Measuring HR analytics maturity: supporting the development of a roadmap for data-driven human resources management

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Abstract

Purpose – Today, companies are struggling to develop their human resources analytics (HRA) capability, although interest in the subject is rapidly increasing. Furthermore, the academic literature on the subject is immature with limited practical guidance or comprehensive models that could support organisations in the development of their HRA capability. To address this issue, the aim of this paper is to provide a maturity model – i.e. HRAMM – and an interdependency matrix through which an organisation can (1) operationalise its HRA capability and assess its organisational maturity; (2) generate harmonious development roadmaps to improve its HRA capability; and (3) enable benchmarking and continuous improvement.

Design/methodology/approach – The research described in this paper is based on the popular methodology proposed by Becker *et al.* (2009) and the procedure for maturity evaluation developed by Gastaldi *et al.* (2018). This method combines academic rigour and field experience in analytics, in a process spanning eight main phases that involves literature reviews and knowledge creation techniques.

Findings – We define HRA maturity through four areas and 14 dimensions, providing a comprehensive model to operationalise HRA capability. Additionally, we argue that HRA maturity develops through an evolutionary path described in four discrete stages of maturity that go beyond traditional analytics sophistication. Lastly, the interdependency matrix reveals specific enablers for the development of HRA.

Practical implications – This paper provides practitioners with useful tools to monitor, evaluate and plan their HRA development path. Additionally, our research helps practitioners to prioritise their work and investment, generating an effective roadmap for developing and improving their HRA capability.

Originality/value – To the best of the authors' knowledge, this study is the first to provide a model for evaluating the maturity of HRA capability plus an interdependency matrix to evaluate systematically the prerequisites and synergies among its constituting dimensions.

Keywords HR analytics, Workforce analytics, People analytics, Human capital analytics, Maturity model, Organisational capability, Development path, Decision-making

Paper type Research paper

1. Introduction

In the past 2 decades, organisations have been forced to operate in an increasingly volatile environment, handling a dynamic and complex workforce (Huselid, 2018; Bechter *et al.*, 2022). Human resources (HR) departments have transformed from purely administrative units to take on a strategic and business-oriented role (Vargas *et al.*, 2018), contributing proactively to the creation of organisational value (Levenson, 2018; Larsson and Edwards, 2021). Additionally, the diffusion of digital technologies has transformed the traditional ways of managing employees (Giermindl *et al.*, 2022; Fernandez and Gallardo-Gallardo,

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2020), providing data and information that can help employers to understand the psychology and behaviours of their staff more clearly (McIver *et al.*, 2018; McCartney and Fu, 2021; Huang *et al.*, 2023). In this context, the organisational capability to use data and analytics to support HR management (HRM) decisional processes has become crucial for organisations to remain competitive (Huselid, 2018; Levenson, 2018; Minbaeva, 2018). More specifically, organisations are becoming increasingly interested in HR analytics (HRA) capability and are willing to replace traditional intuition-based procedures with evidence-based decisional processes (Lunsford, 2019; Loscher and Bader, 2023). Despite the mounting interest (Ramachandran *et al.*, 2023; Bahuguna *et al.*, 2023; Coolen *et al.*, 2023; Thakral *et al.*, 2023), companies are still struggling to systematically develop and implement HRA initiatives (Angrave *et al.*, 2016; Shet *et al.*, 2021; Edwards *et al.*, 2022; Ramachandran *et al.*, 2023). Today, 42% of these analytics projects fail (Bersin, 2021), and the companies themselves report facing a "capability gap" between their current and required analytics capabilities (Minbaeva, 2018).

In this regard, researchers have recently defined HRA as an organisational capability to be nurtured (e.g. Minbaeva, 2018; Falletta and Combs, 2021; Shet *et al.*, 2021), emphasising that it is both complex and multi-faceted (Minbaeva, 2017; Levenson, 2018) and has links with organisational strategy and competitive advantage (Samson and Bhanugopan, 2022). More specifically, prior research has explained that successful HRA development requires close integration among different resources (Ramachandran *et al.*, 2023; Wang *et al.*, 2024), organisational dimensions (Wirges and Neyer, 2022; Coolen *et al.*, 2023) and even across organisational boundaries (Conte and Siano, 2023). However, limited contributions have been put forward on how to develop HRA capability satisfactorily (Marler and Boudreau, 2017; Levenson, 2018; Ramachandran *et al.*, 2023; Wang *et al.*, 2024).

In this regard, maturity models (MMs) have often been used in scientific research to assess and evaluate business analytics (e.g. Chen and Nath, 2018), business intelligence (e.g. Raber *et al.*, 2013) and data analytics capabilities (e.g. Arunachalam *et al.*, 2018). It has been proven that the MM approach can give organisations effective support in developing a specific solution, system or capability from an initial to a desired state of maturity (Marx *et al.*, 2012; Gökalp *et al.*, 2021). However, in the current literature, there are neither MMs for HRA nor specific models for applying analytics capabilities to the HR domain (Bahuguna *et al.*, 2023; Wang *et al.*, 2024). Furthermore, most of the existing MMs are static and do not consider the dimensional interdependencies present in specific domains (Maier *et al.*, 2009; Gastaldi *et al.*, 2018), failing to provide the support organisations need to prioritise their investment and plan their evolutionary paths (Gastaldi *et al.*, 2018).

Thus, this paper aims at filling these gaps by providing an HR analytics maturity model (HRAMM) that can provide support to academics in operationalising HRA capability maturity and to practitioners in understanding how to develop their analytics capabilities. A further purpose of this research is that systematically evaluate the interdependencies among the dimensions constituting HRA capability, proposing a procedure to design and prioritise interventions and investments. Our findings provide researchers with a comprehensive method for the operationalisation of HRA capability maturity, described through four areas (*Technological, Organisational, Functional, Diffusion*), 14 dimensions and 37 further components. In addition, we argue that HRA capability develops through four stages of maturity (*Initial, Limited, Systematic, Strategic*), going beyond the traditional levels of analytics sophistication discussed in prior research (Margherita, 2021). Theoretically, we draw attention to the point that HRA development depends on different organisational dimensions and their effective integration, suggesting that researchers should apply a systematic and interdisciplinary approach in their future research. Lastly, we provide useful methods that can help practitioners evaluate the current maturity of their HRA capability and plan a harmonised path for their development.

2. Theoretical background

The theoretical background has been organised into three main sections. The first focuses on HRA literature, the second on the MM approach and the third summarises prior contributions on business analytics, business intelligence and data analytics MMs.

2.1 HR analytics

Academic literature on HRA has introduced a variety of labels and definitions (Marler and Boudreau, 2017; Margherita, 2021; Thakral *et al.*, 2023), which share statistical and mathematical techniques to support people-related decisions (Larsson and Edwards, 2021; Edwards *et al.*, 2022; Coolen *et al.*, 2023). Recently, scholars have defined HRA as an organisational capability (Levenson, 2018; Minbaeva, 2018; Falletta and Combs, 2021; Samson and Bhanugopan, 2022), stressing its nature rooted in different resources and dimensions (Minbaeva, 2018; Wirges and Neyer, 2022). An organisational capability, indeed, refers to the way in which an organisation combines its resources, knowledge and competencies to systematically perform and extend its output actions (Salvato and Rerup, 2010). Organisational capabilities need to be built, developed and maintained over time, integrating and reconfiguring internal and external resources (Helfat and Peteraf, 2003). In recent research, it has been argued that, similarly, the development of HRA capability also requires integration among different assets and areas (Shet *et al.*, 2021; Ramachandran *et al.*, 2023; Wang *et al.*, 2024), operating across organisational levels and boundaries (Heuvel and Boundarouk, 2017; Minbaeva, 2018). Companies interested in developing their HRA capability should thus move from an individual- and HR-centred approach to one that takes in the composite and organisational facets of HRA (Andersen, 2017).

The debate on the emergence and development of HRA has become particularly relevant due to its current state of maturity in organisations. Recent research (Falletta and Combs, 2021; Shet *et al.*, 2021; Wirges and Neyer, 2022) has shown that most companies are still at a start-up phase involving descriptive analyses and isolated predictive analytics projects (Lismont *et al.*, 2017; Wirges and Neyer, 2022). The systematic use of descriptive (32%) or predictive (5%) analytics is very limited, although most HR decisions are now made on the basis of factual data and information (Wirges and Neyer, 2022). Furthermore, almost half of HRA projects (42%) fail for various reasons (Bersin, 2021), most of them caused by a gap between the analytics capabilities required and those currently available in the organisation (Minbaeva, 2018). Previous studies have explored the main barriers and challenges encountered by companies when establishing and developing their HRA capability. The main difficulties concern data management, the technical and analytical skills required for new HR professionals, and the integration between different information systems (Fernandez and Gallardo-Gallardo, 2020; Peeters *et al.*, 2020). Scholars have also discussed the problems around bringing strategic value to the organisation, including the difficulty to communicate values and results to top-management (Ellmer and Reichel, 2021; Jörden *et al.*, 2022) and to convert HRA results into practical actions (Levenson and Fink, 2017). Lastly, an observation made in recent academic research is that most of the complexities associated with HRA maturity can be traced to the required technical integration and interdepartmental collaboration (Fernandez and Gallardo-Gallardo, 2020). Successful HRA development, indeed, does not depend on simply applying sophisticated (but often isolated) analytics techniques but rather on the effective interaction, integration and consistency of its various socio-technical dimensions (Shet *et al.*, 2021; Wirges and Neyer, 2022; Loscher and Bader, 2023; Ramachandran *et al.*, 2023).

These findings conflict with the traditional definition of HRA maturity. Previous studies, indeed, have often described HRA maturity through three levels of analytics sophistication, i.e. descriptive, predictive and prescriptive (Marler and Boudreau, 2017; Margherita, 2021).

Adopting more advanced analytics techniques does not, however, fully reflect an organisation's HRA maturity (Shet *et al.*, 2021; Wirges and Neyer, 2022; Loscher and Bader, 2023). Isolated predictive projects focused on specific HR issues (e.g. turnover) or processes (e.g. recruitment) have been also found in companies in their early stages of analytics development (Lismont *et al.*, 2017; Wirges and Neyer, 2022; Huang *et al.*, 2023). On the other hand, a company is said to "possess" a capability only when it enables a repeated and reliable execution of specific practices and processes (Helfat and Peteraf, 2003). According to the resource-based view (Wernerfelt, 1984) and capability theory (Teece *et al.*, 1997), thus, the HRA capability of a firm refers to its organisational ability to use data and analytics systematically and continuously to support people-related decisions (Lismont *et al.*, 2017; Shet *et al.*, 2021), generating value competitive advantage for the whole organisation (McCartney and Fu, 2021).

In this regard, academic research into HRA development is still in an embryonic state (Margherita, 2021; Bahuguna *et al.*, 2023; Thakral *et al.*, 2023), with several underdeveloped research areas and gaps (Hamilton and Sodeman, 2019; Qamar and Samad, 2021). Firstly, there are very few studies on how to build, develop and maintain an HRA capability successfully over time (Marler and Boudreau, 2017; Qamar and Samad, 2021; Wang *et al.*, 2024). Secondly, scholars still have to reach consensus on which resources, processes and dimensions need to be considered during HRA development (Angrave *et al.*, 2016), and several works use a silos approach and consider analytics practices as isolated initiatives or projects (Falletta and Combs, 2021). Thirdly, the relationships and interactions between organisational areas and dimensions have only been covered in a limited number of studies (Wirges and Neyer, 2022), often through an approach centred on HR departments and their professionals (Andersen, 2017). These gaps result in a lack of practical research and guidance for practitioners engaged in defining and planning their evolutionary paths or to help them prioritise their work and activities (Levenson, 2018; Fernandez and Gallardo-Gallardo, 2020; Greasley and Thomas, 2020).

2.2 Maturity models

An MM is defined as a "structured collection of elements that describe the characteristics of effective processes at different stages of development" and provides "points of demarcation between stages and methods of transitioning from one stage to another" (Pullen, 2007). The MM approach was developed in the software engineering domain, generating significant savings in process development costs and improvements in quality and productivity (Gökalp *et al.*, 2021). In recent years, management research and practice have become increasingly interested in MMs, since they offer a simple but effective method to assess the quality of organisational capabilities and systems (e.g. Lismont *et al.*, 2017; Gastaldi *et al.*, 2018; Doctor *et al.*, 2023) and develop effective paths for improvement (Wendler, 2012).

The key objective of an MM is to reveal the gaps between the initial and the desired state of a certain capability, providing support for an organisation in generating an effective development path to improve its level of maturity (Becker *et al.*, 2009; Stoiber *et al.*, 2023). As the concept of maturity is associated with a stage growth approach (Monteiro *et al.*, 2020), the evolutionary paths proposed in these models consist of incremental improvements achieved through a set of intermediate states (Sen *et al.*, 2012). The main elements in an MM are maturity levels, model dimensions and assessment instruments (de Bruin *et al.*, 2005). The maturity levels are the different stages of maturity that each constituting dimension could take along its evolutionary path (Monteiro *et al.*, 2020). The characteristics of each level should be distinct and measurable, establishing a well-defined relationship between each level and the preceding and subsequent levels (Becker *et al.*, 2009). The model's dimensions are areas with mutually exclusive capabilities (de Bruin *et al.*, 2005), each containing a number of subcomponents (e.g. activities, practices or objectives). The assessment instruments are qualitative or quantitative tools (e.g. questionnaires, scoring models) to measure the maturity level at each dimension (Monteiro *et al.*, 2020).

The literature proposes three types of MMs, each with a different purpose of use (de Bruin *et al.*, 2005; Maier *et al.*, 2009). Descriptive models assess the as-is maturity state of a certain organisational capability, on the basis of specific dimensions and evaluation criteria (Becker *et al.*, 2009; Maier *et al.*, 2009). Prescriptive models evaluate maturity levels and provide practical guidance on how to develop an improvement path for reaching the desired state of maturity (de Bruin *et al.*, 2005). Eventually, comparative models enable internal and external benchmarking across companies, using data from many participants (Becker *et al.*, 2009). Additionally, MMs can be defined through two different approaches, according to how the dimensions and maturity levels are determined. A top-down approach involves specifying a fixed number of maturity levels and dimensions theoretically (Marx *et al.*, 2012). Alternatively, in a bottom-up approach, the requirements and measures are initially determined and then clustered into maturity levels (Lahrmann *et al.*, 2011).

2.3 Analytics and maturity models

In the past decades, scholars have proposed hundreds of MMs for multiple organisational capabilities (Doctor *et al.*, 2023), including business analytics (e.g. Cosic *et al.*, 2012), data analytics (e.g. Carvalho *et al.*, 2019) and business intelligence (e.g. Lahrmann *et al.*, 2011; Lismont *et al.*, 2017). These terms are often used interchangeably in scientific research (Arunachalam *et al.*, 2018) to define the organisational capability of using data, analytics and evidence-based management extensively to drive decisions and actions (Davenport and Harris, 2007; Chen and Nath, 2018). In this regard, Table 1 shows the 13 most relevant MMs by number of citations (i.e. Scopus), describing their development methodology, dimensions and maturity levels. The most notable MM on analytics capabilities is the Business Analytics MM proposed by Cosic *et al.* (2012), which consists of four areas (*Governance, Culture, Technology, People*) and five maturity stages (*Non-existent, Initial, Intermediate, Advanced, Optimised*). There has been an exponential growth in number of MMs over time (Król and Zdonek, 2020) and recent literature is beginning to provide MMs assessing analytics solutions to assess MMs in specific domains (Brooks *et al.*, 2015), including supply chains (Arunachalam *et al.*, 2018), healthcare (Gastaldi *et al.*, 2018; Carvalho *et al.*, 2019) and manufacturing (O'Donovan *et al.*, 2016; Gökalp *et al.*, 2021).

In most prior models, analytics maturity does not depend solely on the sophistication of the analytics techniques used but, rather, they take in multiple organisational dimensions (Brooks *et al.*, 2015; Król and Zdonek, 2020), ranging from data management (e.g. Gökalp *et al.*, 2021) to cultural influences (e.g. Boonsiritomachai *et al.*, 2016). Firstly, academics have described the structures and technological components underlying business analytics capabilities, including systems integration (e.g. Cosic *et al.*, 2012), data management (e.g. Chen and Nath, 2018) and the technological interface (e.g. Gastaldi *et al.*, 2018). Secondly, prior research has explained that, in order to build analytics capabilities, it is critical for an organisation to acquire, develop and orchestrate the appropriate organisational resources (Gökalp *et al.*, 2021). Organisational structure (e.g. Hausladen and Schosser, 2019), governance (e.g. Cosic *et al.*, 2012), knowledge and information (e.g. Boonsiritomachai *et al.*, 2016), human capital (e.g. Gökalp *et al.*, 2021) and executive leadership and support (e.g. Gastaldi *et al.*, 2018) are all aspects shown to have a substantial impact on the development of business analytics, data analytics and business intelligence (Gökalp *et al.*, 2021). Thirdly, the literature has emphasised the fundamental role played by the processes, applications and functionalities enabled by analytics systems and capabilities (Lahrmann *et al.*, 2011; O'Donovan *et al.*, 2016). These dimensions address the data analytics pipeline (Davenport

Table 1.
Most relevant business analytics, data analytics and business intelligence MMs

ID	Authors	Year	Cit	Model	Object	Method	Dimensions	Levels
1	Arunachalam, Numar and Kawalek	2018	310	Big Data Analytics (BDA)	BDA capabilities for supply chain management	Systematic literature review	Data generation, Data integration and management, Advanced analytics, Data visualisation and Data-driven culture	Incognizant stage (1), Initiation stage (2), Adoption stage (3) and Routinisation stage (4)
2*	Cosic, Shanks, Maynard	2012	86	Business Analytics (BA)	BA capabilities	Design science research approach	Governance, Culture, Technology, People	Non-existent (0), Initial (1), Intermediate (2), Advanced (3), Optimised (4)
3*	Lahrmann, Marx, Winter, Wortmann	2011	79	Business Intelligence (BI)	Impact-oriented BI solutions	Literature review and partial least squares analysis	Deployment; Use; Impact	Likert scale, from 1 to 5
4	Carvalho, Rocha, Vasconcelos, Abreu	2019	45	Data Analytics (DA)	DA for Hospital Information Systems	Systematic literature review and design science research	33 maturity-influencing dimensions, ranging from data repositories to real-time data analysis	Adhocracy (1), Starting the foundations (2), Centralised dictatorship (3), Democratic cooperation (4), Entrepreneurial opportunity (5), Integrated relationships (6)
5*	Raber, Winter, Wortmann	2013	43	Business Intelligence (BI)	BI capabilities	Literature review and Rasch algorithm	Strategy; Social System; Technical System; Quality; Use and Impact	Likert scale, from 1 to 5
6	Olszak and Mach-Kròl	2018	45	Temporal Big Data (TBD)	TBD assets and readiness	Critical literature review and multiple case study approach	Data knowledge, Information Technology, Functionalities, Sustainable development	Atemporal (1), Pre-temporal (2), Partly temporal (3), Predominantly temporal (4), Temporal (5)
7	Lukman, Hackney, Popovic, Jaklic, Irani	2011	40	Business Intelligence (BI)	BI Maturity in Slovenian organisations	Literature review for dimensions; K-Means for levels	Technological, Information Quality, Business	Immature (1), Technologically advanced (2), Advanced Information Management (3), Mature (4)

(*continued*)

ID	Authors	Year	Cit	Model	Object	Method	Dimensions	Levels
8	Boonsiritomachai, McGrath, Burgess	2016	33	Business Intelligence (BI)	BI Maturity for small- and medium-sized enterprises	Multinomial regression analysis	Infrastructure, Knowledge process, Human capital, Culture, Application	Operate (1), Consolidate (2), Integrate (3), Optimise (4), Innovate (5)
9	Gastaldi, Pietrosi, Lessanibahri, Paparella, Scaccianoce, Provenzale, Corso, Gridelli	2018	32	Business Intelligence (BI)	BI Maturity for healthcare services	Clinical Inquiry Research project	Technological, Organisation, Functional, Diffusion	Initial (1), Managed (2), Systematic (3), Disrupted (4)
10	Shah	2022	26	SAM^{DDC} -DAM^{PPC} Model	Analytics maturity in companies	Conceptual literature review	Analytics	Static Analytic Maturity (Descriptive, Diagnostic, Corrective); Dynamic Analytics Maturity (Prescriptive, Predictive, Cognitive)
11	Gokalp, Gokalp, Kayabay, Kocygit, Eren	2021	26	Data Science (DS)	DS MM for manufacturing organisations	Systematic literature review and multiple case studies	Organisation; Strategy Management; Data Analytics; Data Governance; Technology Management; Supporting	Not performed (1); Initiated (2); Managed (3); Established (4); Predictable (5); Innovating (6)
12	O'Donovan, Bruton, O'Sullivan	2016	22	Industrial Analytics Capabilities (IAC)	IAC in large-scale manufacturing facilities	Maturity Model development approach	Open standard; Operation technology; Information technology; Data analytics; Embedded analytics	Likert scale, from 1 to 10
13	Chen, Nath	2018	19	Business Analytics (BA)	BA capabilities	Systematic literature review	Organisation-focused; Technology-focused; Capability-focused; Impact-focused	Likert scale, from 1 to 10

Note(s): [*] MMs published in conference proceedings and not in a peer-reviewed journal
Source(s): Table by authors

Table 1.

and Harris, 2007), among which data reporting (e.g. Chen and Nath, 2018), data visualisation (e.g. Arunachalam *et al.*, 2018) and predictive and prescriptive model development (e.g. Shah, 2022). Lastly, recent research has started to include strategic, cultural and business-related dimensions in the proposed MMs (e.g. Lukman *et al.*, 2011; Chen and Nath, 2018), discussing their impact on the diffusion of analytics (Gastaldi *et al.*, 2018) and on value creation (Shah, 2022). Once organisations have operated on their technological, organisational and functional dimensions, the fundamental question becomes what they are then doing with the information and analytics insights (Lukman *et al.*, 2011). The argument set out in prior research is that companies must have a clear vision, strategy and roadmap to be able to develop and manage analytics capabilities (Gökalp *et al.*, 2021), aligning their operational activities to their business objectives (Lahrmann *et al.*, 2011).

Finally, prior studies have covered the development path of analytics maturity through different maturity levels using a variety of theoretical lenses. Arunachalam *et al.* (2018), for instance, described the assimilation of big data analytics drawing on the diffusion of innovation theory, representing maturity evolution as a sequence of four stages, "*incognizant*", "*initiation*", "*adoption*" and "*routinisation*". Analysing the literature, however, the most significant theoretical lenses applied in maturity modelling are the resource-based view (e.g. Cosic *et al.*, 2012), organisational capability theory (e.g. Raber *et al.*, 2013), the information system view (e.g. Carvalho *et al.*, 2019) and knowledge-based theory (e.g. Shah, 2022). Most of these theories suggest that an organisation's analytics capability matures into levels (i.e. stages) aligned with its ability to create competitive advantage through data and analytics (Chen and Nath, 2018; Carvalho *et al.*, 2019). Gastaldi *et al.* (2018), for instance, explained that business intelligence capabilities evolve from an *initial* to a *disrupted* stage, where analytics are used to generate a strategic value for the company, similarly to other MMs in the literature (e.g. Cosic *et al.*, 2012; Boonsiritomachai *et al.*, 2016; Gökalp *et al.*, 2021). In this regard, research has demonstrated that analytics has the potential to improve organisational performance and competitiveness by enhancing decision-making (LaVall *et al.*, 2011; Chae *et al.*, 2014; Chen and Nath, 2018). More specifically, Shah (2022) explained that analytics brings additional value to the organisation through the power of prediction, a more efficient use of underutilised or unutilised assets and the creation of a valuable, rare, inimitable and irreplaceable bundle of resources. Researchers furthermore agree that higher levels of analytics maturity help organisations achieve their strategic goals, make better decisions, improve business processes, increase profitability and generate competitive advantage (Olszak, 2016; Olzak and Mach-Król, 2018).

Despite growing interest in analytics MMs, academics have not proposed MMs for HRA capability or specific for the HR domain (Lismont *et al.*, 2017; Bahuguna *et al.*, 2023; Wang *et al.*, 2024). Furthermore, most of the proposed MMs are fixed and static (Lahrmann *et al.*, 2011), neglecting the interdependencies between their dimensions and components (de Bruin *et al.*, 2005; Maier *et al.*, 2009). These MMs fail to provide comprehensive and effective guidelines to prioritise interventions during the potential improvement path (Gastaldi *et al.*, 2018).

3. Method

This research was conducted within a collaborative project (Mohrman and Mohrman, 2004; Shani *et al.*, 2008) between a university research centre involved in studying HRA and a global consultancy company specialising in HR digitalisation, HR controlling and HRA development. The project ran from April 2022 to August 2023. The consultancy company was selected as a research partner because of its five years' experience in the HRA field and its interest in developing a model to assess and improve the maturity of HRA capability in organisations. Thus, according to the leading literature on collaborative research (Mohrman and Mohrman, 2004; Shani *et al.*, 2008), a research team consisting of three researchers and four practitioners was set up in May 2022. Four external HRA experts were also consulted during the development of the MM (see the phase covered in Section 3.3.3.), in order to increase the robustness and reliability of the results. All the team members are listed in Appendix 1, together with their institution, expertise and role in the project.

The research team developed the HRAMM through a qualitative approach based on the methodology proposed by Becker *et al.* (2009). This method was selected because it is known to be a rigorous, accurate and comprehensive method for MM development (Pöppelbuß and Röglinger, 2011; Cosic *et al.*, 2015; Brooks *et al.*, 2015). However, Becker *et al.* (2009)'s procedure does not explain how to measure and evaluate dimensional interdependencies and, thus, how to prioritise work and effort. Consequently, we integrated the original method with the procedure proposed by Gastaldi *et al.* (2018), which had been used in prior research to assess and evaluate business analytics maturity. The overall methodology is summarised in Figure 1.

The research process is presented according to a linear logic, but it is important to note that the phases were highly interrelated. The final outputs (see Section 4) are the result of their continuous iteration and interaction. Each stage and its output are described in detail in the next sections.

3.1 Problem definition

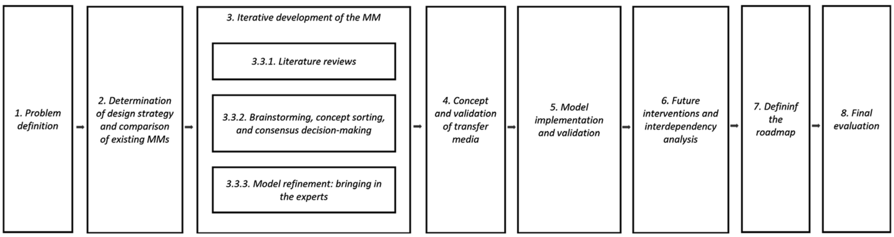
The first stage of the process is to define the problem, which consists of (1) identifying the targeted domain and target group, (2) discussing the relevance of the problem and the intended benefits and (3) determine the conditions for the model's application (Becker *et al.*, 2009). In our study, the HRA capability is the targeted domain and organisations are the target group. We then defined our research objectives and questions. Lastly, we worked to establish the model's completeness, optimisation and comprehensibility during its development, thus confirming the conditions for its application (Becker *et al.*, 2009).

3.2 Determination of design strategy and comparison of existing maturity models

The determination of an effective design strategy requires a comprehensive comparison with existing MMs (Becker *et al.*, 2009; Gastaldi *et al.*, 2018). However, currently, there is no MM on HRA in the academic literature (Bahuguna *et al.*, 2023; Wang *et al.*, 2024). Thus, we followed the strategy to design a completely new MM (Becker *et al.*, 2009).

3.3 Iterative development of the maturity model

The aim of the third stage was to define the fundamental structure of our MM, selecting the best development approach, designing its main elements and then validating their effectiveness (Becker *et al.*, 2009). Firstly, we decided to build a prescriptive MM (de Bruin *et al.*, 2005; LaVall *et al.*, 2011), in line with our objectives. Secondly, we selected a multi-



Source(s): Authors' own work

Figure 1.
Research methodology

dimensional structure because HRA is both complex and multi-faceted. Thirdly, we decided to adopt a top-down approach, based on the consideration that HRA maturity has not been clearly defined. Once the structure and the approach had been determined, the model's levels and dimensions were established in three sub-phases. In the first subphase, we carried out two content-based literature reviews to build a preliminary version of the HRAMM (Section 3.3.1.). In the second, we held five brainstorming sessions, four concept-sorting sessions and six consensus decision-making sessions to define the model's structure (Section 3.3.2.). Lastly, in the third subphase, we ran a series of meetings with four external HRA experts to refine, evaluate and validate the model conceptually (Section 3.3.3.).

3.3.1 Literature reviews. The first step when developing an MM is to understand the academic literature on the targeted domain (i.e. HRA) (Becker *et al.*, 2009; Gastaldi *et al.*, 2018). We, therefore, carried out two literature reviews, consisting of a systematic search and a qualitative content-based analysis (Mayring, 2000). The reviews were carried out on Scopus on 1st February 2022, with an update on 1st January 2024.

Firstly, we conducted an extensive content-based review on HRA capability and its organisational development. Following prior reviews on HRA (e.g. Marler and Boudreau, 2017; Margherita, 2021), we searched for "*HR Analytics*", "*Human Resource Analytics*", "*People Analytics*", "*Talent Analytics*", "*Workforce Analytics*" and "*Data-driven HR*" in the document titles, abstracts and keywords to identify the works published on HRA, restricting our search to documents written in English (Boselie *et al.*, 2005; Fernandez and Gallardo-Gallardo, 2020). Similarly to prior research (Tursunbayevaa *et al.*, 2018) and due to the novelty of the topic (Huang *et al.*, 2023; Wang *et al.*, 2024), no further filters were applied. Two independent researchers then examined the titles and abstracts of the collected articles, removing all the papers whose focus was not HRA. Through this systematic search process, summarised in Appendix 2, we extrapolated 215 papers. The descriptive data of each publication (i.e. author/s, year, journal, volume, issue, keywords and abstract) were imported into an Excel file. According to content-analysis guidelines (Mayring, 2000), the authors reviewed these studies using a coding sheet to record, for each article, the research objective, method, theory and contributions on the most important dimensions, factors and criteria affecting HRA development. Furthermore, we noted the possible stages of development discussed in previous research. The coding scheme was created and updated using an iterative approach, moving back and forth between the papers on HRA and the coding sheet.

Secondly, we conducted a content-based review on data analytics, business analytics and business intelligence MMs, whose terms are often used interchangeably in academic literature (Arunachalam *et al.*, 2018). The purpose of the second review was to understand how these analytics capabilities and solutions have been modelled and evaluated in prior research, assessing whether the dimensions, grouping logics and maturity levels of these MMs could also be applied to the HRA domain. In line with prior research (Gastaldi *et al.*, 2018), we thus combined "*Data Analytics*", "*Business Analytics*", "*Business Intelligence*" and "*Maturity Model*" keywords. Furthermore, we removed articles not written in English (Boselie *et al.*, 2005) and those that did not provide relevant contributions on the maturity of data analytics, business analytics and business intelligence systems or capabilities. This systematic search assembled 48 papers, see Appendix 3. Following the snowball approach (Webster and Watson, 2002), we added to these a further 10 articles published in conference proceedings, as they were often cited in previous research on the topic. Following the qualitative analysis method (Mayring, 2000), then, the collected articles have been reviewed developing a coding template that records descriptive information (i.e. author/s, year, journal, volume, issue, keywords and abstract) and MM evaluation object (e.g. Big Data Analytics capabilities), application domain (e.g. supply chain management), development method, underlying theory, constituting dimensions, grouping logic and maturity levels.

Lastly, the information obtained through the reviews was integrated into a preliminary version of the model (i.e. giving only the areas, dimensions and components), described in Appendix 4. Some of the most relevant references are provided for each dimension. We additionally proposed a first structure of the maturity levels of HRA capability. Appendix 5 provides a definition for each level and the most relevant scientific references.

The knowledge and output generated in this phase to develop a preliminary model were useful inputs for the subsequent development phases.

3.3.2 Brainstorming, concept-sorting and consensus decision-making. As HRA literature is still in its early stages of development (Fernandez and Gallardo-Gallardo, 2020; Bahuguna *et al.*, 2023; Coolen *et al.*, 2023), a purely academic analysis risks excluding elements important for its practical evaluation. Thus, according to Becker *et al.* (2009), the research team also collaborated through knowledge creation and by using creativity and refinement techniques.

Firstly, we held four brainstorming sessions (McGraw and Harbison-Briggs, 1989). In the first two sessions, our objective was to identify all possible areas and dimensions that define HRA. Then, we used the two other sessions to discuss and determine the possible development stages of HRA maturity. Each session lasted at least 2 h and involved all team members.

Secondly, concept-sorting techniques were used to (1) subdivide each dimension into more granular components and sub-components (e.g. metrics and sub-metrics) and (2) organise all the possible dimensions, components and subcomponents into their various maturity levels (e.g. indicators). Concept sorting is a knowledge-generation technique (McGraw and Harbison-Briggs, 1989) that can be used, once the MM is defined, to produce and fine-tune the alternatives for maturity-level measurement (Sen *et al.*, 2012). We met in four sessions lasting at least 2 h each, one for each area of the MM (e.g. the *Organisational Area*, see Section 4 for further details). At each session, the research team worked on the set of components and metrics generated during the brainstorming sessions. Lastly, for each metric and submetric, the team generated and discussed a series of alternative indicators to assess maturity at different levels.

A final six sessions were held to evaluate the evolving model and agree on its various areas, dimensions, components, metrics, indicators and maturity levels. In consensus decision-making, a group finds the best solution to a problem by weighing up the advantages and disadvantages of each alternative solution (Sen *et al.*, 2012). More specifically, four of the six sessions covered the MM's dimensions and components (one for each area), and the other two were used to refine the model levels and their maturity indicators. All six sessions lasted at least 2 h. In the first one, all the members worked individually, transcribing their ideas about model elements, as suggested by Verganti (2017). In the second one, we held an interactive multi-participant virtual session, where the team polished their ideas and agreed which were most promising, selecting and consolidating their MM structure. A consolidated version of the model was eventually outlined.

3.3.3 Model refinement – bringing in the experts. In the final development phase, we discussed the model with four external HRA experts in order to increase its robustness and reliability (Becker *et al.*, 2009). More specifically, two meetings of 1 h each have been organised with each expert. In the first one, the model has been presented to facilitate and solicit their opinions on its structure. In the second one, organised after at least five days, each expert provided comments and suggestions for improvement. During this phase, for instance, we subdivided the concept of organisational *Culture* (D14), into *Analytics credibility* (D14.1), *Analytics dictionary* (D14.2) and *Analytics culture* (D14.3), whereas initially it had been measured only through *Analytics culture* (D14.3). Lastly, the HRAMM was conceptually validated at a meeting with all HRA experts in order to concur on a single model. Before moving on to the next phase, the model's dimensions, components and maturity levels were reviewed to ensure mutual exclusivity and collective exhaustiveness.

The HRAMM, the output of the entire model development process, is presented in Section 4.1.

3.4 Conception and validation of the transfer media

After designing the MM, we defined our transfer media for academic and practitioner communities (Becker *et al.*, 2009), selecting an interactive questionnaire to be administered through an online platform. For each metric and/or sub-metric of the model, the research team prepared a question with four possible answers (indicators) reflecting the different levels of maturity. According to our objectives, each question asked about the company's current HRA maturity level and the maturity level expected in the next three years. This means that, alongside maturity misalignments, the model can also determine where to intervene in the near future to address these capability gaps and, thus, the roadmap objectives (Gastaldi *et al.*, 2018). The questionnaire was reviewed by the research team and the HRA experts involved in the previous phases, ensuring its accuracy, comprehensiveness and understandability.

3.5 Model implementation and validation

Once created, an MM must be implemented in a real organisation representing the target user group for validation purposes (Becker *et al.*, 2009; Gastaldi *et al.*, 2018). This validation phase involved administering the questionnaire to the representatives of the company selected as the final user (Becker *et al.*, 2009), to determine whether the MM effectively assesses its organisational maturity (de Bruin *et al.*, 2005), provides the projected benefits (Becker *et al.*, 2009) and supports the organisation in its capability development (Gastaldi *et al.*, 2018).

The HRAMM, thus, was introduced in a company with over 20,000 employees operating in the tourism sector, here referred to as Ebe for privacy reasons. Ebe was selected for three main reasons. Firstly, the company was running a project to develop its HRA capability led by its HR department, starting from scratch in February 2021. Secondly, its technological infrastructure consists of a collection of information systems that need to be integrated to sustain HRA activities. Thirdly, the company is made up of different departments spread over various geographical areas, thus requiring a selection of granularities in data and analytics. Ebe's characteristics make the company an interesting and representative case of the typical organisation interested in the implementation of HRA, a fact confirmed by the company's managers and the HRA experts involved in the development of the HRAMM.

To implement and validate the HRAMM, in September 2022, we sent the questionnaire to the corporate team at Ebe responsible for HRA development. This team was made up of an HR Analyst, a software engineer for HR information systems management, the head of talent management, three HR business partners and the HR director. We initially gave them time to individually scan and give a preliminary answer to each question in our questionnaire. We then set up a virtual meeting to solve possible unclear questions or items. After this, the corporate team was given one week to work together and agree on the answers to give in the questionnaire. In the next step, we calculated Ebe's HRA maturity by averaging over the areas, dimensions, components and metrics constituting the HRAMM. A numerical value ranging from 1 to 4 (i.e. Initial: 1; Limited: 2; Systematic: 3; Strategic: 4) was thus assigned to each dimension, subdimension, component and metric. Table 2 gives an example of the calculation process for the *Technological Area*. Lastly, the HRAMM's results were discussed again with Ebe's HRA team and the HR vice-president to ensure that the results corresponded to the company's real HRA maturity. The assessment of its maturity levels laid the foundation for the next phases (Sections 3.6. and 3.7).

Table 2. Technological area: calculation process for the current maturity state

Area	Score (formula)	Dimension	Score (formula)	Component	Score (Formula)	Metrics	Scores
Technological	$T1 = \frac{(T1+T2+T3+T4)}{4} = 2,13$	T1. HRA architecture	$T1 = \frac{(T1.1+T1.2)}{2} = 2$	1.1. Technological standards	$T1.1 = 2$	–	–
				1.2. Technological integration	$T1.2 = 2$		–
		T2. Data management	$T2 = \frac{(T2.1+T2.2+T2.3+T2.4+T2.5)}{7} = 2,03$	2.1. Data storing	$T2.1 = \frac{(\sum Scores\,for\,[A]\,data)}{7} = 2,5$	Each component (2.1. to 2.4) is evaluated for the different data categories: [A]*	[A1]: 3; [A2]: 2; [A3]: 3; [A4]: 3; [A5]: 1; [A6]: 3
				2.2. Data modelling	$T2.2 = \frac{(\sum Scores\,for\,[A]\,data)}{7} = 1,83$		[A1]: 3; [A2]: 1; [A3]: 2; [A4]: 2; [A5]: 1; [A6]: 2
				2.3. Data collection frequency	$T2.3 = \frac{(\sum Scores\,for\,[A]\,data)}{7} = 2$		[A1]: 4; [A2]: 1; [A3]: 2; [A4]: 2; [A5]: 1; [A6]: 2
				2.4. Data granularity	$T2.4 = \frac{(\sum Scores\,for\,[A]\,data)}{7} = 1,83$		[A1]: 3; [A2]: 1; [A3]: 2; [A4]: 2; [A5]: 1; [A6]: 2
				2.5. Data integration	$T2.5 = \frac{(\sum Scores\,for\,[A]\,and\,[B]\,data)}{7} = 2$	The component (2.5.) is evaluated for the different data categories [A]* and [B]**	[A1]: 3; [A2]: 1; [A3]: 3; [A4]: 3; [A5]: 1; [A6]: 2 [B1]: 2; [B2]: 2; [B3]: 1
		T3. HRA application	$T3 = \frac{(T3.1+T3.2)}{2} = 2,5$	3.1. Analytics software	$T3.1 = 3$	–	–
				3.2. Visualisation software	$T3.2 = 2$		–
		T4. Interface	$T4 = 2$	–	–	–	–

Note(s): Maturity levels and scores: (i) Initial: 1; (ii) Limited: 2; (iii) Systematic: 3; (iv) Strategic: 4
* [A] HR related data: administrative [A1], HR practices [A2], employee characteristics [A3], manager characteristics [A4], interactions [A5], individual performance [A6]
** [B]Other data: business performance [B1], financial indicators [B2], external data [B3]
Source(s): Table by authors

3.6 Future interventions and interdependency analysis

As explained in the literature review, most MMs provide a static representation of possible maturity levels (Marx *et al.*, 2012), neglecting the idiosyncrasies in the particular domain where the model is applied (Brooks *et al.*, 2015). Furthermore, interdependencies become more significant when dealing with complex and branched organisational capabilities (Gastaldi *et al.*, 2018), as in the case of HRA and analytics capabilities (Ramachandran *et al.*, 2023). Our model takes into consideration the interactions between the various HRA dimensions, prioritising the interventions needed to improve the analytics' effectiveness. Following Gastaldi *et al.* (2018), thus, we added four steps to Becker *et al.* (2009)'s methodology.

In the first additional step, the research team held four virtual meetings with Ebe's HRA team to understand the possible future development paths for improving HRA maturity. Each meeting concentrated on a specific area of the model (e.g. *Technological Area*). The research team embarked on a collective thinking exercise about how to achieve the desired maturity levels, discussing the dimensions to be improved, the type of required investment and the critical issues to achieve the expected maturity levels. The main questions on which the meetings were based are set out in Appendix 6.

In the second step, all notes from the meetings were transcribed and independently cross-analysed by the research team to develop a first understanding of possible dimensional interdependencies. Appendix 7 gives examples of quotes related to the *Technological Area*, showing the transition from these initial statements to defining the final dimensional interdependencies.

In the third step, the researchers brought their ideas together to propose a preliminary version of the matrix of interdependencies among the HRA dimensions. The preliminary matrix was presented and discussed with Ebe's HRA team and the four external HRA experts, mulling over the different dimensional relationships. In this step, for instance, we changed the impact of *HR Analytics Strategy* (O7) on *Analysis* (F11) from "synergic" to "prerequisite" to align with scientific evidence suggesting that HRA initiatives need to be grounded in business issues and strategic challenges (Minbaeva, 2018; Levenson, 2018; Wirges and Neyer, 2022). We also added the relationship (i.e. synergy) between *Reporting* (F10) and *Accessibility* (D12), emphasising the need to prepare reports that could also be used by the final decision-makers.

Lastly, in the fourth step, the research team brought together all reflections and stimuli in a final and comprehensive matrix of prerequisites, synergies and relationships among the different dimensions of the model.

Considering two maturity dimensions (X and Y), we defined four types of interdependencies, as follows:

(1) *Prerequisite*: it indicates that, in order to increase the maturity of Y, it is suggested to have previously reached an acceptable maturity (at least 2) level in X.

(2) *Strong prerequisite*: it indicates that, in order to increase the maturity of Y, it is suggested to have previously reached a good maturity (3 or 4) level in X.

(3) *Synergy*: it indicates that it is suggested to simultaneously improve the maturity of X and Y.

(4) *Strong synergy*: it indicates that it is necessary to simultaneously improve the maturity of X and Y.

The final interdependency matrix is discussed in Section 4.2.2.

3.7 Defining the roadmap

Following Gastaldi *et al.* (2018), once created, the interdependency matrix and the HRAMM can be integrated to define a roadmap for the improvement of HRA maturity. More specifically, the current (and desired) maturity levels were associated with the interdependency matrix to determine four cluster dimensions to be prioritised:

(1) *Strategic*, which includes dimensions that are both mature and relevant (often strong prerequisites) for the evolution of other dimensions. The target company should consolidate its investment in this area.

(2) *Critical*, which includes dimensions that are not mature but relevant (often strong prerequisites) for the evolution of other dimensions. The target company should focus on this area as soon as possible.

(3) *Consolidated*, which includes dimensions that are mature but less relevant for the development of other dimensions. Considering past investment, the target company should invest marginal resources in this area.

(4) *Optional*, which includes dimensions that are not mature and are also less relevant for the development of other dimensions. The target company should consider investing in this area after tacking the critical areas, in a logic of the prioritised and homogeneous development of its HRA capability.

The clusters were created following a three-step process. We started by calculating the current maturity (CM_j) and desired maturity (DM_j) score for each dimension, averaging the current maturity levels of their constituting sub-dimensions (CM_{ij}; DM_{ij}). We then gave a score to each prerequisite or synergy ($PSxy_{ij}$), (1) 1 point for each synergy in the dimension, (2) 2 points for each strong synergy, (3) 3 points for each prerequisite and (4) 4 points for each strong prerequisite. We next calculated a comprehensive relevance value (RV_j) for each dimension by summing the scores on the row (X) corresponding to that specific dimension (Y).

$$CM_j = \sum_{i=1}^{n} CM_{ij} \Big/ n \; \forall j = 1 \ldots N$$

$$DM_j = \sum_{i=1}^{n} DM_{ij} \Big/ n \; \forall j = 1 \ldots N$$

$$RV_j = \sum_{i=1}^{n} PSxy_{ij} \Big/ n \; \forall j = 1 \ldots N$$

Lastly, each dimension was assigned to one of the four clusters. The four clusters are described and analysed in Section 4.2.3.

3.8 Final evaluation

The final phase of the methodology concentrates on evaluating the benefits and improvements reached through the application of the HRAMM (Becker *et al.*, 2009; Gastaldi *et al.*, 2018). In this phase, usefulness, quality and effectiveness acted as evaluation criteria. The research team held two further meetings with Ebe's HRA team to discuss the results and the limitations relating to the implementation of the HRAMM and the interdependency matrix. The usefulness and practical contributions of the model are discussed in Section 5, together with its limitations.

4. Results

The results of this research process are set out in two sections. The HRAMM is presented and described in Section 4.1. In Section 4.2, we then introduce the results obtained through the implementation of the model in Ebe, presenting its maturity scores (Section 4.2.1), interdependency matrix (Section 4.2.2) and cluster analysis (Section 4.2.3).

4.1 HR analytics maturity model

The final HRAMM is presented in Tables 3–7. The model has 14 dimensions and 37 components, all of which are described in Table 3. The dimensions are grouped into four main areas:

(1) *Technological Area*, which describes the technological architecture required to develop reliable HRA capability (e.g. technological infrastructure that enables data collection and management activities).

(2) *Organisational Area*, which represents the organisational resources and processes used by the organisation to develop, manage and control HRA capability (e.g. internal competencies for the operational management of HRA).

(3) *Functional Area*, which represents the different functionalities offered by HRA (e.g. ability to carry out predictive analytics).

(4) *Diffusion Area*, which evaluates the pervasiveness of HRA in the organisation (e.g. diffusion of an analytics mindset).

We have then defined four maturity levels for each dimension:

(1) *Initial*: the dimension is not yet present or its implementation path is in its infancy.

(2) *Limited*: the dimension is present, but its implementation path has only been developed in a limited manner.

(3) *Systematic*: the dimension is fully implemented and systematically managed.

(4) *Strategic*: the dimension is fully implemented and strategically exploited.

The model with its integrated levels and dimensions provides a detailed and simple way to assess current and desired HRA maturity. Tables 4–7 show, for each area, the configuration of each dimension, component and metric for the four maturity levels.

4.2 Implementation results

The following sections present the results achieved by implementing the HRAMM and interdependency matrix.

4.2.1 Maturity levels. Figure 2 describes Ebe's position in each area of the HRAMM. The dimensions were selected at the granularity level to provide a simple and clear picture of the company's current and desired level of maturity.

4.2.2 Interdependency matrix. Figure 3 shows the final framework representing the interdependencies between the dimensions of the HRAMM. The matrix enables two different types of analysis. Firstly, using a vertical analysis, it is possible to determine the dimensional prerequisites and synergies that are required and/or suggested to enhance the maturity of a specific dimension. For instance, reporting (F10) requires a mature technological infrastructure (T1) and high-quality data (T2). Secondly, using a horizontal analysis, it is possible to detect the impact that a specific dimension has on the others. For instance, an improvement in the competencies of the HRA team (O5) could enable more sophisticated reporting (F10) and/or statistical analysis (F11).

4.2.3 Cluster analysis. Figure 4 is the final output produced after applying the HRAMM in the target company, and it represents the four clusters explained in Section 3.7. The arrangement of the individual dimensions in the graph depends on the values of CM_j and RV_j. The size of the circles, representing the various dimensions of the HRAMM, is proportional to the difference between the current state of maturity (CM_j) and the desired state (DM_j) in three years' time. Larger circles represent the maturity dimensions that Ebe is

Table 3. Definitions and metrics of the HRAMM

Area	Dimension	Definition	Components	Definition	Metrics
Technological	T1. HRA architecture	Describes the articulation of the HRA technological architecture (monolithic systems, data warehouse, etc.)	1.1. Technological standards	Represents the technological reference standards used for interoperability between systems, data modelling and integration	–
			1.2. Technological integration	Describes both internal (corporate application) and external integration (external applications)	
	T2. Data management	Describes the technological elements that enable data collection and management	2.1. Data storing	Describes the ability of the HRA technological architecture to collect and store required data (e.g. data warehouse)	Each component (2.1. to 2.4) is evaluated for the different data categories: [A]*
			2.2. Data modelling	Describes the ability of the HRA technological architecture to provide well-structured data and make them available	
			2.3. Data collection frequency	Describes the ability of the HRA technological architecture to collect required data with different frequencies (e.g. once a year)	
			2.4. Data granularity	Describes the ability of the HRA technological architecture to collect required data with different level of granularity (e.g. team)	
			2.5. Data integration	Describes the ability of the HRA technological architecture to integrate data from different organisational sources (e.g. automatic, batch)	The component (2.5.) is evaluated for the different data categories [A]* and [B]**
	T3. HRA application	Represents the technological applications that enable data analysis and data visualisation	3.1. Analytics software	Describes the technological applications enabling data analysis	
			3.2. Visualisation software	Describes the technological applications enabling the visualisation of data and results	
	T4. Interface	Represents technologies at the basis of the interface constructed and adopted by users to access the HRA system (e.g. access modalities)			

(*continued*)

Table 3.

Area	Dimension	Definition	Components	Definition	Metrics
Organisational	O5. HRA competencies	Evaluates the organisation's internal competencies for the technological supervision, operational management and utilisation of HRA within the organisation	5.1. Team competencies	Evaluates the accumulated knowledge and competencies on HRA by the company's internal resources dedicated to its operational management (e.g. dedicated team)	The component (5.1) is evaluated for the different competencies desired [C] ***
			5.2. Technological supervision	Evaluates the accumulated knowledge and competencies on HR Analytics technological infrastructure by the company's internal resources dedicated to its technological supervision (e.g. dedicated IT staff)	
			5.3. Organisational experience	Measures the current degree of accumulated organisational experience in the analytics field	
	O6. Operating model	Evaluates the level of internal organisation/coordination for HRA development, management and control	6.1. Defined processes	Assesses the presence and level of consolidation of organisational processes related to HRA	
			6.2. Dedicated resources	Assesses the presence and number of resources allocated to the development, management and control of HRA	
			6.3. Defined roles	Assesses the presence and level of definition of roles dedicated to the development, management and control of HRA	
			6.4. Defined responsibilities	Assesses the presence and level of definition of clear responsibilities for the development, management and control of HRA	
	O7. HRA strategy	Evaluates the presence of a HRA strategy. Strategy means defining a structured and formalised long-term action plan, with the objective of setting, planning and coordinating actions aimed at achieving a predetermined goal in relation to HRA	7.1. Dedicated budget	Describes the share of corporate budget allocated to HRA in relation to the overall budget	
			7.2. Strategic definition	Evaluates the presence and consolidation of an organisational strategy dedicated to HRA	
			7.3. Strategic alignment	Evaluates the presence and the level of integration (alignment) between the HRA and the organisational strategy	
			7.4. Board and top-management support	Measures the degree of interest and support provided by the board and upper management regarding HRA initiatives and issues	

(*continued*)

Area	Dimension	Definition	Components	Definition	Metrics
Functional	F8. Data governance	Evaluates the actions implemented by the HR Analytics system to improve the quality of input data and ensure reliable output	8.1. Data integrity	Assesses whether the systems ensure and verifies data integrity	Each component (8.1. to 8.5) is evaluated for the different data categories: [A]*
			8.2. Data accuracy	Assesses whether the systems check for errors in data collected and stored through the technological infrastructure	
			8.3. Data completeness	Assesses whether the system verifies that there are no missing values/incomplete data	
			8.4. Data confidentiality	Assesses whether the system ensures and verifies data confidentiality	
			8.5. Data availability	Assesses whether the system ensures and verifies data accessibility for authorised users	
	F9. Measurement	Represents the functionalities of HRA that support the construction of metrics to evaluate specific HR aspects (e.g. leadership quality) or processes (e.g. selection rate)			The component (F9) is evaluated for the different application fields [D]***
	F10. Reporting	Evaluates the quality of the reporting and the way in which reports are produced and distributed to users	10.1. Report frequency	Measures how often the system is able to automatically generate reports	
			10.2. Report distribution	Measures the system's ability to automatically distribute reports to the right people	
			10.3. Visualisation effectiveness	Evaluates the quality and customisability of the produced report	
	F11. Analysis	Evaluates the organisational ability to perform specific HRA analysis	11.1. Explanatory	Evaluates the ability of HRA to perform – or support users during the development of these analyses – exploratory or descriptive analyses	
			11.2. Predictive	Evaluates the ability of the HRA to perform – or support users during the development of these analyses – predictive analyses	
			11.3 Prescriptive	Evaluates the ability of the HRA to perform – or support users during the development of these analyses – prescriptive analyses	

(*continued*)

Table 3.

Table 3.

Area	Dimension	Definition	Components	Definition	Metrics
Diffusion	D12. Accessibility	Evaluates the share of users that can access to HRA infrastructure and information (e.g. who is able to access HR Analytics results)			The component (D12) is evaluated for the different profiles [E]*****
	D13. Adoption	Represents the adoption level of HRA practices and results to support the decision-making and set operational and strategic objectives	13.1. Objectives support	Measures the adoption of HR Analytics solutions (and their results) to proactively define operative and strategic objectives related to people	
			13.2. Decisional support	Evaluates the adoption of HRA to support decisional processes or proactively take people-related decisions	
	D14. Culture	Represents the diffusion of an analytical mindset in the HR department and/or in the whole organisation	14.1. Analytics credibility	Assesses the credibility that HRA indicators and results have within the organisation	
			14.2. Analytics dictionary	Assesses the presence and diffusion of a common and shared language to discuss HRA and its results within the organisation	
			14.3. Analytics culture	Assesses the diffusion of an analytical culture within the organisation. Analytical culture means the habit of approaching problems, opportunities and consequent decision-making using data support	

Note(s): * [A] HR-related data: administrative [A1], HR practices [A2], employee characteristics [A3], manager characteristics [A4], interactions [A5], individual performance [A6]
** [B]Other data: business performance [B1], financial indicators [B2], external data [B3]
*** [C] Desired competencies: statistical [C1], behavioural [C2], HR-related [C3], business [C4], communication [C5], coding [C6], IT [C7], privacy [C8], ethics [C9], security [C10]
**** [D]Application field: administrative [D1], recruitment and selection [D2], team organisation and way of working [D3], performance management and compensation [D4], training [D5], employee's behaviour and wellbeing [D6], leadership evaluation [D7], communication and information management [D8]
***** [E] Profiles: person responsible for HRA [E1] HR department [E2], business units [E3], top-management [E4], employees [E5]
Source(s): Table by authors

Dim	Components	Level 1: Initial	Level 2: Limited	Level 3: Systematic	Level 4: Strategic
T1. HRA architecture	1.1. Technological standards	The HRA system does not support any interoperability standards	The HRA system has interoperability standards for less than 50% of applications and there is only one interoperability standard supported by the HRA system	The HRA system has interoperability standards for less than 80% of applications and there are a few interoperability standards supported by the HRA system	The HRA system has interoperability standards for more than 80% of the applications and the majority of the interoperability standards are supported by the HRA system
	1.2. Technological integration	The HRA system's integration with other internal and/or external applications is performed manually	Less than 50% of other internal and/or external applications are integrated and automatically shares data with the HRA system	A portion between 50 and 80% of other internal and/or external applications are integrated and automatically shares data with the HRA system	The HRA system is completely integrated with internal and external applications, enabling the automated exchange of information flows
T2. Data management	2.1. Data storing*	The HRA system's technological infrastructure does not enable storage of [A] data	The HRA system enables the collection of [A] data, but using a database that does not automatically distinguish them from other kinds of data, making it inefficient to store and retrieve them when needed	The HRA system infrastructure enables the collection of [A] data automatically in a dedicated section of the database, that is however not organised according to relational logic	The HRA system architecture enables the collection of [A] data automatically in a dedicated section of a database that is structured internally according to relational logics
	2.2. Data modelling*	The HRA system's technological infrastructure does not enable [A] data to be available in a well-structured manner	The HRA system infrastructure enables automatic modelling for less than 50% of [A] data because manual processing is still fundamental to ensure consistency in data structures	The HRA system infrastructure enables automatic modelling for more than 50% of [A] data, but manual intervention is needed when data volume/velocity/variety/veracity are challenging	The HRA system enables automatic modelling for more than 80% of [A] data, also when dealing with high volume/velocity/variety/veracity
	2.3. Data collection frequency*	The HRA system's technological infrastructure collects [A] data sporadically	The HRA system ensures the collection and updates of [A] data, considering specific users' requirements or timeliness constraints in less than 50% of cases	The HRA system ensures the collection and updates of [A] data, considering the users' requirements and specific timeliness constraints in between 50 and 80% of cases	The HRA system ensures the collection and updates of [A] data, considering the users' requirements and specific timeliness constraints in more than 80% of cases

(*continued*)

Table 4. Maturity levels of the HRAMM: technological area

Table 4.

Dim	Components	Level 1: Initial	Level 2: Limited	Level 3: Systematic	Level 4: Strategic
	2.4. Data granularity*	The HRA system's technological infrastructure collects [A] data not considering different granularities	The HRA system enables the management of statically different granularities of [A] data considering a few dimensions at a time	The HRA system enables the management of statically different granularities of [A] data considering as many dimensions as needed (multidimensional structures)	The HRA system enables the management of different granularities of [A] data considering as many dimensions as needed. It enables rolling-up and/or drilling-down operations to dynamically adapt the level of granularity of each dimension of interest for the analysis
	2.5. Data integration**	The HRA system's technological infrastructure does not enable integration of [A, B] data with other internal and/or external ones	The HRA system enables the manual integration of [A, B] data with other internal and/or external data, which is shown to be inefficient when carrying out analyses	The HRA system enables automatic integration of [A, B] data with other internal and/or external ones according to a set of dimensions that drive the users towards a predefined reasoning path	The HRA system enables automatic integration of [A, B] data with internal and/or external data and indicators, considering both structured and unstructured data-items
T3. HRA application	3.1. Analytics software	The HRA system's technological infrastructure does not provide for any analytical tool	The HRA system is primarily based on the use of Microsoft Excel as an analytical tool	The organisation has a wide set of analytical tools for HRA that enable automatic analyses, but some sophisticated functionalities require advanced competencies (e.g. coding, etc.)	The organisation provides a wide set of sophisticated analytical tools for HRA that enable automatic and sophisticated analyses in a very efficient and effective way due to a user-friendly interface
	3.2. Visualisation software	The HRA system's technological infrastructure does not support any visualisation tool	The HRA is primarily based on using Microsoft Excel and/or Power Point as a visualisation tool	The organisation provides a set of sophisticated visualisation tools for HRA that enable automatic and real-time updating, but their management is centralised (users cannot choose what to visualise)	The organisation provides a set of sophisticated visualisation tools for HRA that enable automatic and real-time updates, and users can customise their dashboard according to their needs
T4. Interface		The HRA system does not provide any interface for supervisors	The HRA's technological infrastructure presents a command-line interface for supervisors (i.e. user types characters to query the software), that is present only locally on specific clients	The HRA's technological infrastructure presents a client-server interface (i.e. point and click), more user-friendly and accessible also via proxies from different locations	The HRA's technological infrastructure presents an advanced web-based interface, which has both a web and a desktop/mobile application to adapt to any device and location from which access is required

Note(s): * [A] HR-related data: administrative [A1], HR practices [A2], employee characteristics [A3], manager characteristics [A4], interactions [A5], individual performance [A6]
** [B]Other data: business performance [B1], financial indicators [B2], external data [B3]
Source(s): Table by authors

Table 5. Maturity levels of the HRAMM: organisational area

Dim	Components	Level 1: Initial	Level 2: Limited	Level 3: Systematic	Level 4: Strategic
O5. HRA competencies	5.1. Team competencies*	There is no proper HRA capability development; or, if there is one, the organisation is still in the early stages of development of [C] competencies	[C] competencies are owned by a small percentage of people in charge of running HRA (e.g. just promoters, technicians and specialists) and marginally known by the remaining portion	[C] competencies are owned by a significant percentage of people in charge of running HRA, and they are spreading also to the remaining portion	[C] competencies are owned by the vast majority of people in charge of running HRA
	5.2. Technological presidium	Technological supervisors do not have the required skills and competences to manage the HRA technological architecture, or their competences are limited and outdated	Technological supervisors' have general competencies in setting up a technological architecture	Technological supervisors' have competencies in setting up and the ordinary maintenance of a HRA technological architecture	Technological supervisors' have competencies in setting up and the ordinary maintenance of the HRA system; these are regularly updated and compliant with the latest norms in terms of risk management and extraordinary maintenance
	5.3. Organisational experience	The organisation has no analytics systems in any BU or their development is very limited	The organisation has development analytics systems in some BUs and some analytics practices are being tested on few BUs as pilot projects	The organisational has developed analytics systems and analytics practices in most BUs and analytics	Analytics systems and analytics practices can be considered as consolidated, structured and spread across the entire organisation
O6. Operating model	6.1. Defined processes	There are no specific organisational processes dedicated to HR Analytics	There are organisational processes dedicated to HRA, but they cover a limited set of procedures (e.g. just the operative stages of collecting and modelling data)	There are organisational processes dedicated to HRA, and they cover a significant part of related procedures (e.g. both the operative and IT-related procedures concerning infrastructure's management)	There are well-structured and compelling organisational processes specific to the HRA that are periodically reviewed to ensure they cover the whole set of needed practices
	6.2. Dedicated resources	There are no resources dedicated to HR Analytics practices	There are resources that dedicate some effort to HRA practices as a small part of their main job	There are individuals that are specifically dedicated to HRA and cover operative and IT procedures	The company has an ad-hoc organisational unit/team dedicated to HRA to cover the whole set of needed practices

(*continued*)

Table 5.

Dim	Components	Level 1: Initial	Level 2: Limited	Level 3: Systematic	Level 4: Strategic
	6.3. Defined roles	There are no people in charge of HRA operations, or at most a bunch of random tasks is assigned if needed	There are people in charge of HRA operations but in an informal manner	Specific and formal roles have been defined among people involved in HRA practices, but the coordination between activities is still limited and informal	Roles have been clearly and formally defined for each staff member dedicated to HRA activities, which ensures a good level of coordination and collaboration
	6.4. Defined responsibilities	There is no one with specific responsibility for HR analysis, or at most random and loose constraints are set	Responsibilities consist of informally shared constraints to who is available to perform single tasks	Responsibilities are formally set and shared among individuals in charge of developing, implementing and managing HRA practices	Responsibilities are formally set following a clear logic inside the team/unit in charge of covering every aspect of HRA, from operative to governance-related ones
O7. HRA strategy	7.1. Dedicated budget	There is no dedicated budget for HRA-related activities	The budget dedicated to HRA operations is among the least prioritised of all strategy-related practices	A fixed portion of between 1 and 10% of the overall company's budget is dedicated to HRA-related activities	The budget dedicated to HRA is highly prioritised and counts for more than 10% of the overall company's budget
	7.2. Strategic definition	HRA aspects and decisions are not part of any strategic plan	HRA decisions are undertaken coherently between each other but without the support of a clear overall picture	HRA decisions are included within a wider set of static strategic decisions that however lack agility in the case of unforeseen events or opportunities	HRA decisions are included into a compelling and resilient strategic plan
	7.3. Strategic alignment	HRA-related activities are run in parallel with respect to the company's other activities and disregarding the company's overall strategy	HRA-related activities are run in compliance with some strategic decisions, but however they have a poor connection with the company's overall strategy	HRA-related activities are derived from a strategic guideline deriving from the overall company's strategy	HRA activities are included in a compelling and well-defined strategy that has a strong strategic impact on organisational strategy
	7.4. Board and top management support	Board and top management do not play an active role when dealing with HRA	Board and management are interested in HRA practices, but they do not consider them as a priority	Board and top management are interested in HRA practices and treat them as any other operation	Board and top management are enthusiastic about HRA practices and are perceived to have a leading role in that HRA is seen as fundamental to gain competitive advantage

Note(s): * [C] Desired competencies: statistical [C1], behavioural [C2], HR-related [C3], business [C4], communication [C5], coding [C6], IT [C7], privacy [C8], ethics [C9], security [C10]
Source(s): Table by authors

Dim	Components	Level 1: Initial	Level 2: Limited	Level 3: Systematic	Level 4: Strategic
F8. Data governance	8.1. Data integrity*	There is not any proper HRA system; or, if there is one, it does not check for eventual alteration of the integrity of [A] data	The HRA system relies on simple and sporadic checks concerning the integrity of [A] data	The HRA system relies on automated and frequent checks concerning the integrity of [A] data	The HRA system has a high-level security mechanism to ensure [A] data integrity (e.g. asymmetric key and hash functions)
	8.2. Data accuracy*	There is not proper HRA system; or, if there is one, it does not check for eventual issues concerning the accuracy of [A] data	The HRA system relies on manual sporadic accuracy checks concerning the accuracy of [A] data	The HRA system relies on automated and frequent checks concerning the accuracy of [A] data	The HRA system has a high-level security mechanism to ensure data accuracy (e.g. automatic cleaning), used before loading data into the database
	8.3. Data completeness*	There is not any proper HRA system; or, if there is one, it does not check for eventual issues concerning the completeness of [A]	The HRA system relies on manual and sporadic checks concerning completeness of [A] data	The HRA system relies on automated and frequent checks concerning the completeness of [A] data but neglects the root causes of each null value	The HRA system has tools that enable sophisticated automated checks concerning the completeness of [A] data and that automatically recognise if the specific null values
	8.4. Data confidentiality*	There is not any proper HRA system; or, if there is one, it does not check for eventual issues concerning the confidentiality of [A] data	The HRA system relies on manual and sporadic checks concerning the confidentiality of [A] data to ensure that privacy issues are monitored	The HRA system relies on automated and frequent checks concerning the confidentiality of [A] data to ensure that privacy issues are monitored	The HRA solution has a high-level security mechanism to ensure the confidentiality of [A] data (e.g. asymmetric key mechanism)
	8.5. Data availability*	There is not any proper HRA system; or, if there is one, it does not check for eventual issues concerning the availability of [A] data and continuity of service	The HRA system relies on manual and sporadic checks concerning the availability of [A] data to ensure continuity of service of about 90%	The HRA system relies on automated and frequent checks concerning the availability of [A] data to ensure continuity of service of about 95%	The HRA solution has a high-level mechanism to ensure the availability and access control of [A] data (e.g. intranet solutions, intrusion detection systems)

(*continued*)

Table 6. Maturity levels of the HRAMM: functional area

Table 6.

Dim	Components	Level 1: Initial	Level 2: Limited	Level 3: Systematic	Level 4: Strategic
*F9. Measurement***		There is not any proper HRA system; or, if there is one, it does not enable the generation of any metric for [D] field	The HRA system enables the manual generation of metrics related to [D] field	The HRA system automatically generates, at a fixed frequency, pre-determined metrics related to [D] field	The HRA system provides real-time metrics related to [D] field that could be personalised by the user through a user-friendly interface
*F10. Reporting***	10.1. Report frequency	There is not any proper HRA system; or, if there is one, it does not produce actual reports inherent to [D] field	HRA reports concerning [D] field are produced and updated at adequate frequencies for the dynamicity of the represented reality in less than 50% of cases	HRA reports concerning [D] field are produced and updated at adequate frequencies for the dynamicity of the represented reality in more than 50% of cases	HRA reports concerning [D] field are produced and updated in real-time. Moreover, reporting frequency is flexible and could be adapted according to specific needs/requests
	10.2. Report distribution	There is no proper HRA system that delivers reports or, if there is one, it does not distribute anything about [D] field except if requested specifically or in extraordinary cases	More than 50% of reports produced about [D] field are sent proactively, but manually, in digital format (e.g. via email) to the various users	More than 50% of reports produced about [D] field are sent automatically (e.g. via email) by the system to the various users	More than 50% of reports about [D] field can be accessed in a personalised manner directly from the system by individual users
	10.3. Visualisation effectiveness	There is no proper HRA system or, if there is one, it does not exploit tools for displaying HRA reports	The HRA system's report displaying systems make the results difficult to interpret for non-expert employees (more than 50% of total users)	The HRA's report-displaying systems present the results in a homogeneous but clear manner to the totality of the users	The HRA's report-displaying systems enable the customised visualisation of results, so they are clear and effective to each user

(continued)

Dim	Components	Level 1: Initial	Level 2: Limited	Level 3: Systematic	Level 4: Strategic
F11. Analysis	11.1. Explanatory	HRA organisational capability does not enable to carry out analytics	HRA organisational capability enables users to perform basic descriptive analysis (e.g. sum, mean)	HRA organisational capability enables users to perform more advanced descriptive analysis (e.g. correlation)	HRA organisational capability enables the execution of all possible explanatory analytical techniques (e.g. structural equation modelling)
	11.2. Predictive	HRA organisational capability does not enable analytics	HRA organisational capability enables users to perform basic predictive analytics (e.g. linear regression analysis)	HRA organisational capability enables users to perform more advanced descriptive analyses (e.g. multivariate regression analysis)	HRA organisational capability enables the execution of all possible predictive analytical techniques (e.g. predictive models)
	11.3 Prescriptive	HRA organisational capability does not enable analytics	HRA organisational capability enables users to perform basic prescriptive analyses (e.g. optimisation techniques)	HRA organisational capability enables users to perform more advanced prescriptive analyses (e.g. simulation techniques)	HRA organisational capability enables the execution of all possible prescriptive analytical techniques (e.g. machine learning techniques)

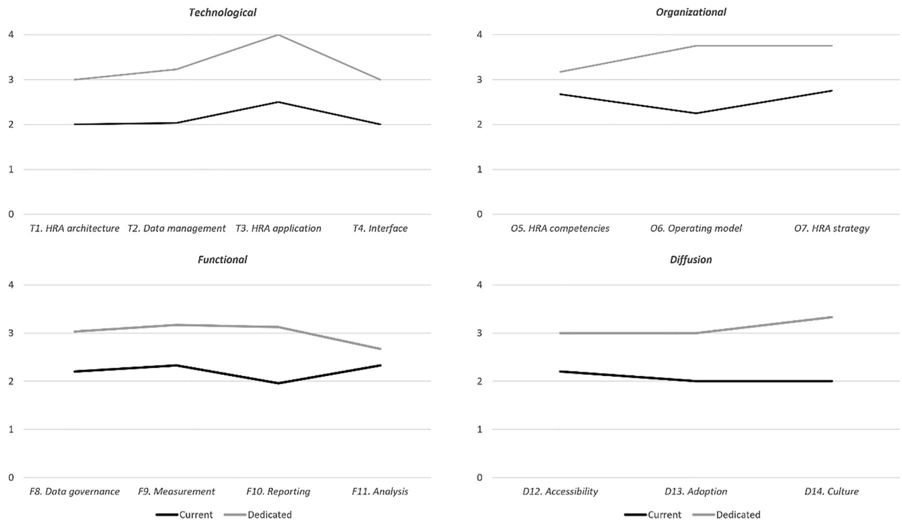
Note(s): * [A] HR-related data: administrative [A1], HR practices [A2], employee characteristics [A3], manager characteristics [A4], interactions [A5], individual performance [A6]
** [D]Application field: administrative [D1], recruitment and selection [D2], team organisation and way of working [D3], performance management and compensation [D4], training [D5], employee's behaviour and wellbeing [D6], leadership evaluation [D7], communication and information management [D8]
Source(s): Table by authors

Table 6.

Table 7. Maturity levels of the HRAMM: diffusion area

Dim	Components	Level 1: Initial	Level 2: Limited	Level 3: Systematic	Level 4: Strategic
*D12. Accessibility**	–	There is no proper HRA system or, if there is one, its functionalities are not available to [E] profiles	The 50% of the HRA functionalities are available to [E] profiles (e.g. operative measurements, descriptive analytics' results and general reports)	A significant number of the HRA system's functionalities are available to [E] profiles (e.g. any kind of measurement and report, strategic insights from predictive and prescriptive analyses, any data quality warrantee) but delivered in a general, non-customised format	The HRA system's whole set of functionalities is available to [E] profiles and delivered in a customised manner
D13. Adoption	13.1. Support to objectives	There is no proper HRA system or, if there is one, managers do not use HRA solutions to support the definition of objectives	HRA insights are used to support the definition of objectives relating to people management, when a decision needs confirmation	Operative and strategic objectives relating to people management cannot be defined if HRA insights are disregarded	Operative and strategic objectives related to people management are defined using HRA insights
	13.2. Decisional support	There is no proper HRA system or, if there is one, decision-makers do not use HRA solutions to support their work	HRA insights are used to support decisions on people when evidence needs confirmation	Decisions on people cannot be made if HRA insights are disregarded	Decisions on people are driven by HRA insights
D14. Culture	14.1. Analytics credibility	There is no proper HRA system or, if there is one, just the promoters responsible for its development use the HRA indicators and results	Indicators and results from the HRA system are considered exclusively by the HR department and the promoters of HR Analytics practices	Indicators and results from the HRA system benefit high consideration in the HR department and in a limited number of other business units	Indicators and results from the HRA system are felt as the grounding foundation of taking people-related decisions across the company
	14.2. Analytics dictionary	There is no proper HRA system or, if there is one, a specific glossary is used among the promoters responsible for its development	A common glossary on HRA is now spreading across the HR department	A common, specific language about HRA is now spreading across the other units/departments outside HR	The organisation has a structured, shared and established language for discussing HRA matters
	14.3. Analytics culture	There is no proper HRA system or, if there is one, just the promoters responsible for its development believe in a culture that gives analytics a strategic role	The culture of driving people-related decisions with HRA is spreading across the HR department	The culture of driving people-related decisions with HRA is spreading across the other units/departments outside HR	HRA has re-shaped the idea of doing business and taking decisions based on data. This feeling is shared across the organisation

Note(s): * [E] Profiles: person responsible for HRA [E1] HR department [E2], business units [E3], top-management [E4], employees [E5]
Source(s): Table by authors



Source(s): Authors' own work

Figure 2. Ebe's position on the different dimensions of the HR analytics maturity model

Key:
↑ : Strong prerequisite
⌂ : Prerequisite
••: Strong synergy
• : Synergy

		Technological				Organizational			Functional				Diffusion		
		T_1. HR Analytics Architecture	T_2. Data Management	T_3. HR Analytics Application	T_4. Interface	O_5. HR Analytics Competencies	O_6. Operating Model	O_7. HR Analytics Strategy	F_8. Data Governance	F_9. Measurement	F_{10}. Reporting	F_{11}. Analysis	D_{12}. Accessibility	D_{13}. Adoption	D_{14}. Culture
Technological	T_1. HR Analytics architecture		•	•	•			••	⌂	⌂	⌂		⌂		
	T_2. Data Management	•		••	•	•	•	••	↑	↑	⌂	⌂	⌂		
	T_3. HR Analytics Application	•	••			••	•	••			↑	↑			
	T_4. Interface	•						•			↑		⌂	↑	
Organizational	O_5. HR Analytics Competencies		•	••			••	•	↑	⌂	⌂	⌂		↑	⌂
	O_6. Operating Model		•	•		••		••	⌂	•	•	•		⌂	⌂
	O_7. HR Analytics Strategy	••	••	••	•	•	••				••	↑		⌂	••
Functional	F_8. Data Governance		••							↑	↑	↑	⌂	⌂	
	F_9. Measurement						•				••	⌂	••	•	•
	F_{10}. Reporting						•	••		••		⌂	••	•	•
	F_{11}. Analysis						•						••	•	•
Diffusion	D_{12}. Accessibility									••	••	••		⌂	•
	D_{13}. Adoption									•	•	•			
	D_{14}. Culture						••	••		•	•	•	•	⌂	

Source(s): Authors' own work

Figure 3. Prerequisites and synergies among the dimensions of the HR analytics maturity

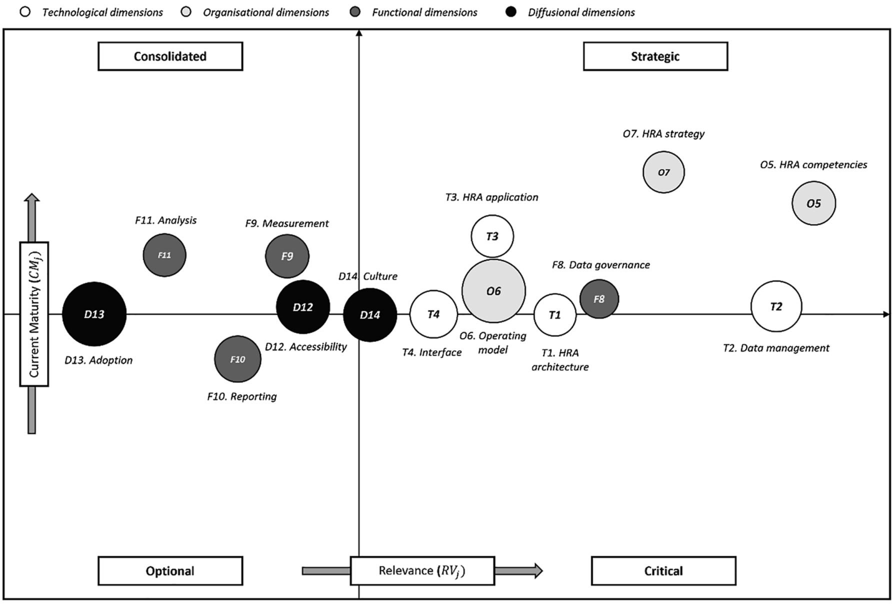


Figure 4.
Relevance and maturity for HR Analytics *at Ebe*

Source(s): Authors' own work

most interested in improving. The figure gives a visual representation of the critical and strategic dimensions, providing a map to guide investment and improvement work.

5. Discussion

Recent research has emphasised the paradox that exists between management interest in HRA and the limited scientific contributions on its organisational development (Marler and Boudreau, 2017; Levenson, 2018; Ramachandran *et al.*, 2023; Wang *et al.*, 2024). To redress this limitation, we responded to the recent call for further studies on HRA capability development (Levenson, 2018; Ramachandran *et al.*, 2023) and its constituting dimensions (Minbaeva, 2018; Wirges and Neyer, 2022). We have thus provided an HRAMM and an interdependencies matrix that operationalise and assess HRA capability maturity, evaluating its dimensional interdependencies. The HRAMM and its application in a real organisation generated different theoretical contributions, discussed on the basis of five main paragraphs in the following section (see Section 5.1). Lastly, the paper discusses the practical contributions (see Section 5.2) and research limitations, proposing directions for future research (see Section 5.3).

5.1 Theoretical contributions

Academics have conceptualised HRA as an HR practice (Marler and Boudreau, 2017), an HR process (Huselid, 2018) or a more generic HRM approach (Larsson and Edwards, 2021) based on different statistical principles and methods (Margherita, 2021). Additionally, previous studies defined HRA maturity through the three levels of sophistication used in analytics techniques, i.e. descriptive, predictive and prescriptive analytics (Marler and Boudreau, 2017; Margherita, 2021). Recent research, however, has argued that the adoption of sophisticated analytics techniques is often related to isolated projects and, thus, does not fully represent the real HRA maturity of a company (Shet *et al.*, 2021; Wirges and Neyer, 2022; Loscher and Bader, 2023). This aligns with prior research on business analytics, business intelligence and data analytics capabilities (Cosic *et al.*, 2012; Gastaldi *et al.*, 2018; Gökalp *et al.*, 2021), which has often assessed and modelled analytics maturity considering multiple organisational dimensions (Brooks *et al.*, 2015; Król and Zdonek, 2020), ranging from technological systems (e.g. Raber *et al.*, 2013) to organisational culture (e.g. Lukman *et al.*, 2011).

In this paper, HRA capability is thus defined as the organisational capability to systematically implement, manage and strategically exploit data and analytics in order to support people-related processes and decisions. In this regard, we provide for the first time a comprehensive operationalisation of HRA capability, described through four areas (*Technological, Organisational, Functional, Diffusion*), 14 dimensions and 37 further components. Furthermore, this research shows that HRA capability develops through an evolutionary path defined by four stages of maturity (i.e. *Limited, Initial, Systematic, Strategic*). Our work, therefore, expands on prior discussions concerning analytics evolution which focus on the sophistication of analytics techniques (Margherita, 2021). The study also emphasises the importance of considering the interaction and harmonious integration of different organisational dimensions. More specifically, the HRAMM lists which organisational resources, processes and structures are involved in the emergence and development of this capability, while the interdependencies matrix reveals their dimensional interdependencies, enriching prior studies on the organisational development of HRA (e.g. Minbaeva, 2018; Bechter *et al.*, 2022).

Additionally, the maturity and interdependency analyses suggest that technological and organisational factors are fundamental enablers for the development of HRA capability (Heuvel and Bondarouk, 2017; Marler and Boudreau, 2017; McCartney and Fu, 2021; Wang *et al.*, 2024). On the one hand, information technologies enable the collection, management and analysis of employee data, providing the "raw" material to conduct any type of analytics practice or project (Lukman *et al.*, 2011; Boonsiritomachai *et al.*, 2016). On the other hand, individual competencies, governance rules and organisational structures enable their effective application, control and future development (Gökalp *et al.*, 2021). In this regard, our findings indicate that the development of an HRA capability requires the harmonious, balanced and synergic development of both organisational and technological dimensions. An investment made in one dimension will trigger an investment in the other, and each will capitalise on the investments made in the other, respectively. Interventions in these areas are particularly important since they have a significant impact on the functionalities that HRA could introduce in the organisation and its decision-makers (see F8. *Data governance,* F9. *Measurement,* F10. *Reporting,* F11. *Analysis*). Reports, statistical analyses and analytics initiatives necessarily require high-quality data, adequate analytics technologies and access to a multi-disciplinary community of knowledge and competencies (Qamar and Samad, 2021).

Technological infrastructure and organisational resources enable the emergence and initial implementation of HRA initiatives, bringing to the business table the first results of HRA functionalities. The later maturity stages of this capability, however, also require the development of strategic dimensions (Lukman *et al.*, 2011; Gastaldi *et al.*, 2018; Gökalp *et al.*, 2021). In this regard, top-management's interest in HRA has an effect on the company's HRA budget and so on the technological infrastructures and human capital that will be available to the HRA team for its development work. More specifically, during HRA development, the organisational resources allocated to analytics and their weight within the HR and business strategy affect each other along the various stages of maturity in a continuous cycle (Belizón and Kieran, 2022; Falletta and Combs, 2021). Interest in HRA increases when a company's board sees the results of HRA projects (Minbaeva, 2018; Hamilton and Sodeman, 2019). Positive results, then, often depend on an improvement in technologies and people's individual skills (Peeters *et al.*, 2020). Companies interested in improving their HRA capability, thus, need to leverage these dimensions, carefully balancing investments, the launch of analytics initiatives and the promotion of the results obtained (Levenson, 2018; Minbaeva, 2018).

Lastly, our findings suggest that cultural dimensions are important to exploit the true potential of analytics initiatives and so generate value for the organisation (Lukman *et al.*, 2011; Gökalp *et al.*, 2021). In prior research (McIver *et al.*, 2018; Minbaeva, 2018; Levenson, 2018), scholars have explained that the real success of HRA needs to be evaluated within a framework that considers the strategic impact that analytics results had generated through change management practices. The effective transformation of analytics into management actions, however, depends on cultural and adoption variables, including analytics culture, HRA credibility and whether the decision-makers habitually use data to support their decisional processes (i.e. see D13. *Adoption* and D14. *Culture*). Similarly to technological and organisational resources, cultural and adoption dimensions show strong interdependencies with the strategic variables. The legitimisation process of HRA practices (Belizón and Kieran, 2022) is indeed facilitated when the organisation possesses an analytics culture, in that analytics results are understood and can be converted into business actions (Ramachandran *et al.*, 2023).

5.2 Practical contributions

Research based on MMs (Becker *et al.*, 2009) and interdependencies analyses (Gastaldi *et al.*, 2018) provide different benefits to practitioners interested in assessing and developing their HRA capability (Lismont *et al.*, 2017; Gastaldi *et al.*, 2018; Doctor *et al.*, 2023). We can group the benefits into three main practical contributions.

Firstly, we provide an HRAMM that can be used to assess the current and desired state of HRA capability. The model provides practitioners with a useful tool to monitor and predict the quality of their analytics development actions. Additionally, the HRAMM could be periodically re-used to measure analytics maturity and to adjust the development path in line with organisational changes.

Secondly, this study proposes a procedure to measure and evaluate HRA dimensions thoroughly and comprehensively by analysing their interdependencies. In this regard, we mapped the relationships among analytics dimensions, describing the different interactions in terms of prerequisites and synergies to be leveraged in order to extend the maturity of their HRA capability in a successful way. Furthermore, we suggest that the level of maturity should be consistent with the organisation's structures and business strategies, to ensure an effective and harmonious development.

Thirdly, we proposed a method for grouping the various dimensions into four clusters, according to their strategic relevance and level of priority. This procedure enables the generation of an effective roadmap to develop and improve HRA capability, suggesting to practitioners how they can prioritise and plan their investments. Clusters and priority scores can be periodically updated, adjusting the prioritisation hierarchy. Both the HRAMM and the prioritisation procedure were introduced in Ebe, demonstrating the actual applicability of our research results.

5.3 Limitations and future research directions

This paper provides different theoretical implications that could support academics in designing and defining their path of future research activities.

Firstly, echoing a number of recent studies (e.g. Minbaeva, 2018; Levenson, 2018; Wirges and Neyer, 2022), we emphasise the need for future research to study HRA as an organisational capability. In line with the resource-based view (Wernerfelt, 1984) and capability theories (Teece *et al.*, 1997), researchers should consider HRA capability maturity as a function of an organisation's ability to use data and analytics to create strategic value, organisational success and competitive advantage (Olszak, 2016; Olzak and Mach-Król, 2018), aligning with the application of analytics in other distinctive domains (e.g. healthcare, supply chain, manufacturing) (e.g. Cosic *et al.*, 2012; Boonsiritomachai *et al.*, 2016; Gastaldi *et al.*, 2018; Gökalp *et al.*, 2021).

We suggest that future research should investigate whether HRA capability maturity (or the maturity of specific analytics dimensions – e.g. HRA competencies, analytics credibility) has an impact on the development and outcomes of specific HRA initiatives (e.g. turnover prediction, algorithmic recruitment), using the HRAMM as a validated assessment and measurement method. Furthermore, future studies could analyse the interaction between HRA and other organisational capabilities, applying a more systemic approach (Levenson, 2018) and defining which ones facilitate and/or hinder the respective development.

Thirdly, future research could investigate antecedents, moderators and outcomes of HRA capability development, using the proposed model to analyse the relationship between macro-, micro- and individual-level variables and HRA maturity. For instance, a first stream could empirically examine possible antecedents of analytics maturity (e.g. organisational culture, values or structures). A second stream could analyse which factors (e.g. collaboration with universities or research centres) speed up the growth of HRA maturity over the years. Lastly, our model can be applied to test the consequences of analytics maturity on different organisational performances, including financial performance, innovation or employees' well-being.

Finally, this paper contains potentially limiting factors that could be solved through further research. The HRAMM was defined using a theoretical top-down approach for both maturity dimensions and levels. This approach was selected considering the immature stage of HRA research and that its maturity is yet to be defined. Researchers could in the future design or improve our model using a bottom-up approach, starting their analysis from the HRAMM proposed in this paper. Furthermore, while accurate and comprehensive, our model assigns equal weights to each dimension, component, metric and maturity level. This approach means that it is unclear how to measure and evaluate effectively both the synergies and the prerequisites among dimensions in relation to the stage of maturity. Eventually, the interdependencies and the findings discussed derive from a single case study. Future research should expand the implementation of the model to a larger number of companies so as to understand whether the dynamics presented in this research can be further generalised or whether there are contextual (e.g. industry, geographical area) or organisational factors (e.g. number of employees, organisational structure) that alter our findings (Coolen *et al.*, 2023).

6. Conclusions

In prior research, HRA is seen as a fundamental organisational capability (Minbaeva, 2018) to be developed to maintain effective HRM in an increasingly dynamic and uncertain environment (Huselid, 2018; Bechter *et al.*, 2022). The increasing academic and management interest has, however, translated into only a limited number of scientific contributions (Marler and Boudreau, 2017; Ramachandran *et al.*, 2023; Wang *et al.*, 2024) and practical guidelines (Minbaeva, 2018; Levenson, 2018; Larsson and Edwards, 2021) on its organisational development. This research presents an HRAMM that operationalises HRA capability maturity, listing all its constituting dimensions and providing organisations with a useful tool to assess, evaluate and monitor the evolution of their HRA capability. Furthermore, the proposed interdependencies matrix identifies and evaluates the dimensional interdependencies (i.e. in terms of synergies and prerequisites) among the analytics constituting dimensions, supporting practitioners in designing and planning a harmonised path for HRA capability development. To conclude, this study provides useful theoretical implications for future research, emphasising the need to approach HRA as an organisational capability (Minbaeva, 2018). In this regard, we propose a measurement tool that can be used to analyse the relationship between HRA capability maturity and other macro-, micro- and individual-level variables, including other organisational capabilities, organisational culture, analytics effectiveness and employees' well-being.

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Appendix

The supplementary material for this article can be found online.

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