Ajzen, 2010). For the given context, one would therefore expect a notion of self-efficacy that is more directly connected to the individual adoption of a specific HRA tool or system. Furthermore, the attitude of a survey participant is derived from four beliefs solely centred around the personal enjoyment of using HRA (Vargas et al., 2018). This notion contrasts with the *Technology Acceptance Model* that connects the attitude towards a technology to the beliefs about the perceived usefulness and perceived ease of use of a technology (Davis, 1989) and the *Unified Theory of Acceptance and Use of Technology* that connects the respective attitude to a performance and effort expectancy (Ajzen, 2002; Venkatesh et al., 2003).

2.3. Underlying conceptual framework

Due to the limitations of the conceptual framework of Vargas et al. (2018) described herein, we aim to scrutinise the framework and extend it to ML-based HRA tools. Our further analyses are based on the assumptions described above, which are founded on the current state of knowledge. We also distinguish between the process steps of knowledge, persuasion and decision (Rogers, 2003) in an ML-based HRA tool's adoption process. In the knowledge step, personal beliefs are evaluated regarding the ability to utilise an ML-based HRA tool for a given task and form an expectation about the PBC. In the persuasion phase, personal beliefs are evaluated regarding the consequences of using the provided HRA tool and form a tool and task-specific attitude. In addition, personal beliefs are evaluated regarding the opinions of others regarding the use of the provided HRA tool and form an expectation about the relevant social norm (corporate or national culture). In the decision step, personal beliefs are evaluated regarding the PBC, attitude as well as perceived norm and help decide whether to adopt the provided HRA tool. Furthermore, we expect PBC and attitudes to be influenced by the technical characteristics of the provided ML-based HRA tool, in which case we distinguish between the known characteristics of trialability, transparency, degree of automation and fairness and potential unknown characteristics.

3. Research approach

3.1. Method

To fill the derived conceptual framework for individual adoption with salient beliefs, it is necessary to dive deep into the line of reasoning employed by end-users. We aim to explore these beliefs by applying the "focused ethnographic interview" methodology proposed by Merton and Kendall (1946). We opted for a qualitative research approach because it can provide new insights into individual adoption in an explanatory manner. In addition, the open-ended nature of the interview questions allows for the collection of a wide range of information, including personal perspectives and experiences. The interview procedure was semi-structured around several pieces of information and nudges, used as potential triggers for spontaneous reactions. During the interview, detailed discussions were held on hypothetical but realistic implementation scenarios for the specific HRA tool. Particular attention was paid to employees' understanding of the presented tool, their ideas about its future use in HRM processes and their perceptions of the risks and benefits of using it in various HR applications throughout the organisation. In addition, the interviews provided information about the overall intentions of the interviewees as well as any changes in their intention to adopt the HRA tool when providing various information and explanations. This approach follows the interpretive tradition of explorative methods, in that it seeks a deep understanding of human experience rather than rigid explanations of cause and effect – as in positivist epistemology (Einola and Khoreva, 2023).

3.2. Empirical environment

This study examines a German federal agency from the social insurance industry with about 20,000 employees in the period between 2022 and 2023. The in-depth public sector study approach provides a context in which high legal requirements for the individual adoption of HRA can be investigated and commercial secrecy is not a concern (Desouza et al., 2020; Busuioc, 2021). While the organisation frequently uses descriptive analytics based on advanced dashboarding tools, as well as sporadic diagnostic regression-based analytics, this project is the first to incorporate complex ML models to implement predictive analytics use cases within HR.

Our main objective in selecting the interview population was to obtain a diverse sample of HRA users in terms of personal characteristics (age and gender), seniority and statistical background in order to represent the diverse workforce of the organisation as well as the different usage objectives in the different personas. Table 1 provides an overview of the 12 interviewees. Team leaders supervising one to 21 employees, and heads of departments with 21 to 50 employees, from HR and operational departments, are the main users of the HRA tool. Half of the employees interviewed would work with the HRA tool in the near future, and half of those interviewed were potential recipients for further applications. Each interview lasted between 58 and 98 min.

3.3. Research object

The specific ML-based HRA tool investigated herein predicts individual voluntary turnover (excluding age-related reasons and termination on the part of the employer) probabilities within the next 6 months for each employee, using the random forest algorithm (Breiman, 2001). The tool is trained on a fully anonymised dataset with monthly data over a three-year time horizon and includes 30 predictors originating from the same federal agency in which the interviews were conducted. Work-related predictors include commuting distance, sick days, salary, salary increases in recent years, seniority and others. Demographic data such as gender, age, number of children and education level are also included. The ML predictions are evaluated in an out-of-sample test dataset. Instead of treating the ML model as a black box, post-hoc XAI explanations at the local (employee-specific) and global (organisation-wide) levels are used to extract the effects of the predictors. The confusion matrix used to assess predictive accuracy, as well as some visualisations of the XAI results at the local and global level, were used as nudges during the interviews (see Fig. 1). The visualisation of organisation-wide explanations shown in Fig. 1 describes how a single predictor influences the employee turnover prediction (strength, positive/negative contribution) on average, considering all employees in that local interval (Apley and Zhu, 2020). Additionally, the visualisation of employee-specific explanations breaks down the probability of voluntary turnover for each employee and quantifies it in terms of increasing or decreasing effects. The mean value represents the average employee turnover risk of all employees predicted in the model.

Table 1
Interview population of future HR Analytics users.

#	Organisational section	Department	Position	Sex	Seniority (y)
I1	Corporate development	Employer branding & image	Team lead	w	20 to 25
I2	Internal corporate consultancy	Management of future vacancies	Team lead	m	15 to 20
I3	Insurance claim processing	Operational workforce management	Department administration	w	30+
I4	Insurance claim processing	Operational workforce management	Head of department	m	30+
I5	Human Resources	Organisation design	Organisational consulting	m	30+
I6	Human Resources	Organisation design	Team lead	m	0 to 5
I7	Human Resources	Organisation design	Department administration	w	25 to 30
I8	Human Resources	Personell planning & controlling	Associate	m	10 to 15
I9	Human Resources	Personell planning & controlling	Project lead	m	15 to 20
I10	Human Resources	Recruiting, development & diversity	Team lead	w	30+
I11	Human Resources	Strategic workforce planning	Senior data analyst	w	0 to 5
I12	Human Resources	Strategic workforce planning	Analyst	m	20 to 25

3.4. Data analysis

Given the inductive nature of the study, we coded the transcripts manually, following the methodology proposed by Gioia et al. (2013), which has demonstrated its validity in numerous renowned publications over the last decade (e.g., Friedman and Ormiston, 2022; Schuessler et al., 2023; Mula et al., 2024). All interview transcripts were coded independently by the first and second authors using MAXQDA[1] software. A total of 392 codes resulted. In the initial coding phase, we strictly adhered to the terms, phrases and descriptions of the interviewees, so that many first-order categories emerged. After eight interviews, both authors re-checked their coding to improve the reliability of the process and increase its rigour and authenticity. After coding all transcripts, first-order categories were compared against each other. Disagreements regarding interpretation, and thus coding, if any, were resolved through discussion. In the next step, for the second coding (axial coding), the first and second authors looked for similarities between and differences among the many first-order categories, in order to summarise and condense them. To this end, we went through each interview transcript as well as the first-order categories again. Subsequently, we discussed each passage and then reconciled different interpretations and conclusions to generate suitable second-order categories (Gioia et al., 2013).

Based on the TPB (Ajzen, 1991), each of the second-order categories was independently assigned to PBC, attitude or norm (aggregated dimensions) by the first and second author (as determinants of an individual intention to adopt HRA) and then discussed. Subsequently, all second-order categories were critically reflected in correspondence with the framework provided by Vargas et al. (2018). The third author, who participated directly in project meetings and reviewed relevant project documents, critically reflected on the results in the final analysis step. Additionally, the coding of the entire interview material was repeated to verify validity. The re-coding of the first author, 11 months after the first coding, resulted in an overlap of 90.4 % (intra-coder reliability). Coding by a person not previously involved in the research process resulted in an appropriate accordance of 79.0 % (inter-coder reliability) (Miles and Huberman, 1994).

The second-order categories and the aggregated dimensions formed the basis for the framework developed for the present study, and the first- and second-order categories, as well as the aggregate dimensions, became the basis for building the data structure (see Fig. 3).

4. Results

4.1. Factors influencing the individual intention to adopt ML-based HR analytics

The results regarding the beliefs and experiences that influence individuals' intention to adopt ML-based HRA (RQ1) are presented below. First, the findings on PBC are illustrated (see Table 2), following which, after describing attitudes towards the adoption of the tool (see Table 3), the perceived norms (see Table 4) of the interviewees are presented.

4.1.1. PBC

Algorithm-based efficacy describes all the capabilities and characteristics that interviewees attribute to and expect from an ML-based HRA tool, which allows them to utilise it in their daily work. Prediction

[1] https://www.maxqda.com/

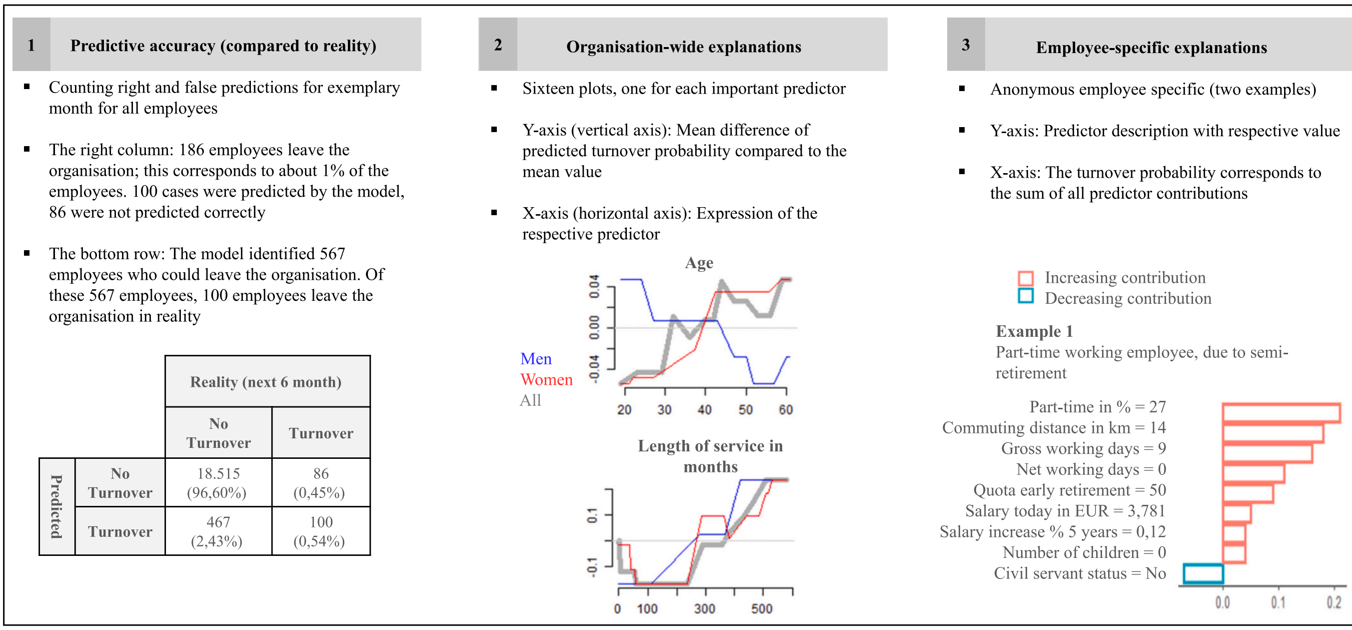

Fig. 1. Information provided as nudges during the interviews: Predictive accuracy report, predictor effect explanations on the organisation-wide and employee-specific level.

quality captures the prediction accuracy of the tool, whereby the interviewees seem to require a sufficient level of prediction accuracy to view it as applicable. For our model, prediction accuracy is rated differently by I1 and I11. Another key factor for algorithm-based efficacy is traceability. The lines of reasoning by I10 reveal that the HRA tool's feasibility stems from explanations of the ML model and how this helps to optimise the organisational retention of top performers at the individual level. I12 points towards the XAI visualisations provided as an important distinction compared to popular Generative Artificial Intelligence models such as ChatGPT. While scepticism towards these technologies is generally high, trust-building and achieving actionable insights can partially be attributed to traceability. The third driving factor for algorithm-based efficacy is applicability in practice. Among other things, the interviewees consider the extent to which the tool is mature and ready for use, its susceptibility to errors and the basic functions (e.g., the selection of different prediction periods) that it offers.

In addition, data-based efficacy plays an important role when forming the PBC. In our case, the opinions of the interviewees regarding the composition of the dataset differed widely. Some interviewees, like I2, identified missing and crucial predictors of voluntary turnover from their point of view, which had a critical impact on their evaluation of the tool. Others, like I9, were very satisfied with the included predictors. If they identified turnover predictors in the data, which they might consider important, data-based efficiency was considered high. Similarly, if the contribution and importance of the predictors in the XAI visualisations are as expected, then data-based efficiency seems to increase. Additionally, we find that dataset reliability plays an important role in the intention to adopt the HRA tool. For instance, I10 directly attributed the reliability of the department responsible for managing the database to the tool. Others, like I11, questioned the timeliness and quality of the data, its realism or rapid changes in the included turnover predictors.

In our study, competence-based self-efficacy reflects the beliefs an individual holds regarding their ability to use the ML-based HRA tool successfully in their daily work. Some interviewees, like I6, quickly understood the nudges shown, were interested in them and interpreted the information in detail. In their daily work, these people mostly take on analytical tasks and often have a background in statistics, which indicates that they have more pronounced quantitative skills. Others, like I8, were overwhelmed with the interpretation and had no deep interest in the information provided to them. In addition, the interviewees considered it necessary to have a certain level of HR knowledge, to be able to apply the results of the tool in practice and to derive potential application scenarios. The findings on our interviewees' PBC-related adoption of ML-based HRA tools, which are presented in Table 2, match interview insights into the dimensions related to the Theory of Planned Behaviour.

4.1.2. Attitude

The interviewees' attitude towards the adoption of HRA was influenced, among other things, by its perceived compatibility. The assessment of the task technology fit was very different (see I3 and I7), with the added value and the concrete integrability of the ML-based HRA tool in everyday work being questioned and analysed. The interviewees' attitudes also seemed to be influenced by whether the results of the HRA tool revealed novel HR insights. Like I9, almost all interviewees stated that the tool could help identify at least some novel factors for employee voluntary turnover – and thus provide a basis for the development of personnel measures. It is notable that the consistency of the tools' predictions with personal intuition is an important determinant of attitude. Provided that the results matched the intuition, this manifested in an improved attitude, and vice versa.

In addition, considerations related to the improvement achieved by the tool seemed to have an impact on attitude. In our study, the extent to which implementation effort and technological innovation were perceived as impactful by the interviewees was important in this context (see Table 2). Some, like I4, felt that the innovative nature of the HRA tool enables new approaches to old challenges (such as demographic challenges) and improves previous processes (e.g., the quality of workforce planning). Essentially, innovation brings new perspectives and approaches. Others, like I11, critically questioned implementation efforts in terms of a cost-benefit trade-off.

A few interviewees questioned the personal consequences of adopting the HRA tool and evaluated them accordingly. I9 and I11 were particularly afraid that superiors use the HRA tool inappropriately (e.g., findings led to monitoring by the superior or mobbing), that false predictions led to negative effects (e.g., in the allocation of tasks) or that

Table 2
Interviewees' PBC related to the adoption of ML-based HRA tools.

Example Insights	1st-order Categories	2nd-order Categories	Aggegate Dimension
"*... actually, quite impressive prediction quality.*" (I1, 34) "*... if you look at the absolute numbers, 467 and 100, prediction accuracy doesn't look so great.*" (I11, 102)	Prediction quality	Algorithm-based efficacy	PBC
"*I understood that the higher the absenteeism due to illness, the higher the probability that these people will leave the organisation, which would allow me as a personnel manager to conclude: How high is my sickness rate? […] Unfortunately, my department has a very high sickness rate, and it would be exciting for me to see whether this has led to increased turnover – that the sick days were perhaps even the criterion.*" (I10, 104) "*I do not know how to calculate the predictions. I do not know how the database must be prepared, how the model must be fed and so on. But if I look specifically at the XAI visualisations, I can already work with that. […] You first must deal with it [like a new software program] to be able to use it. […] A little bit of scepticism is quite healthy, but ChatGPT has now increased our trust somewhat.*" (I12, 171)	Traceability		
"*I would need 5 or 10 years and not the individual level of an employee, but I would have to look at the entire department, and I would have to look at certain levels, e.g., professional groups.*" (I11, 162)	Applicability		
"*All these flexible working time models with remote working etc. are not integrated into the model. After all, these affect 50 % of our employees.*" (I2, 108) "*These are very important predictors that I could then use for the future. So that would be very helpful, very helpful.*" (I9, 92)	Composition of the dataset	Data-based efficacy	
"*So you certainly calculated this from the data collected by Mr. […], I assume? From there, the data basis is safe for me – and from there I also trust in the numbers.*" (I10, 242) "*So, for example, the economic situation, the issue of security, the issue of a personal family situation. The factors change. I hire someone who does not have any children, and then I know, well, maybe in 5 years there will be children. That means I cannot exert any influence. Likewise, what about changing health situations?*" (I11, 128)	Reliability		
"*I understood the figures shown.*" (I6, 85) "*But at the moment, it slays me and everything – honestly.*" (I8, 249)	Quantitative skills	Competency-based self-efficacy	
"*I cannot say anything about that [how to adopt the tool specifically]. My colleagues in the HR department are more closely involved in this issue. I cannot assess the potential.*" (I12, 167)	HR knowledge		

misunderstandings occurred. Findings relating to the interviewees' attitude to the adoption of ML-based HRA tools are presented in Table 2.

4.1.3. Norm

The adoption of (ML-based) HRA tools is also limited by the 'legal framework'. The interviewees stated that possible applications of the tool were severely limited or not possible due to legal conditions and the strict interpretation of data protection regulations in the public sector. Interestingly, some interviewees mentioned experiences with – from their point of view – overly strict data protection rules for historical organisational initiatives. For example, I8 stated that sensitive personal data should also be included in the tool and used for individual decision-making. Organisational councils have far-reaching co-determination rights that go beyond the law and enable employee representatives to object to various decisions affecting the entire organisation, thus obstructing adaptation. The interviewees perceived that initiatives based on employee data were – in principle – prevented. Among other things, organisational councils receive evaluations of all HR reports requested in the IT system, and they strictly ensure that each employee processes only the amount of information needed to complete tasks.

Culture is an important factor in the adoption of HRA (Vargas et al., 2018), where we distinguish between the social norm and organisational culture. During our interviews, some interviewees critically evaluated their social norm's compliance with the adoption and use of the HRA tool. For example, in terms of the individual employee's privacy, they questioned whether the analysis of personal data was acceptable from their point of view, or with whom the responsibility for ensuring appropriate use lay. Others, like I11, saw no threat to (personal) privacy. From the interviewees' responses, we were also able to find indications of the anchored organisational culture, which in our case tends to have a hindering effect on the HRA tool. The interviewees stated that there were many people with reservations and sceptics who viewed changes to previous processes or systems as negative; in addition, decision-making processes within the authority were often perceived as not rational and were very time-consuming. Moreover, the adoption of the HRA tool was a complicated undertaking because employees had difficulty dealing with predictions and uncertain expectations. Interview insights on subjective norms regarding adoption of ML-based HRA tools are presented in Table 4.

4.2. Impact of ML characteristics

The results for how the characteristics of ML affect behavioural beliefs (RQ2) are presented below. Our findings are successively illustrated in terms of trialability, transparency, automation, self-learning capabilities and fairness, as well as their effect on beliefs and experiences.

Table 3
Interviewees' attitude to the adoption of ML-based HRA tools.

Example Insights	1st-order Categories	2nd-order Categories	Aggegate Dimension
"*I just wanted to add, because I think that our organisation is so big, that you do not have to look at individual employees. I cannot use that method at all.*" (I3, 109)	Task technology fit	Compatibility	Attitude
"*Through the tool, managers are encouraged to be active in their role.*" (I7, 362)			
"*Then I can look at this and analyse the most important factors that influence why this employee is leaving and use this to initiate optimisation.*" (I9, 120)	Novel HR insights		
"*Of course, this creates trust when you see that even without algorithms.*" (I3, 64)	Consistency with intuition		
"*No, there must be a mistake. It says that the probability of turnover is higher for civil servants.*" (I5, 115)			
"*I see this as a great support, and it goes much further than what we could do in the past. […] You can draw insights from the data that give the organisation a positive kick in any case.*" (I4, 283)	Technological innovation	Improvement through innovation	
"*I think it is great that such an approach has been found at all.*" (I6, 160)			
"*It is always nice to try something out, but of course, the question is then always cost and benefit. Does it bring us anything?*" (I11, 162)	Implementation effort		
"*I am afraid of the surveillance now that the supervisor monitors me like this: do I go or not?*" (I11, 206)	Anxiety	Personal concerns	
"*On the negative side, my responsible tasks could be taken away from me, because there would be a risk that I would leave the organisation.*" (I9, 212)			

Table 4
Interviewees' subjective norms regarding the adoption of ML-based HRA tools.

Example Insights	1st-order Categories	2nd-order Categories	Aggegate Dimension
"*Data protection is a very important topic in our organisation. […] Because we run analyses here that can be evaluated on a personal basis, and conclusions can be drawn about a person*" (I6, 180)	Data use/protection	Legal framework	Norm
"*This is very sensitive data with which the tool works – highly explosive in terms of data protection. Therefore, it cannot be implemented in this form.*" (I7, 326)			
"*And when it comes to data protection […] I think [it] tends to protect those who have something to hide rather than benefit others. […] Instead of excluding variables, you might have to take other variables in addition.*" (I8, 351–359)			
"*The problem is: The implementation of tools like this in-house must be approved by the organisational councils. From my work as an organisational consultant, I also know that software like this is not simply approved*" (I5, 169)	Co-determination rights of organisational councils		
"*That would just be too much intrusion into my personal life for my supervisor to have that information to hand.*" (I9, 258)	Social norm	Culture	
"*My boss has all my data at his disposal. He knows how many children I have, and he also knows where I live. He also knows when I'm sick and how much I earn.*" (I11, 214)			
"*We have many doubters – there is not only the political thing in the house.*" (I7, 366)	Organisational culture		
"*The management always tries to be supportive, of course, but decisions are not made as quickly as in the private sector.*" (I9, 240)			

4.2.1. *Trialability has an impact on attitude*

Overall, we observe a positive effect of trialability on the intention to adopt the provided HRA tool. Similar to the findings of Vargas et al. (2018), our interviewees believe that it is important to try out the ML model before it is implemented in the organisation, in order to gain experience of using it. They argue that a high level of trial and error makes it easier to assess the accompanying consequences of actually applying the ML model, which in turn could lead to an increase or a decrease in one's attitude regarding the tool. On the one hand, trialability helps to assess whether the ML model provides a presumed improvement through innovation (technological innovation):

"*I like to try something like this out in practice […]. ML does not really help here yet. I think we always have to make our own experiences with applications. […] They have to prove themselves in practice somewhere. And if they do not, then I have to analyse that. Where is the problem, or where does it not bring the benefit that I had hoped for? And, if necessary, I have to adapt it.*" (I4, 283).

On the other hand, trialability helps to mitigate any potential personal concerns of employees:

"*For matters that are more critical, it is wise to first try things out, test them, see where adjustments can be made, involve the people and initially test it in a small area to then see how it is received […] But having these sceptics around all the time makes everything a bit more difficult.*" (I11, 222).

4.2.2. *ML transparency has an impact on both attitude and PBC*

We observe positive and negative effects of transparency on the intention to adopt the provided tool. At the beginning of the interviews, we asked the interviewees about their intention to adopt the employee turnover predictions in their daily work. Interestingly, most initially saw little to no application in the tool's predictions when it came to pure predictive accuracy without understanding the effects of the predictors:

"*Unfortunately, I am not able to determine the value added because I have not performed any [proving] calculations [...]. Therefore, I could honestly plan better for the future based on historical data.*" (I9, 98).

However, the more transparency provided by the presentation of multiple predictor effects, the more diverse and extensive the applications identified by the interviewees (in their areas of responsibility), improving their attitude via the perception of compatibility of the tool and especially the personal task-technology fit. Besides reflecting on how the predictions could be used (e.g., for workforce planning and identifying future staff shortages), the interviewees also recognised that the tool provides explanations for turnover. Thus, it offers opportunities to either mitigate turnover at an individual level or derive strategic and organisation-wide initiatives that address employee wellbeing (e.g., increasing remote working opportunities) and employer attractiveness (e.g., increasing childcare offerings). The discussions in all interviewees about possible applications of the tool in other HRM processes, made possible by transparency, indicate a higher algorithm-based efficacy.

In addition, providing more transparency can have a positive or a negative effect on one's attitude when the derived predictor effects contradict personal intuition (compatibility). On the one hand, our interviewees found contradicting evidence useful in questioning their personal intuition:

"*But it definitely brings insights that straighten out the picture and probably bring it closer to reality. Yes, I would use it if I had to decide for my hotdog stand.*" (I1, 135).

On the other hand, a few interviewees questioned the functionality of the provided tool when identifying evidence that contradicted their own intuition (conformity with intuition, Table 3). Furthermore, our results suggest that these interviewees demanded a high degree of traceability to help them understand the underlying calculations of the ML model (algorithm-based efficacy):

"*I [...] want to understand what is happening behind the system, [...] In Excel, you can see how the calculation is done and what the result will be. With machine learning, you probably won't be able to see it that way. The machine learns based on the data and then outputs something. So, I always need a certain level of traceability for each step.*" (I9, 294).

To summarise, we find that transparency influences attitudes via the perception of compatibility in two ways (personal task-technology fit and conformity with intuition), as well as PBC via algorithm-based efficacy, also in two ways (applicability and traceability).

4.2.3. Degree of automation through ML decision-making influences attitude and PBC

We mostly observe a negative effect of the degree of automation on the intention to adopt the provided ML model. All interviewees agreed that decisions should only be augmented with the help of the tool and that a fully automated decision-making process should not be implemented. Several reasons regarding attitude, especially personal concerns, were given for this, such as the fact that the interpersonal component must not be lost, especially when decisions are made on an individual basis:

"*At the top level, they want numbers, and there's also the risk that when they see those numbers, they do not want to deviate from them […]. However, the human factor, and the perspective and the focus on the individual employees, is simply lost as a result. The decision-makers who normally have management responsibility, who actually manage people, have to look at the results.*" (I1, 52).

I4 pointed out that automation is only useful if the model does not make a single mistake. This in turn is reflected in the expected accuracy of the tool (algorithm-based efficacy):

"*[For automation], the probability of correct predictions is not yet high enough, not until the hundred per cent mark is reached. Until then, decisions are up to personnel analysis by management – instead of letting the machines think completely.*" (I4, 275).

The interviewees believed that the responsibility and rational towards decisions lies with humans (an ML-augmented decision process) and questioned whether the provided ML model is suitable for drawing the right conclusions and deriving appropriate actions from a prediction. This translates to a low perceived applicability (algorithm-based efficacy):

"*If you were to go only by the machine: a woman has a salary of 3,000. We will just raise it to 4,000 – but a man does not get that raise. [...] I would see it critically in the first instance. In any case, it does not replace the interpersonal connection. Well, I do not work together with the machine, especially not in a subordinate relationship. Ultimately, such a decision must be made by a manager.*" (I7, 402).

4.2.4. The self-learning capabilities of ML affect PBC

Unexpectedly, we identified the perceived learning capabilities of the provided ML model as a further relevant ML characteristic influencing the algorithm-based efficacy (PBC). A few interviewees associated continuous learning with ML and expected continuously increasing accuracy due to future learning iterations with more data or feedback loops:

"*[With] ML and Artificial Intelligence work – as far as I have now generally heard – the more you feed, let's say, the machine with information, the better it becomes. And that's exactly the direction it should go if you use it more often and feed it with more and more data. It will get better and better, and that will also reduce the error rate, in my opinion.*" (I9, 182).

Interestingly, some of the interviewees translated the automated self-learning characteristics they were aware of from a reinforcement learning ML model in another context to this specific ML model, without knowing whether these feedback loops were actually implemented:

"*[ML]… is a self-learning system, and the more often I run it, the better my predictions become. In this respect, if I have understood correctly, we are still at the start. And the more data is fed in and compared with real things, the more accurate the predictions will be – at least that's what I would expect.*" (I2, 85).

4.2.5. (Un-)Fairness does not affect the intention to adopt

As noted in the literature review, increased ML transparency can also affect perceptions of ML fairness. In the interviews, we specifically asked about the fairness perception in hypothetical scenarios (e.g., What requirements do you have for the model in terms of fairness or equal opportunity? Would you remove certain data from the dataset, for example, for reasons of fairness or equal opportunity? From the position of your supervisor making decisions about you, do you have any reservations or concerns about using the model?). Interestingly, none of the interviewees mentioned significant caveats regarding fairness aspects. For example, excluding protected group variables from the dataset was not suggested by any interviewee. We were able to ascertain this even after providing a list of predictors used in the ML model as well as XAI visualisations that (1) listed protected group variables such as gender or age and other data that require extensive protection, such as health-related information, (2) clearly documented differences between protected group variables and their impact and (3) were considered the basis for local (employee-specific) or global (organisation-wide) decision-making – and thus varying degrees of impact on individual employees. Several arguments were made by the interviewees as to why the HRA tool in its current state is fair and no adjustments are needed. First, I9 referred to the objectivity of the data and the responsibility for any consequences:

"*You cannot influence the fact that our organisation is over 70% women, so you cannot do anything by saying that we now have to hire only men. That would be discriminatory. That is why I do not think it is so bad. Those are the facts, that is the database, you cannot change that. Or that older workers are less likely to quit. As a human being, as a decision-maker, you also have the information, and you have to interpret it accordingly.*" (I9, 280).

Second, I1 made a similar argument, pointing out the possible lower prediction accuracy of the tool when predictors are eliminated. The interviewee argued that differences are not unfair if they are based on differences between protected groups that can be explained by real facts, which he exemplified in terms of intergenerational differences:

"*My father was in the same company for 30 years, my mother worked in the same company for over 40 years. So that is the thing, for me, that would be unthinkable. I would not exclude predictors like age or gender […]. I can understand that you want to leave such factors out so as not to discriminate against anyone […], but it would also just be out of touch with reality. […]. I would claim that there are significant differences, and that tells me that it must not be left out at all.*" (I1, 151).

Overall, we found no evidence that the interviewees had changed their intention to adopt the HRA tool due to the different treatment of women or men, or younger and older employees. This can be explained by the above statement that potentially unfair discriminatory decisions should be corrected by human judgment in an augmented (non-automated) decision-making process.

4.3. *Refined model: Individual intention to adopt HR analytics*

The results of our study are summarised in a qualitative model, as illustrated in Fig. 4. Vargas et al.'s (2018) framework forms the basic structure on which the various factors influencing PBC, attitude and norms are concretised. As a further addition, the influences of ML characteristics emerge. Please note that ML characteristics have effects on zero (fairness), one (self-learning capabilities) or two (transparency, automation and trialability) constructs of behavioural beliefs.

5. Discussion and implications

Notwithstanding the asserted importance of HRA, research examining its impact on organisational performance remains underdeveloped (Marler and Boudreau, 2017). While recent studies find evidence for the effects of HRA and organisational performance, this link is mediated by an organisational shift to more evidence-based management practice. Moreover, it is argued that HRA can only provide a benefit for an organisation when predictions and estimations are incorporated into neutral and evidence-driven decision-making (McCartney and Fu, 2022). Evidently, a respective shift requires a congruent employee mindset and therefore a strong intention to incorporate HRA into their daily work. Our study contributes to this ongoing debate by extending and contextualising current knowledge on the adoption of ML-based HRA for a specific use case.

5.1. *PBC, attitude and norms influence an individual's intention to adopt HRA*

Regarding salient beliefs and experiences, Vargas et al. (2018) find five factors determining the individual adoption of HRA: technology self-efficacy (PBC), quantitative self-efficacy (PBC), attitude towards using HRA, social influence and tool trialability. Vargas (2016) investigates a larger number of possible factors influencing the user level of adoption, whereby general self-efficacy and data availability, which were queried in the survey with narrowly specified items, showed no significant influence. Therefore, we investigate the personal perspectives, experiences and spontaneous reactions of knowledgeable employees in a specific use case with field data. This particularly provides a lens for a deeper understanding of the individual adoption of ML-based HRA. For example, we find evidence that interviewees with higher quantitative skills, as well as overall competency-based self-efficacy (e.g., HR knowledge), were more open to incorporating the displayed HRA tool in their work. In addition to technological aspects, the input data on which the ML-based HRA tool is trained was highly important to the interviewees. We therefore suggest that data-based efficacy, as an aggregation of the composition and reliability of the dataset, is another important dimension of a potential user's efficacy. The findings published by Omrani et al. (2022) suggest similar relationships in terms of data, albeit their study argues that concerns about discrimination in the use of Artificial Intelligence reduce trust. In addition, we find evidence that attitudes towards the adoption of HRA are made up of a wide variety of aspects. These can be divided into three categories, namely the assessment of the tool's compatibility in daily work, an assessment of the potential for improving the tool in organisational processes and personal concerns. Venkatesh et al. (2003) find similar results in their model of technology use. In their work, performance expectancy, as the "extent to which an individual believes that using the system will help them improve their job performance", represents a relevant factor similar to the perceived usefulness of the Technology Acceptance Model (Davis, 1989). Regarding the norm, the interview data also divides this factor into legally established norms and (organisationally) culturally determined aspects.

Proposition 1:	For ML-based HRA, an understanding of related studies is not sufficient to explain individual adoption. Instead, we propose additional important determinants for PBC (data-based and algorithm-based efficacy), attitude (compatibility of tools and tasks, personal concerns, improving practices through innovation) and norm (organisational culture and legal framework).

5.2. *Most ML characteristics have an influence on behavioural beliefs*

Furthermore, our results suggest that several additional ML characteristics drive perceived algorithm-based efficacy as well as attitudes to the use of the displayed ML tool. First, to make ML-based HRA useful, predictors' diagnostic results – provided by the XAI visualisations – are an important facilitator in terms of coalescing employee turnover predictions (Chowdhury et al., 2022). Identifying additional uses of the HRA tool when understanding the causes of employee turnover suggests a more evidence-based management practice, which is theorised as an important enabler of HRA in an organisation (McCartney and Fu, 2022). The studies by Kim et al. (2023) and Haque et al., 2023 reveal that XAI visualisations in particular contribute to user understanding and adoption, when appropriately designed. To summarise, in most cases, higher transparency leads to a higher attitude and PBC. We thus provide an empirical example demonstrating that with sufficient ML transparency, the various burdens on users (emotional, mental, prejudices, etc.) (Park et al., 2021) can be overcome when introducing ML-based HRA. However, in line with other research (Schmidt et al., 2020), we also find that these effects can be reversed when the rational explanations of the model and the reasoning of experts contradict each other.

Second, our interviewees were reluctant to automate an entire decision, for example a promotion, by delegating it to the HRA tool, as most of them did not expect the respective tool to possess the necessary skills to solve the task adequately on its own. This finding is similar to the results by Dietvorst et al. (2018), who identified a significant aversion to fully automated predictive analytics tools that vanishes when participants get at least some degree of control over the underlying decision. Lee and Cha (2023) confirm this notion by showing that choosing augmentation over automation is one of the two key factors in adopting Artificial Intelligence recruitment systems.

Third, we observe a difference in the beliefs of the interviewees, who expect the displayed HRA tool to have self-learning capabilities or not. In sum, our empirical data indicates that interviewees are more forgiving of an error-prone prediction in the first case, as maybe because they expect the HRA tool to subsequently improve upon its past mistakes and thus increase algorithm-based efficacy. Note that this finding is in line with Reich et al. (2023) and Berger et al. (2020), both of whom identify self-learning capabilities as an important factor in mitigating algorithm aversion. Our study extends these interesting points by the fact that self-learning ability may be taken for granted by using the ML term, while such abilities (e.g., reinforcement learning) are not even implemented.

Fourth, as proposed by Vargas et al. (2018), our interviewees were interested in trying out the displayed HRA tool to assess its capabilities and then form an attitude on it. In addition, indicators of initial anxiety about the ML-based HRA tool's capabilities were apparent (see Table 2), which can be addressed with trialability. This finding is in line with the *Innovation Diffusion Theory* (Rogers, 2003). In summary, we therefore propose:

Proposition 2:	Several ML characteristics influence attitude and PBC in relation to the intention to adopt ML-based HRA: (a) the degree of transparency created, (b) the choice of automated usage, (c) the implementation of self-learning capabilities and (d) the enabling of trialability.

Consistent with Neumann et al. (2022), we find no reference in the interviews to ethical considerations regarding the adoption of the ML-based HRA tool in our empirical setting from public sector. Our results show that fairness and non-discrimination were not critically questioned, even when potential biases were highlighted by XAI visualisations and the interviewees were explicitly asked about them. This outcome is alarming, as HRA, and especially ML, can foster discrimination and create various risks for employees and the organisation (Tursunbayeva et al., 2022). For example, according to the General Data Protection Regulation of the European Union, the use of an ML model that includes protected class variables for individual decision-making can be considered a legal case of discrimination, referred to as "disparate treatment" (Goodman and Flaxman, 2017). Lee and Cha (2023) confirm that solving the fairness problem remains complex, even if this complexity mitigates discovering an unfair decision basis.

Proposition 3:	Fairness does not matter for the individual deciding whether to adopt ML-based HRA and must be ensured by other appropriate measures.

5.3. Implications for practice

In practice, organisations seeking to leverage the potential of efficiency gains through ML-based HRA might try to increase adoption at the individual level. Our results reveal that various adjustable modifiers exist during adoption, in particular the degree of automation in algorithm-based decision-making and provided transparency. Most importantly, technical measures (such as XAI) can positively or negatively influence both PBC and attitude, because providing understandable visualisation allows the user to compare the included predictors, as well as their effects with their intuition.

However, in trying to increase the intention to adopt ML-based HRA on an individual level, organisations should be careful to avoid pitfalls. For instance, negative examples have already demonstrated that biases can lead to unfair decisions based on ML (e.g. Alon-Barkat and Busuioc, 2023). With the risk of resulting high social and economic damage, the consideration of ethical challenges is necessary in HRA projects (Langer and König, 2021; Edwards et al., 2022). As legislation for the responsible use of ML comes into force soon (AI HLEG EU, 2019), organisations need to address such potential unfairness proactively. Thus, our finding, namely that ethical considerations and fairness of HRA in the early adoption stages were not challenged by the interviewees, is alarming and should therefore be paid careful attention in practice. Neumann et al. (2022) note that specifically the early adoption phases of ML applications are characterised by (1) a focus on positive business cases, (2) reliance on external partners, (3) change management processes to increase acceptance and (4) little to no real recognition of ethical considerations such as algorithm accountability and fairness. Thus, we specifically advise organisations to ensure proactively the inclusion of ethical considerations in the early stages of adoption and to implement internal policies and approval procedures with the help of internal or external expertise.

Ultimately, the responsible use of ML-based HRA can only be achieved when HR professionals have the knowledge necessary to evaluate ML models critically, based on the transparency provided by technical measures such as XAI visualisations and internal guidelines (Langer and König, 2021). However, Vargas et al. (2018) note that HR professionals have low levels of quantitative self-efficacy (fear of maths/statistics, lack of quantitative training, low awareness of analytics, lack of resources and organisational support to promote analytics and its tools). Our results extend these findings, which suggest investing in training initiatives that demonstrate the importance of achieving ML transparency and in turn encourage the acquisition of skills specifically to interpret performance statistics of ML algorithms or XAI visualisations.

5.4. Limitations and further research

There are two main points that limit the findings of this study. First, our qualitative approach is based on the manual coding of interview transcripts; however, we took several measures to ensure the validity of our findings during the coding process and after the final analysis (see Fig. 2). For example, the credibility of our findings was established by independent coding by two of the authors in three coding steps. In addition, our results were critically reflected on the basis of existing evidence (Vargas et al., 2018) and by the third author. The findings were verified by inter-coder and intra-coder reliability (Miles and Huberman, 1994).

Second, while the methodological choice of a single case study has a solid foundation in HRM, and recent studies using this method advance the field considerably (e.g., Ellmer and Reichel, 2021; van den Broek et al., 2021; Wikhamn, 2023), this methodological choice limits the transferability of our findings (Flyvbjerg, 2006). Nonetheless, it offers the advantages of an in-depth investigation of HRM practices with a heterogeneous interviewee population (e.g., diverse backgrounds and experience) and an examination of deep cause-effect relationships (from ML characteristics to HRA adoption) that are overlooked in broader studies. In our particular case, the results thus pave the way for future quantitative studies that can explain the individual adoption of HRA more holistically and further develop the previous framework by Vargas et al. (2018), which can only explain about 35 % of the observed variance. To achieve this, the exploratory and qualitative nature of our study leaves the following concrete possibilities for future research. First, future studies should examine multiple organisations to further validate the transferability of the three propositions for individual HRA adoption. Second, we invite future research to formulate and quantitatively test hypotheses based on our proposed qualitative model. Especially, the effects of the automated usage of ML predictions and ML transparency provide interesting opportunities in this regard, as they both affect PBC as well as attitude. In addition, our study is not able to provide insights into the effect strength of the assumed causal relationships between ML characteristics and the intention to adopt. Third, we focus on the first implementation of an ML-based HRA tool, which means that the key beliefs and experiences identified, as well as underlying ML characteristics, may not apply to a more mature stage of ML adoption. Therefore, given that information systems research has found a considerable number of factors influencing the intention to use HRA (e.g. Mahmud and Islam, 2022), future research could investigate whether the effects and significance of certain factors change over the course of the implementation and utilization phase. For example, does the importance of ML transparency decline as users of ML-based HRA gain experience over time and learn that the system provides (in-)accurate results? Fourth, we agree with the widespread view that HRM systems need to be tailored to the individual case (e.g., Wikhamn, 2023), which is why we also call for more qualitative research examining the individual adoption of technological advances in ML-based HRA.

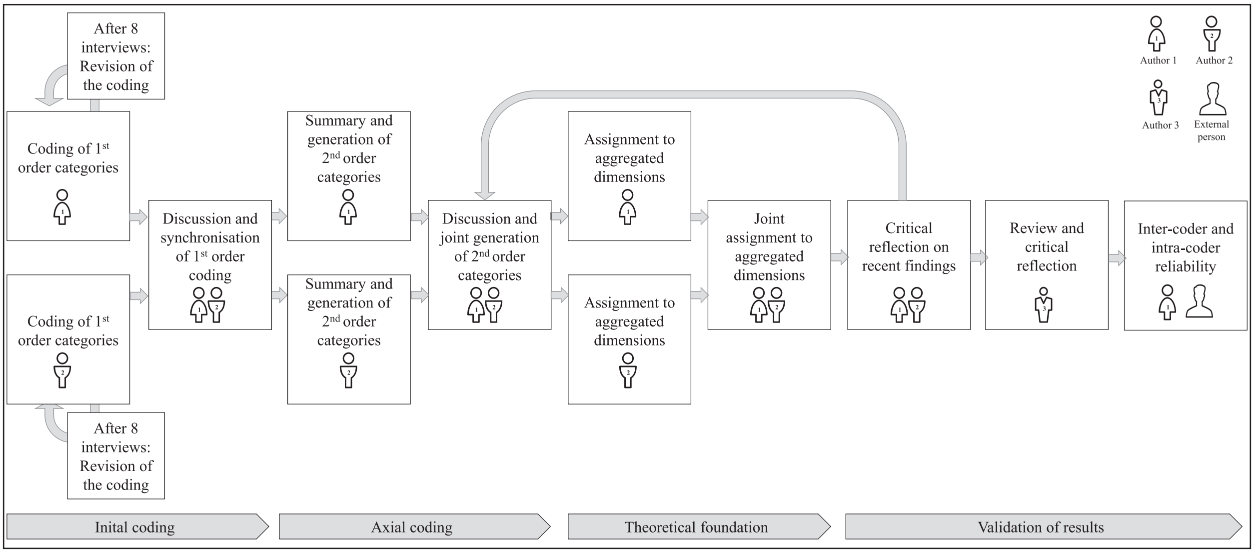

Fig. 2. Interview coding process, including critical reflection steps to ensure reliability.

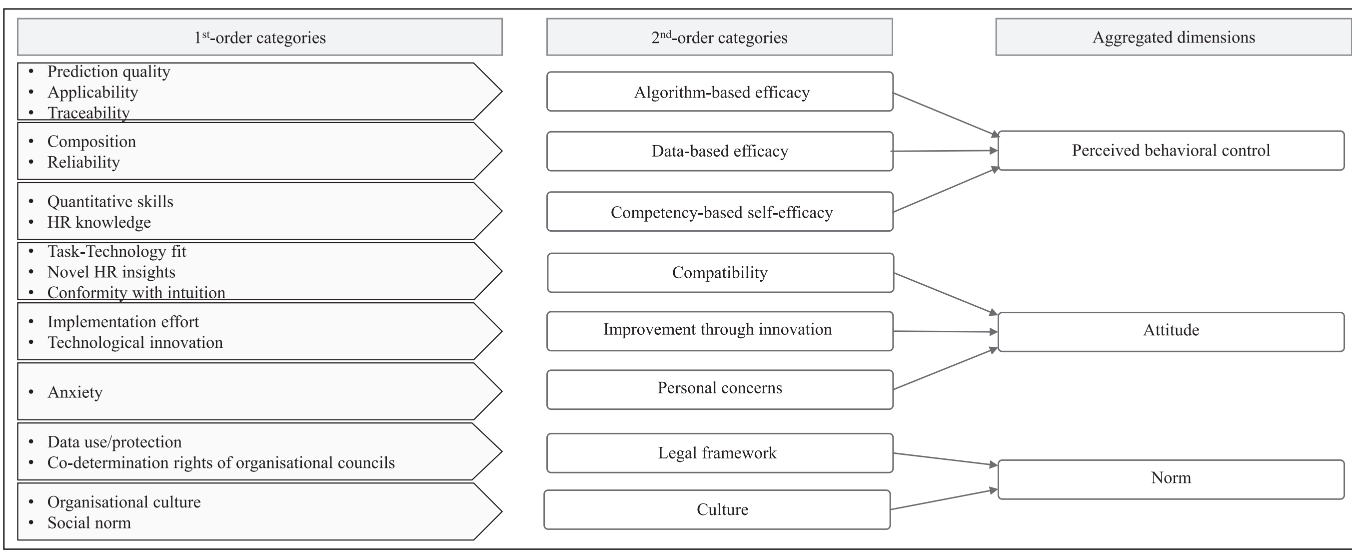

Fig. 3. Data structure (first-order categories summarised by key topic).

6. Conclusion

In contrast to existing technological tools, ML-based HRA generates unique challenges, most notably the potential opacity of the rationality used by models to formulate predictions, as well as the potential to automate HRM decision-making fully. This study provides deeper insights into behavioural beliefs determining the decision to adopt ML-based HRA from an individual perspective and sheds light on how ML characteristics affect it. Based on the focused interview methodology, we introduce novel propositions and an extended qualitative framework with new constructs of important factors from the perspective of end-users of individual HRA adoption. Investigating the lines of reasoning also reveals that potential ML model users do not include fairness considerations in their decision to neglect or adopt the tool. We hope our findings help to guide both the interdisciplinary research on HRA and organisations to a successful path in their mission to achieve the responsible proliferation of ML-based HRA.

Declaration of generative AI in scientific writing

No usage of generative AI tools.

Declaration of 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.

CRediT authorship contribution statement

Svenja M. Hülter: Writing – original draft, Validation, Software, Formal analysis, Data curation. **Christian Ertel:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Ansgar Heidemann:** Writing – original draft, Visualization, Resources, Project administration, Data curation.

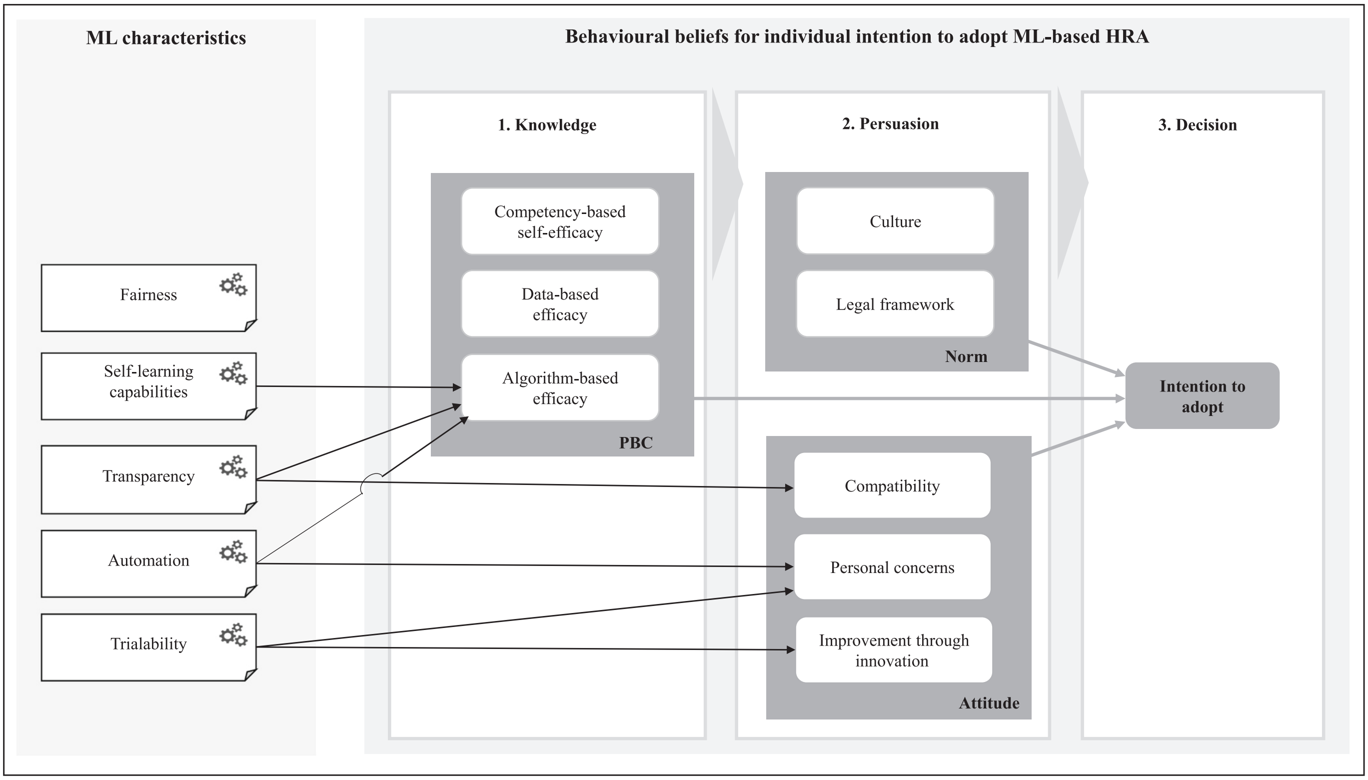

Fig. 4. Proposed qualitative model for individual intention to adopt HRA based on ML characteristics.

Data availability

The data that has been used is confidential.

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