Title: **Measuring HR Analytics maturity: Supporting the development of a roadmap for data-driven talent management**

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Abstract: Organisations and their human resource departments are progressively leveraging on digital technologies and factual data to support people-related decisions, in an approach known as HR Analytics (HRA). Academics defined HRA as an organisational capability rooted in different organisational dimensions and resources. Despite the increasing interest, academics have still to reach a consensus on what HRA really encompass. Additionally, there is still limited research on how to successfully build, develop, and manage these analytics capabilities. Academic literature lacks practical guidance that could support practitioners in defining and planning their development path, prioritising investments and activities. The aim of this work, thus, is to provide a model to assess and evaluate the current and desired state of HRA maturity. Then, we propose a procedure to comprehensively measure and evaluate HRA dimensions and their relationships, enabling the generation of an effective development roadmap. The research has been developed using an augmented version of the methodology proposed by Becker et al., (2009), integrated with the procedure proposed by Gastaldi et al., (2018). Eventually, our research demonstrated that HRA is defined through 14 dimensions and 37 further components. Additionally, we revealed that analytics capabilities are developed through an evolutionary path characterised by 4 discrete stages of maturity. During its development, HRA needs to be considered as a dynamic capability, evaluating its various intersections with the organisation. The results of this research open the door for interesting future research focusing on the organisational effects of HRA.

Keywords: HR Analytics, people analytics, talent Analytics, Maturity model, Organisational capability, Dynamic capability.

Word count: 8711 (without references and tables)

1. Introduction

Over the past years, advances in digital technologies have significantly improved the processes of data collection and analysis in business settings (Gandomi and Haider, 2015; Schiemann et al., 2018). Human Resource (HR) departments (Rasmussen and Ulrich, 2015; Boudreau and Cascio, 2017; Huselid, 2018) as well as other business units (Holsapple et al., 2014) are progressively leveraging on factual data (McIver et al., 2018) to take HR decisions (Sharma and Sharma, 2017), in an approach known as HR Analytics (HRA) that is now considered an organizational capability to nurture (Levenson, 2018; Minbaeva, 2018). Through HRA, employee's information and behaviour are made more accessible, interpretable and actionable (Tursunbayeva et al., 2018; McCartney and Fu, 2021), improving the related decision-making (Minbaeva, 2018) and organisational outcomes (Aral et al., 2012).

Attracted by analytics opportunities, companies tend considering HRA as a priority for their business (Leonardi and Contractor, 2018). If, at the beginning of this millennium HRA had basically not yet entered into the business language (Levenson, 2018), today a Google search on the topic produces over 4 billion results. Despite mounting interest and substantial growth in practice (McCartney et al., 2020), however, companies are facing difficulties in developing proper HRA (Angrave et al., 2016). In addition, there is also limited research on how successfully build and develop HRA capabilities (Angrave et al., 2016; Marler and Boudreau, 2017; Levenson, 2018). The objective of this paper is to provide an evolutionary model for harmoniously developing an HRA capability.

The remained of the paper is organised as follows. In Section 2, we explain the theoretical background of this research. In Section 3, the methodological process is presented. In Section 4, we present the model and the results related to its implementation in a target company. In Section 5, results are discussed. Eventually, in Section 6, we discuss the theoretical and practical contributions of our work. Additionally, model limitations and fruitful directions for future research on the topic are presented.

2. Theoretical background

The theoretical background has been organised into two main paragraphs. The first one focuses on HRA literature and reveals its main research gaps. The second one focus on Maturity Model's (MM) concepts and elements.

2.1. HR Analytics

In the last two decades, HR practices have undergone radical changes. Organisations and their HR departments have been forced to operate in an uncertain and volatile environment, facing an increasingly diverse, dynamic, and complex workforce (Prerna, 2015; Huselid, 2018). HR departments experienced a transformation from an administrative to a more strategic and business-oriented role (Vargas et al., 2018), which aims at proactively participating to the organizational value creation (Ulrich and Dulebohn, 2015). Additionally, the diffusion of digital technologies has transformed the traditional ways of managing employees (Fernandez and Gallardo-Gallardo, 2020), providing data and information to better understand personnel's psychology and behaviour (McIver et al., 2018). The availability of cheap information systems also for HR processes increased data collection and processing capabilities (Schiemann et al., 2018), decreasing at the same time data management and storage costs (Boudreau and Cascio, 2017; McIver et al., 2018; Dalhbom et al., 2019).

Organisations have been fascinated by the outstanding promises associated to data analytics, willing to replace traditional intuition-based procedures with evidence-based decisional processes (Dalhbom et al., 2019). According to latest literature, HRA can align business and HR strategies (Shrivastava et al., 2018; Fernandez and Gallardo-Gallardo, 2020), solve business issues (McIver et al., 2018), reduce operational costs (Wei et al., 2015), improve organisational effectiveness and efficiency (Tursunbayeva et al., 2018), add value through more effective HRM (Margherita, 2022) and, eventually, generate competitive advantage (Minbaeva, 2017). In this context, the emerging field of HRA started gaining attention both from academics and practitioners (Marler and Boudreau, 2017; Leonardi and Contractor, 2018).

Scientific literature describes HRA as an evidence-based HR practice that adopts statistical and mathematical methods to serve the needs of different decision makers and executives, generating a broad spectrum of potential outcomes (Marler and Boudreau, 2017; Margherita, 2021). Recently, academics defined HRA as an organisational and systemic capability (Levenson, 2018; Minbaeva, 2018), rooted in different organisational processes and dimensions (Minbaeva, 2018; Margherita, 2021). Organisational capabilities refer to the way in which organisational resources, knowledge, and competencies are combined together to perform and extend output actions (Salvato and Rerup, 2010). Capabilities enable the connection between organisational intentions and desired outcomes, generating value and competitive advantage for their organisations (Winter, 2000). More specifically, organisational capabilities can be thought into one of two interconnected categories. Ordinary capabilities enable the administration and governance of the firm's activities, performing a defined static set of acitivites. On the other hand, dynamic capabilities enable the organisation to build and renew resources, reconfiguring them to innovate and/or to respond to external or internal changes (Teece, 2017). In this regard, literature (Levenson, 2018; Minbaeva, 2018) recommends that both researchers and practitioners should approach HRA as an organisational capability, focusing their attention on its complex and branched organisational structured. HRA is based on different actors, processes, and organisational resources, and its successful development depends on the correct interaction, consistency, and integration among these ingredients. If HRA is treated and developed as an organisational capability, thus, it will "stay" in the organisation even if analytics responsible should leave it (Minbaeva, 2018).

Despite the increasing interest, HRA is still consider an underdeveloped and underexplored research field (Tursunbayeva et al., 2018; McCartney and Fu, 2021), characterised by definitional ambiguities (Margherita, 2021) conceptual confusion (Fernandez and Gallardo-Gallardo, 2020), and several research gaps (Qamar and Samad, 2021). First, scholars have still to reach a consensus on which organisational resources and dimensions are involved in its development (Angrave et al., 2016), with the few present studies that use a silo approach and neglect the systemic nature of HRA solutions (Levenson, 2018). Second, only a limited number of studies analysed the relationships and the interactions between its elements and dimensions. Current academic research, indeed, lacks a crosswise approach to integrate the different factors involved in the building and development of HRA capability (Levenson, 2018). Third, current research lacks comprehensive models and frameworks enabling the assessment, evaluation, and improvement of HRA maturity. Eventually, there is still limited research on how to successfully build, develop, and manage HRA capabilities (Marler and Boudreau, 2017). More specifically, academic literature lacks practical research and guidance that could support practitioners in defining and planning their development path (Levenson, 2018), prioritising investments, efforts, and activities.

The successful implementation of HRA, thus, relies on the understanding of its constituting elements, their relationships, and their integration with the existing organisation solutions. In this regard, the main objective of this research is to provide a model able to comprehensively describe and evaluate the maturity of HRA organisational capabilities. The model and the research procedure proposed in this study, thus, aims at providing organisations with a tool to define, plan, and implement their evolutionary path, supporting practitioners in their prioritisation of investments and interventions.

2.2. Maturity models

To get a general understanding of what MMs are and what they are used for, this paragraph discusses their basic concepts and elements. First, from a linguistic perspective, the concept of maturity has been associated to a "state of being complete, ready, or mature" (Lahramann et al., 2011). In engineering fields, maturity is normally measured for so called organisational capabilities, described as the ability of an organisation to complete certain activities or reach specified goals (Wendler, 2012). In academic literature, the maturity topic is addressed by researchers to outline the condition for an organisation to reach the desired state of maturity for their intended purpose (Lahrmann et al., 2011).

In this regard, MM first emerged in information systems literature (Gibson and Nolan, 1974) to support organisations in their development path from an initial state of the system to a desired state (Marx et al., 2012). Researchers defined MM 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 key objective of these models, thus, is to reveal the gaps between the initial and the desired state of a certain capability, providing a support to generate an effective development path through which increasing the overall maturity of the system (Becker et al., 2009; Blondiau et al., 2015). Being the concept of maturity associated to a stage growth approach (Monteiro et al., 2020), the evolutionary paths proposed by these models are characterised by incremental improvements through a set of intermediate states (Sen et al., 2012).

Maturity levels, model dimensions, and assessment instruments are the main elements of a MM (de Bruin et al., 2005; Marx et al., 2012; Monteiro et al., 2020):

- *Levels:* are the different maturity steps that each dimension can assume during the evolutionary path (Monteiro et al., 2020). The characteristics of each level should be distinct and measurable, ensuring a well-defined relationship of each level to its predecessor and successor (Fraser et al., 2002).
- *Dimensions:* represents a specific area of mutually exclusive capabilities (Marx et al., 2012). Then, each dimension is further represented by a number of sub-components (e.g., activities, practices, or objectives) (deBruin et al., 2005).
- *Assessment tools:* are qualitative or quantitative (e.g., questionnaires, scoring models) that enable the evaluation of the maturity levels for each dimension (Fraser et al., 2002).

In academic literature, it is possible to find three types of MMs, differentiated by their purpose of use (de Bruin et al., 2005; Becker et al., 2009; Maier et al., 2009). First, descriptive models assess the as-is maturity state of a certain organisational capability, considering specific dimension and evaluation criteria (Becker et al., 2009). These models are used for diagnostic purpose (Maier et al., 2009). Second, prescriptive models evaluate maturity levels and provides practical guidance to develop an improvement path to reach a desired maturity state (de Bruin et al., 2005; Becker et al., 2009). Eventually, comparative models enable internal and external benchmarking across companies, using data from a large numbers of participants (de Bruin et al., 2005; Maier et al., 2009). Additionally, MMs can be specified through two different approaches, according to how dimension and levels are determined. On one side, using a top-down approach, a fixed number of maturity levels and dimensions are theoretically specified (Marx et al., 2012). On the other side, using a bottom-up approach, the requirements and measures are initially determined, and then clustered into maturity levels (Lahrmann et al., 2011; Marx et al., 2012). Despite some theoretical suggestions, there is no single method to select one of the approaches (Monteiro et al., 2020).

Researchers and practitioners are increasingly interested in MM since they offer a simple but effective method to assess the quality of their capabilities and develop a path for improvements (Wendler, 2012). In the last 50 years, scholars proposed hundreds of MMs for multiple organisational capabilities (de Bruin et al., 2005), including business analytics (e.g., Cosic et al., 2012; Cosic et al., 2015) and business intelligence systems (e.g., Gastaldi et al., 2018; Lahrmann et al., 2011). However, most MMs in the literature are fixed and static models (Lahrmann and Marx, 2010), neglecting the interdependencies between their dimensions and components (de Bruin et al., 2005; Maier et al., 2009). These models fail in providing comprehensive and effective guidelines for prioritising interventions during the potential improvement path (Popovič et al., 2012). Additionally, the importance of interdependencies increases in complex and branched organisational systems (Gastaldi et al., 2018).

For complex systems, such as HRA, thus, it is fundamental to evaluate and analyse the interdependencies among the dimensions constituting the organisational capability. In this regard, this research provides a comprehensive model and an interdependencies matrix that identify and analyse the relationship between dimensions, providing a set of indicators of relevance for each dimension.

3. Methodology

The model has been developed and applied within a project of collaboration between Politecnico di Milano and a project partner[1], integrating academic research rigour and analytics field knowledge. The aim of the project, in line with our research objectives, was the creation of a model capable of leading organisations during their HRA capability development. For this reason, a dedicated team was formed in December 2021, including both researchers and practitioners. Table 1 represents all team members together with their professions, expertise, and roles into the project.

Table 1. Project team members description.

Member	Profession	Expertise	Year of expertise	Role in the project
Researcher 1	PhD Candidate	HRA; HRM	2 years	Development and improvement of the maturity model and reporting of projects results
Researcher 2	Associate Professor	Business Intelligence; HRM, MM	10 years	Coordinator of the overall project improvement of the MM
Researcher 3	Full Professor	HRM, Change management, MM, Digital transformation	30 years	Support in the coordination of the overall project
Researcher 4	PhD Candidate	HRA; HRM	2 Years	Engagement of project partner practitioners
Practitioners 1	Senior manager in HR transformation and Digitalisation	HRA; HRM; HR transformation and digitalisation mechanism	3 years	Validation and application of the maturity model in project partner's clients
Practitioners 2	Senior consultant	Operation management; Statistical data and quantitative methods for research	2 years	Validation and application of the maturity model in project partner's clients

Our research has been developed using an augmented version of the methodology proposed by Becker et al., (2009), which is one of the most rigorous, accurate, and comprehensive methodological framework for the development of MMs ((Pöppelbuß and Röglinger, 2011; Cosic et al. 2012; Brooks et al., 2015). Additionally, it has already applied for several organisational capabilities in different domains (e.g., Lahrmann et al., 2011; Cosic et al., 2015). This methodology, however, does not explain how measuring and evaluating dimensional interdependencies, and thus, how to prioritise efforts and activities. For this reason, we integrated the original framework with the methodological procedure proposed by Gastaldi et al. (2018).

The entire methodology, thus, is composed by 8 main phases, summarised in Figure 1. The research process is presented in a linear logic, but it is important to note that phases were highly interrelated. The final outputs (i.e., see Section 4), indeed, are the result of their continuous iteration and interaction. In the next eight paragraphs each stage and its output will be described in detail.

[1] The project partner is a global leader in consulting that provides different services for HRM, actuarial and pension services, monitoring and investment management of institutional investors and wealth management networks. The company also support their clients in implementing ESG (Environmental, Social, and Governance) and DEI (Diversity, Equity, and Inclusion) strategies.

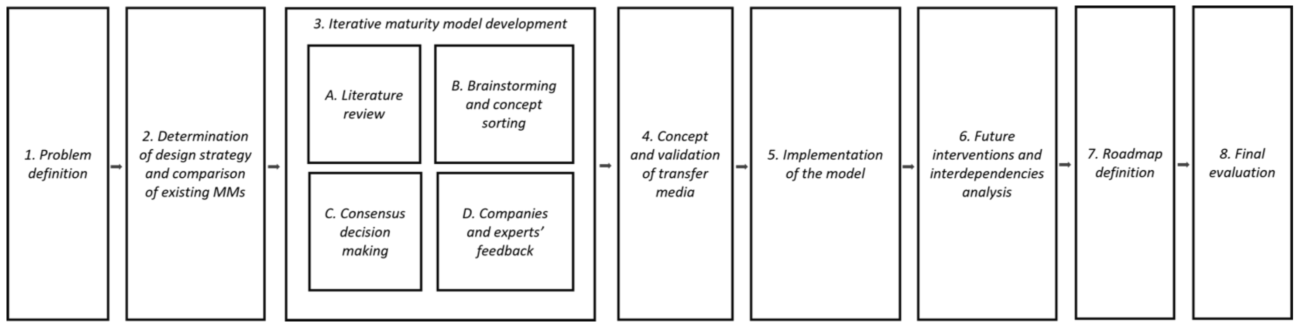

Figure 1. Research methodology

3.1. Problem definition

The first stage of the process is the problem definition, which concerns the identification of the targeted domain and the target group; the discussion of problem relevance and intended benefits; and the determination of the conditions for model application (Becker et al., 2009). First, we defined our research objectives and research questions, bearing in mind the research problems and the project objectives. As already specified in Section 2, current research provided little guidance concerning the development path for HRA capability (Marler and Boudreau, 2017; Levenson, 2018; Minbaeva, 2018). Additionally, the interest in better understanding how developing HRA is demonstrated by the project partner's requests and objectives.

The research questions (RQs) are:

- ***RQ1:*** *Which are the characteristics defining HRA capability?*
    - *RQ1.1: Which are the dimensions that define HRA capability?*
    - *RQ1.2: Which are the different maturity levels that an organisation can reach for HRA capability?*
- ***RQ2:*** *Which are the relationships between the dimensions constituting HRA capability?*
- ***RQ3:*** *Which is an effective method to define a roadmap to develop HRA capability?*

This paper, thus, aims at developing a comprehensive model able to assess and improve HRA capability, presenting a roadmap that guide organisations during their evolutionary path. More specifically, the intended benefit of this study is to provide a tool that helps practitioners in prioritising and planning interventions to reach the desired level of HRA maturity. For this purpose, we determined targeted domain and target group for our model, which was defined to evaluate the level of maturity of *HRA capability* (targeted domain) inside *organisations* (target group). Finally, model completeness, optimisation, and comprehensibility have been ensured during its development, guaranteeing its conditions for 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). Scholars, however, have still to reach a consensus on what HRA encompass and on which dimensions are involved in its development (Angrave et al., 2016; Fernandez and Gallardo-Gallardo, 2020). Thus, academic literature completely lacks models that measure or evaluate HRA capabilities within an organisation. For this reason, we decided to define a strategy to design a completely new MM.

The next sub-paragraph explains in detail the iterative design process defined for our model, documenting each step of the process, the parties involved, the applied methods, and the main outputs (Becker et al., 2009).

3.3. Iterative maturity model development

The third stage, considered the central phase of the procedure model (Becker et al., 2009), aims at defining the fundamental structure of our MM, selecting the best development approach, designing its main elements, and, finally, validating and testing its effectiveness.

First, in line with our objectives, we decided to build a prescriptive model, characterised by multiple dimensions and further successive levels of detail. Prescriptive model was selected because it enables the development of a roadmap for maturity improvement (de Bruin et al., 2005; LaValle et al., 2011). Multi-dimensionality was selected due to HRA complex and articulated nature. Then, we decided to adopt a top-down approach, which we considered the most suitable to describe HRA capability. A top-down approach, indeed, should be used when the domain is relatively naïve and organisational maturity is not clearly defined and explained (de Bruin et al., 2005; LaValle et al., 2011), as in the case of HRA. The structure of the model is better explained and represented in paragraph 4.1.

Once the structure and the approach were determined, model levels and dimensions were defined and validated through 3 iterative sub-phases: (A) a content-based literature review to build a preliminary MM; (B) five sessions of brainstorming and four sessions of concept-sorting to define model structure; (C) six sessions of consensus decision-making to refine the model; (D) collection of feedback from three companies interested in HRA to consolidate and validate the MM.

A. Literature review

We firstly conducted a review on business analytics and business intelligence MMs, in order to understand how these solutions have been modelled and assessed by previous researchers. More specifically, we wanted to define their constituting structure and dimensions, identify and select possible metrics by which assessing their maturity, and determine potential logics to group metrics and dimensions. Thus, a query was defined combining business analytics, data analytics, business intelligence, and maturity model keywords. The search strategy has been performed on Scopus database, selected for its popularity and update rate, on 1st February 2022, obtaining 71 papers. Figure 2 represents in detail the entire search process.

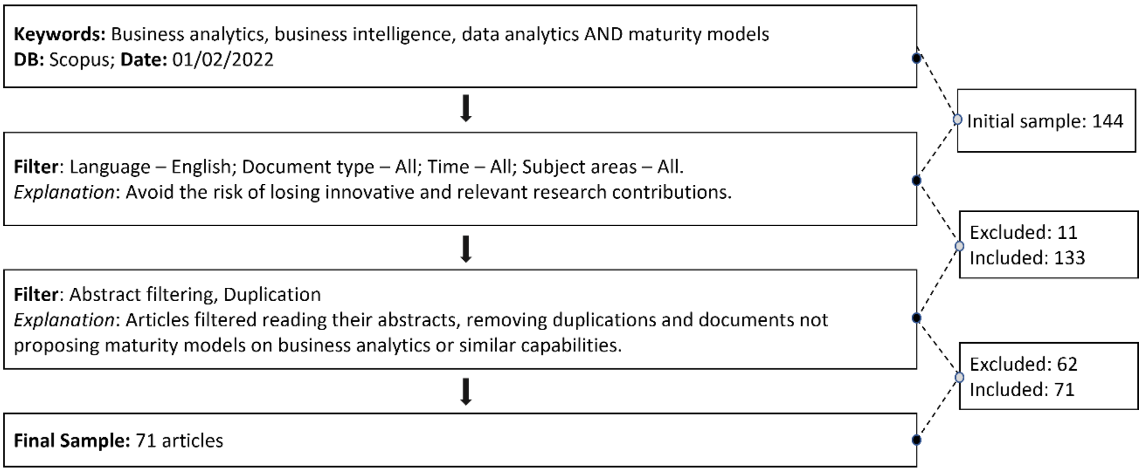

Figure 2. Search process for the literature review focused on MMs dedicated to business analytics, data analytics or business intelligence systems.

As reported in Section 2, HRA is characterised by definitional ambiguities and conceptual confusion (Margherita, 2021; McCartney and Fu, 2021), with academics that have yet to clearly define what does HRA really encompass (Fernandez and Gallardo-Gallardo, 2020). For this reason, we conducted another extensive content-based review, focusing our attention on HRA and its specific elements and characteristics. In this second review, we wanted to develop a comprehensive understanding of its success factors, constituting dimensions, and important criteria determining the maturity of analytics capability. Additionally, we assessed whether the metrics used to assess the maturity of BA and BI systems (as well as their grouping logics) identified and selected in the first review could be applied to HRA. Our query strategy was based on search terms used by previous reviews on HRA (e.g., Marler and Boudreau, 2017; Qamar and Samad, 2021; Margherita, 2022). Our search was conducted again on the Scopus database on 1st February 2022, extrapolating at the end 117 papers. Figure 3 presents the search process and final sample of reviewed articles.

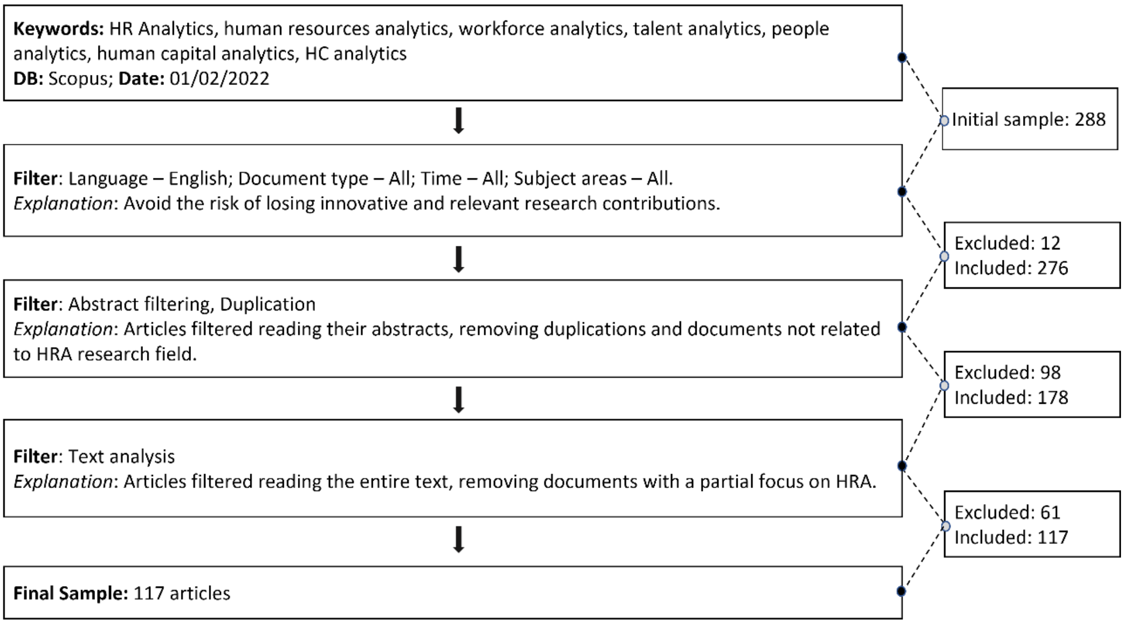

Figure 3. Search process for the literature review focused on the HR Analytics research field.

The first sample of documents has been used to extrapolate relevant areas, dimensions, components, metrics, and maturity levels previously used to build models on business analytics systems. The second sample of articles, then, has been reviewed using a coding sheet, where most important elements, characteristics, and possible factors affecting HRA maturity have been recorded. The coding scheme has been created using an iterative approach, moving back and forth between previous models on analytics solutions, reviewed papers, and the coding sheet. In Appendix A is reported the final coding sheet, corresponding to a simplified version of the final model (representing only areas, dimensions, and components). For each dimension, some of the most relevant literature citations are provided.

These reviews enabled the production of a preliminary version of the HRA maturity model, which has been progressively refined through phase B, C and D, integrating the contribution of different practitioners. It is important to note that the output of this first phase comes from the joint effort of the 4 researchers reported in Table 1. The initial model, despite several limits, provided a fundamental conceptual base to discuss with practitioners and focus their contributions.

B. Brainstorming and concept-sorting

HRA literature is still in its early stages of development (Fernandez and Gallardo-Gallardo, 2020). As a matter of fact, current academic research proposed limited and conceptual contributions on HRA (Marler and Boudreau, 2017), providing little guidance concerning its practical implementation and organisational development (Levenson, 2018; Minbaeva, 2018). A purely academic analysis, thus, risks excluding important elements for the practical evaluation of this capability. For this reason, 5 brainstorming sessions (McGraw and Harbison-Briggs, 1989) have been organised within the project team, presenting the initial model to the practitioners and involving them in its development. Each session lasted at least 2 hour and involved all project team members. The objective of the first two sessions was to identify all the possible areas and dimensions characterising HRA. Two further sessions, then, were used to discuss and determine the possible stages of HRA maturity. Eventually, in the final session, the team produced a first draft of possible components and metrics to comprehensively assess HRA maturity. The final output of this second sub-phase, thus, is an updated version of the initial model and a list of potentially relevant areas, dimensions, components, metrics, and maturity levels deemed suitable for the model.

Concept-sorting technique, then, has been used to decide how to subdivide each dimension into more granular components and sub-components (e.g., metrics and sub-metrics), and how to decline each dimension into the different maturity levels (e.g., indicators). Concept sorting is a knowledge generation technique (McGraw and Harbison-Briggs, 1989) that is useful after model definition to produce and refine alternatives for maturity level measurement (Sen et al., 2012). Thus, four sessions were organised, one for each area of the maturity model (e.g., *Organisational* one, see Section 4 for further details). Each session lasted at least two hours. In each session, first, the team worked on the set of components and metrics generated during the brainstorming sessions. Then, for each metric or sub-metric, the team generated and discussed a set of alternative indicators to assess maturity at different levels. Eventually, alternative indicators have been selected and refined, explicating through peer discussions the reasons for fitting the alternatives of different metrics or sub-metrics into the same maturity level.

C. Consensus decision-making

In consensus decision-making a group find the best solution to a problem by evaluating advantages and disadvantages of each alternative solution (Sen et al., 2012). This technique is particularly useful after brainstorming activities (McGraw and Harbison-Briggs, 1989). Six sessions of consensus decision-making, thus, were organised to evaluate the evolving model and converge on its various areas, dimensions, components, metrics, indicators, and levels. Specifically, four sessions have been used to discuss model dimensions and components (one for each area), while two further sessions have been used to refine model levels and their maturity indicators. Each session lasted at least two hours. In the first one, as suggested by Verganti (2017), all members worked individually transcribing their ideas about the model elements. In the second one, during virtual sessions of multi-participant interactive dialogues, the team discussed individual thoughts and doubts. In this phase, the team refined ideas and converged on the most promising ones, selecting and consolidating the model structure. Eventually, a consolidated version of the model has been outlined.

This entire process (B and C), explained in a linear logic, has been performed iteratively until all team members agreed on an interim model structure, which is the output of this third phase.

D. Companies and experts' feedback

In the last phase of model development, we sent an email to eight companies asking for a feedback on the MM. Companies were chosen from a list of organisations that had previously collaborated with the project partner and had shown interest and expertise in analytics field. Three companies responded positively to our invitation. Table 2 reports companies characteristics and expertise in the analytics domain.

Table 2. Description of the three companies that had provided feedback on the maturity model.

Company	Dimension	Industry	Area	Description	Analytics expertise
A	*700-1000 employees*	*Banking services*	*Italy*	The company is a banking services provider that operates with credit intermediation	Analytics have been already implemented and used using for administrative activities
B	*100-500 employees*	*Consultancy*	*Global*	The company is a network of independent companies specialised in auditing services or corporate, accounting, and financial consulting	Analytics are being implemented in a multi-year project in its first year
C	*More than 1000 employees*	*Consultancy*	*Global*	The company is a network of independent companies, affiliated to an international cooperative, providing several consultancy services, from accounting to legal services	Analytics have been already implemented and used to support talent management decisions

Then, two meetings of one hour each were organised with each of the three organisations. In the first one, the model has been presented to the practitioners to facilitate and solicit their opinions on the model structure. In the second one, organised after at least five days, companies provided comments and suggestions for improvement, which were discussed in more detail with the research team.

Eventually, the final MM has been validated with the help of three experts in the fields of analytics, people management, and MM . The three experts were selected for their experience on the topic, having previously collaborated on another MM related to the business analytics domain. Before moving on the following phase, indeed, model dimensions, components, and levels were revised in order to ensure mutual exclusivity and collective exhaustiveness. The validated model, output of the entire model development process, is presented in paragraph 4.1.

3.4. Conception and validation of transfer media

After the design of the MM, we defined our transfer media for academic and practitioner communities (Becker et al., 2009), opting for an interactive questionnaire to be administered through an online platform. For each metrics and/or sub-metric of the model, thus, the team produced a question with four possible answers (indicators) reflecting the different levels of maturity. According to our project and research objectives, each questions asked the current HRA maturity level and the expected maturity level to be achieved in the next three years, considering their strategic plans and/or feasible targets. The model, in this way, it is able not only to consider maturity misalignments but also to determine the gaps to fill in the near future, and thus, the roadmap objectives.

The initial questionnaire was sent to the three companies consulted for the consolidation of the model (see Table 2), asking them to complete it and indicate possible unclear elements. Then, two virtual meetings were scheduled with each company’s representative to discuss their answers, doubts and possible modifications. In the first meeting, we made sure that the questionnaire and the model presented good levels of accuracy, comprehensiveness, and understandability. In this phase, questions have been analysed to reveal possible doubts or inconsistencies. In the second meeting, possible corrections or changes to the questionnaire were discussed with the respondent and the project team. The output of this phase, finally, is a validated version of our transfer media. The questionnaire has not been attached to the papers because of the agreements with the project partner.

3.5. Implementation of the model

After the validation phase, the model has been applied in a target company[2], selected as final user. The company was chosen from a group of organisations collaborating with some universities in research centres

[2] The target company is an Italian enterprise operating in the tourism sector, with more than 19,000 employees. The company belongs to a larger international group based in Germany.

dedicated to social analytics issues. In particular, this company went through a one-year development project for HRA capability development, where its maturity levels changed considerably.

First, the questionnaire was sent to the corporate team dedicated to the analytics project, in order to give them the time to scan and preliminarily answer each question. Then, a virtual meeting was organised to solve unclear questions or inconsistent answers. Finally, the maturity of each dimension was calculated by averaging over the components, metrics, and sub-metrics forming the dimension, and then, discussed with company representatives to ensure that maturity results corresponded to the real organisational conditions. The assessment of the maturity level laid the foundation for the next phases, inspired by the work of Gastaldi et al., (2018).

3.6. Future intervention and interdependencies analysis

Most MMs provide a static representation of maturity levels, neglecting the relationship among the different dimensions that occur during a development path (Marx et al., 2012). In line with our research objectives (see Section 1), thus, we added three steps to the traditional methodology.

First, the team scheduled four virtual meetings with the company's representatives to understand the possible development path for their HRA maturity. In each meeting, dedicated to a specific area of the model, the group initiated collective thinking on how achieving the desired maturity levels reported in the questionnaire in the next three years, starting from their current condition. More specifically, the dimensions to be improved, the type of required investment, and the critical issues to achieve expected maturity levels were discussed withing the project group. Meetings were recorded in order to be analysed afterwards.

Second, we organised two meetings with the three experts already involved in the validation phase, presenting them implementation results. In the first meeting, brainstorming has been used to reason and generate possible development strategies to reach the desired state of HRA maturity for the target company. In the second meeting, consensus decision-making has been used to converge and select the best strategies. Different selection criteria were used, such as the degree of integration with existing enterprise systems and consistency with current business strategy.

Third, all meeting discussions have been transcribed and independently cross-analysed by the team of researchers, in order to develop a first understanding of possible development paths and dimensional interdependencies. Then, researchers integrated their ideas proposing a preliminary version of the model representing the interdependencies among its dimensions, which was also validated with the three experts. The preliminary framework has been presented and discussed also with the target company, reflecting on the different relationships among the dimensions and sub-dimensions. Eventually, the research team integrated all these reflections and stimuli in a final and comprehensive framework of prerequisites, synergies, and relationships among the different dimensions of the model. Considering two dimensions (X and Y), four types of interdependencies were defined:

- Strong prerequisite: it indicates that to increase the maturity of the dimension Y, it is necessary to have previously reached a good maturity (3 or 4) level in X.
- 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.
- Strong synergy: it indicates that it is necessary to simultaneously improve the maturity of X and Y.
- Synergy: it indicates that it is suggested to simultaneously improve the maturity of X and Y.

The final interdependencies matrix is reported in paragraph 4.2.2.

3.7. Roadmap definition

The objective of this seventh phase was to define a roadmap for HRA maturity improvement, integrating the assessment model and the interdependencies matrix. More specifically, we associated the current (and expected) maturity levels of the various dimensions of the HRA model with the interdependencies matrix to determined four clusters of dimensions to be prioritized.

- *Strategic*: it includes dimensions that are mature but also relevant (often strong prerequisites) for the evolution of other dimensions. The target company should consolidate investments in this area.
- *Critical*: it 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.
- *Consolidated*: it includes dimensions that are mature and less relevant for the development of other dimensions. Considering past investments, the target company should invest marginal resources in this area.
- *Optionable*: it includes dimensions that are not mature but also less relevant for the development of other dimensions. The target company should consider investing in this area this area after having tackled the critical area, in a logic of prioritised homogeneous development of HRA capabilities.

The process for creating these prioritised cluster consisted of three steps. First, we calculated current (CM_j), and desired (DM_j), maturity score for each dimension, averaging the current maturity levels of its constituting sub-dimensions (CM_{ij}). Second, we associated to each prerequisite or synergy a predefined set of scores ($PSxy_{ij}$). More specifically: (i) 1 point for each synergy of the dimension; (ii) 2 points for each strong synergy; (iii) 3 points for each prerequisite; (iv) 4 points for each strong prerequisite. Next, we calculated a comprehensive relevance value (RV_j) for each dimension by summing the scores on the row (X) corresponding to that specific dimension (Y).

$$CM_j = \sum_{i=1}^{n} CM_{ij}/n \quad \forall j = 1 \dots N$$

$$DM_j = \sum_{i=1}^{n} DM_{ij}/n \quad \forall j = 1 \dots N$$

$$RV_j = \sum_{i=1}^{n} PSxy_{ij}\,/n \quad \forall j = 1 \dots N$$

Third, each dimension was assigned to one of the previously described clusters. The four clusters are described in detail in paragraph 4.2.3. This set of indicators, calculated for each dimension, provides a useful tool to the target company to approach clusters and dimensions characterising their development path with different modalities, resources, and timings.

3.8. Final evaluation

The final phase of the methodology is dedicated to the evaluation of the benefits and improvements reached through the application of the MM (Becker et al., 2009). In this phase, usefulness, quality, and effectiveness have been used as evaluation criteria. In this regard, two meetings were organised with the company representatives to discuss the results and the limitations related to the implementation of the MM and the interdependencies matrix. In these meetings, the target company also provided some suggestions for improving the overall approach. The usefulness and practical contributions of the model are discussed in Section 6 together with its limitations.

4. Results

The results of the research process described above are reported in three main paragraphs. In paragraph 4.1., the general MM and its main constituting dimensions are reported. In paragraph 4.2., we introduce the results obtained through the implementation of the model in the target company, presenting its maturity scores (Section 4.2.1.), interdependencies matrix (Section 4.2.2.), and cluster analysis (Section 4.2.3.).

4.1. HR Analytics Maturity Model

The final HRA MM is reported in Table 3. The model encompassed 14 dimensions and 37 components. As accomplished by Gastaldi et al. (2018), the dimensions are grouped in four main areas:

- *Technological area:* it describes the technological architecture required to develop reliable HRA capabilities, considering the technological infrastructure, its components and features (e.g., technological infrastructure that enable data collection and management activities);
- *Organisational:* it represents the organisational resources and processes used to by the organisation to develop, manage, and control HRA capabilities (e.g., internal competencies for the operational management of HRA);
- *Functional:* it represents the different functionalities offered by HRA (e.g., ability of performing advanced statistical analysis);
- *Diffusion:* it evaluates the pervasiveness of HRA capabilities in the organisation (e.g., diffusion of an analytics mindset in the organisation and in the different departments).

Four maturity levels, then, have been defined for each dimension:

- *Initial:* the dimension is not yet present or its implementation path is in its infancy;
- *Limited:* the dimension is present but its implementation path has been developed in a limited manner;
- *Systematic:* the dimension is fully implemented and systematically managed;
- *Strategic:* the dimension it fully implemented and strategically exploited.

The model, integrating these levels and the 14 dimensions, provides a detailed and simple way to assess current HRA maturity and to develop effective development paths.

Table 3. HR Analytics Maturity Model (HRA MM)

Area	Dimension	Definition	Components	Definition	Metrics	Indicator example (Lv.4)
Technological	T1. HRA architecture	It describes the articulation of the HR Analytics technological architecture (i.e., monolithic systems, data warehouse, etc.).	1.1. Technological standards	It represents the technological reference standards used for interoperability between systems, data modelling or integration.	-	"The company has a centralised architecture enabling modelling and integration (e.g., DWH). Moreover, the system is interoperable by most of the analytical tools in the company"
			1.2. Technological integration	It describes both internal (i.e., corporate application) and external integration (i.e., external applications)		"The HRA technological architecture is completely integrated with internal and external application, enabling the automated exchange of information flows"
	T2. Data management	It describes the technological elements that enable data collection and management activities.	2.1. Data storing	It describes the ability of HRA technological architecture to collect and store required data (e.g., data warehouse).	Applied for A. HR related data: administrative, HR practices, employee's characteristics, manager's characteristics, interactions, individual performance	"The company has a centralised databased that collects all administrative data, structured and interconnected according to relational logic"
			2.2. Data modelling	It describes the ability of HRA technological architecture to provide and make available well-structured data		"The solution enables the automatic extraction and transformation of administrative data before loading them into the database, in order to guarantee homogeneity in data structures (managing both structured and unstructured data)"
			2.3. Data collection frequency	It describes the ability of HRA technological architecture to collect required data with different frequencies (e.g., once a year)		"Administrative data are collected and updated with each change, according to specific timelines constraints"
			2.4. Data granularity	It describes the ability of HRA technological architecture to collect required data with different level of granularity (e.g., team)		"Administrative data are stored in multi-dimensional structures enabling flexible rolling-up and drilling-down operations, according to the desired level of granularity"
			2.5. Data integration	It describes the ability of HRA technological architecture to integrate data coming from different organisational sources (e.g., automatic, batch)	Applied for A. and B. Other data: business performance, financial indicators, external data	"The solution enable the dynamic and automatic integration of financial indicators, considering both structured and unstructured data-items"
	T3. HRA application	It represents the technological applications that enable data analysis and data visualisation activities.	3.1. Software for analytics	It describes the technological applications enabling data analysis	-	"HRA analysis are performed on different analytical tools (e.g., R, Stata) according to the analytics needs"
			3.2. Software for visualization	It describes the technological applications enabling data and results visualisation		"HRA results and data are reported using different visualisation tools (e.g., PowerBI, Tableau) according to the analytics needs"
	T4. Interface	It represents technologies at the basis of the interface realisation, adopted by users to access the HRA system (e.g., access modalities)	-	-	-	"The HRA solution presents an advanced interface (e.g., web-based) which has web and desktop application with the same features and functionalities"

Organizational	O5. HRA competencies	It evaluates the organisation's internal competencies for the technological supervision, operational management, and utilisation of HRA within the organisation.	5.1. Team competencies	It evaluates the accumulated knowledge and competencies on HRA by the company's internal resources dedicated to its operational management (e.g., dedicated team)	C. Desired competencies: statistical, behavioural, HR-related, business, communication, coding, informatic, privacy, ethics, security	"The resources dedicated to HRA present adequate statistical competencies to perform and interpret any type of analytics techniques and results"
			5.2. Technological presidium	It 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 figures).	-	"Technological supervisors presents all the required skills to build, develop, manage and control the HRA technological infrastructure"
			5.3. Organisational experience	It measures the current degree of accumulated organisational experience on the analytics field.	-	"The organisation has enough experience to dynamically re-adapt analytics governance and practices to gain the best synergies and benefits"
	O6. Operating model	It evaluates the level of internal organisation/coordination for HRA development, management and control.	6.1. Defined processes	It assesses the presence and level of consolidation of organisational processes related to HRA.	-	"The organisation has formally defined well-structured and compelling internal processes specific to HRA"
			6.2. Dedicated resources	It assesses the presence and number of resources allocated to the development, management, and control of HRA.		"The firm has an ad-hoc organisational unit or team dedicated to HRA practices"
			6.3. Defined roles	It assesses the presence and level of definition of roles dedicated to the development, management, and control of HRA.		"Roles have been clearly and formally defined for each figure dedicated to HRA activities, which guarantee a good level of coordination and collaboration"
			6.4. Defined responsibilities	It assesses the presence and level of definition of clarified responsibilities for the development, management, and control of HRA.		"Duties and responsibilities have been clearly and formally defined for each figure dedicated to HRA activities"
	O7. HRA strategy	It evaluates the presence of a HRA strategy. Strategy means the definition of 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	It describes the share of corporate budget allocated to HRA in relation to the overall budget.	-	"The budget dedicated to HRA is prioritised as all the other strategic investments"
			7.2. Strategic definition	It evaluates the presence and consolidation of an organisational strategy dedicated to HRA.		"HRA activities are included in a compelling and well-defined strategy that has a strong strategic impact on organisational strategy"
			7.3. Strategic alignment	It evaluates presence and the level of integration (alignment) between the HRA strategy and the organisational one.		"HRA activities and strategy are mutually influential and contingently defined with respect to the overall organisational strategy"
			7.4. Board and top management support	It measures the degree of interest and support provided by the board and top management regarding HRA initiatives and issues.		"Board and top-management are enthusiastic about HRA and directly support its activities"
			7.5. Decision-makers analytics understanding	It measures the decision-makers understanding of analytics principles (e.g., methods, statistics, rules, results).		"Organisational decision-makers have a great understanding of the analytics principles behind HRA results"

Functional	F8. Data governance	It evaluates the actions implemented by the HR Analytics system to improve the quality of input data and ensure reliable output	8.1. Data integrity	It assesses whether the systems ensures and verifies data integrity.	Applied for A. HR related data: administrative, HR practices, employee's characteristics, manager's characteristics, interactions, individual performance	"The HRA solution has high-level security mechanism to guarantee data integrity (e.g., asymmetric key and hash functions)"
			8.2. Data accuracy	It assess whether the systems check for errors in data collected and stored through the technological infrastructure.		"The HRA solution has high-level security mechanism to guarantee data accuracy (e.g., automatic cleaning)"
			8.3. Data completeness	It assess whether the system verifies that there are not missing values/incomplete data.		"The company has tools that enable automated frequent verification of the completeness of data and that recognize if the specific null value/missing value/non-existing value"
			8.4. Data confidentiality	It assesses whether the systems ensures and verifies data confidentiality.		"The HRA solution has high-level security mechanism to guarantee data confidentiality (e.g., asymmetric key mechanism)"
			8.5. Data availability	It component assesses whether the systems ensures and verifies data accessibility to authorised users.		"The HRA solution has high-level mechanism to guarantee data availability and access controls (e.g., intranet solutions, intrusion detection systems)"
	F9. Measurement	It represents the functionalities of HRA that support the realisation of metrics to evaluates specific phenomena (e.g., leadership quality) or HR processes (e.g., selection rate).	-	-		"The HRA solution support the organisation in defining useful metrics to monitor specific phenomena (e.g., leadership quality)"
	F10. Reporting	It evaluates the quality of the reporting and the way in which reports are produced and distributed to users	10.1. Report frequency	It measures how often the system is able to automatically generate reports.	Applied for D. Application fields: administrative, recruitment and selection, team organisation and way of working, performance management and compensation, training, employee's behaviour and wellbeing, leadership evaluation, communication and information management	"Reporting on recruitment and selection activities is produced when needed and constantly updated. Reporting frequency, thus, is flexible and could be adapted according to specific needs/requests"
			10.2. Report distribution	It measures the system's ability to automatically distribute reports to the right people.		"More than 50% of produced reports, related to recruitment and selection activities, can be accessed in a personalised manner directly from the HRA system by individual authorised users"
			10.3. Visualisation effectiveness	It evaluates the quality and customisability of the produced report.		"Reports produced for recruitment and selection activities effectively convey visual messages and are customizable according to individual user needs"
	F11. Analysis	It evaluates the organisational ability to perform specific HRA analysis.	11.1. Explanatory	It evaluates the ability of HRA to perform - or support users during the development of these analysis - exploratory or descriptive analyses.	-	"HRA organisational capability enable the execution of all possible explanatory analytical techniques (e.g., structural equation modelling)"
			11.2. Predictive	It evaluates the ability of the HRA to perform - or support users during the development of these analysis - predictive analyses.		"HRA organisational capability enable the execution of all possible predictive analytical techniques (e.g., predictive models)"
			11.3 Prescriptive	It evaluates the ability of the HRA to perform - or support users during the development of these analysis - prescriptive analyses.		"HRA organisational capability enable the execution of all possible prescriptive analytical techniques (e.g., simulation)"

Diffusion	D12. Accessibility	It evaluates the share of users that can access to HRA infrastructure and information (e.g., who is able to access HR Analytics results).	-	-	Applied for E. Profiles: HRA responsible, HR department, business units, top management, employees	"More than 70% of individuals operating in the HR department have access to the HRA solution"
	D13. Adoption	It represents the adoption level of HRA practices and results to support the decision-making and set operational and strategic objectives	13.1. Objectives support	It measures the adoption of HR Analytics solutions (and their results) to proactively define operative and strategic objectives related to people.	-	"Operative and strategic objectives related to people management are defined using HRA insights"
			13.2. Decisional support	It evaluates the adoption of HRA to support decisional processes or proactively take people-related decisions		"Most decision-makers in the organisation use HRA insights to take decisions about people"
	D14. Culture	It represents the diffusion of an analytical mindset in the HR department and/or in the whole organization.	14.1. Analytics credibility	It assess the credibility that HRA indicators and results have within the organisation	-	"Top-management and decision-makers consider HRA results and insights very credible and trustworthy"
			14.2. Analytics dictionary	It assess the presence and diffusion of a common and shared language to discuss about HRA and its results within the organisation.		"The organisation has a structured, shared, and established language to discuss about HRA"
			14.3. Analytics culture	It assess the diffusion of an analytical culture within the organisation. Analytical culture means the habit of approaching problems, opportunities, and consequent decision using data support.		"HRA re-shaped the idea of making business and taking decisions based on data. This feeling is shared all across the organisation"

4.2. Implementation results

The following paragraphs reports the results achieved through the implementation of our methodological procedure (see Section 3) in the target company.

4.2.1. Maturity levels

Figure 4 describe the positioning of the target company in each area of the HRAMM. Dimension have been selected as granularity level to provide a simple and clear visualisation of the company's current and desired level of maturity. The maturity scores are 2,65 for the *Technological area*; 2,31 for the *Organisational*; 2,27 for the *Functional*; and 2,04 for the *Diffusion area*. Overall, the target company has passed the second stage (i.e., *Limited*) of the HRAMM and started its development path towards the third stage (i.e., *Systematic*).

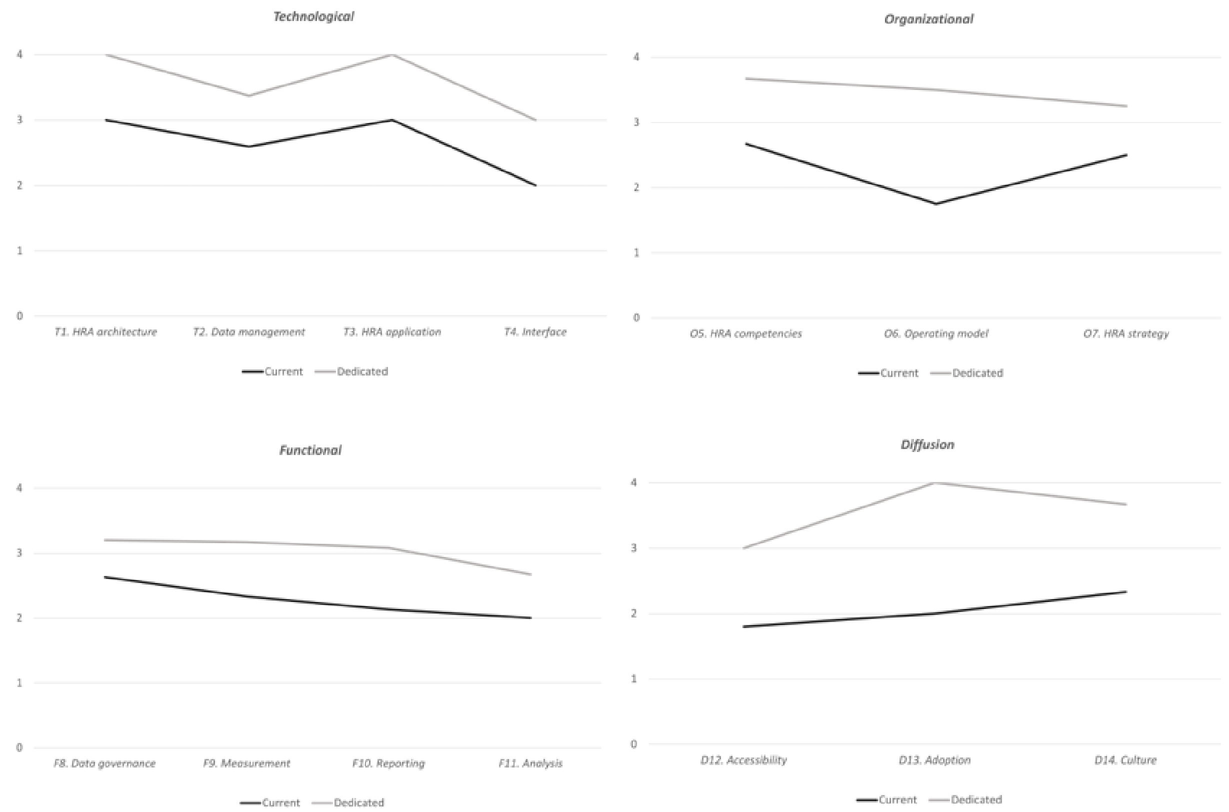

Figure 4. Target company position on the different dimensions of the HR Analytics maturity model.

4.2.2. *Interdependencies matrix*

Figure 5 represents the final framework representing the interdependencies between the dimensions of the HRAMM. Also in this case, dimensions have been selected as level of granularity to provide an accurate and comprehensible tool the to target company.

Legend

↑ : Strong prerequisite

⌂ : Prerequisite

●●: Strong synergy

● : Synergy

X \ Y		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						●●	●●		●	●	●	●	⌂	

Figure 5. Prerequisites and synergies among the dimensions of the HR Analytics maturity.

The matrix enables two different types of analysis. First, through a vertical analysis (e.g., considering as Y dimension *F10. Reporting*) it is possible to determine dimensional prerequisites and synergies that are required and/or suggested to enhance the maturity of a specific dimension. For instance, reporting activities requires a mature technological infrastructure and high-quality data. Second, through a horizontal analysis (e.g., considering as X dimension *O5. HR Analytics competencies*) it is possible to detect the impact that a specific dimension produces on the others. Thus, an improvement in the skills of those responsible for HRA could enable more sophisticated reporting activities and/or statistical analysis.

4.2.3. *Cluster analysis*

Figure 6 is the final output produced through the application of the HRAMM in the target company and represents the four clusters explained in paragraph 3.7. The arrangement of the individual dimension in the graph depends on the values of CM_j and RV_j. The size of the circles, representing the various dimensions of the HRA MM, is proportional to the difference between the current state of maturity (CM_j) and the desired state (DM_j) in 3 years. In brief, the larger circles represent the maturity dimensions that the target company is more interested to improve. The cut-off point for CM_j scores has been defined at 2,5 (midpoint between

1 and 4). For RV_j scores, instead, the cut-off point has been set at 0,8 after discussing its possible value with the target company representatives.

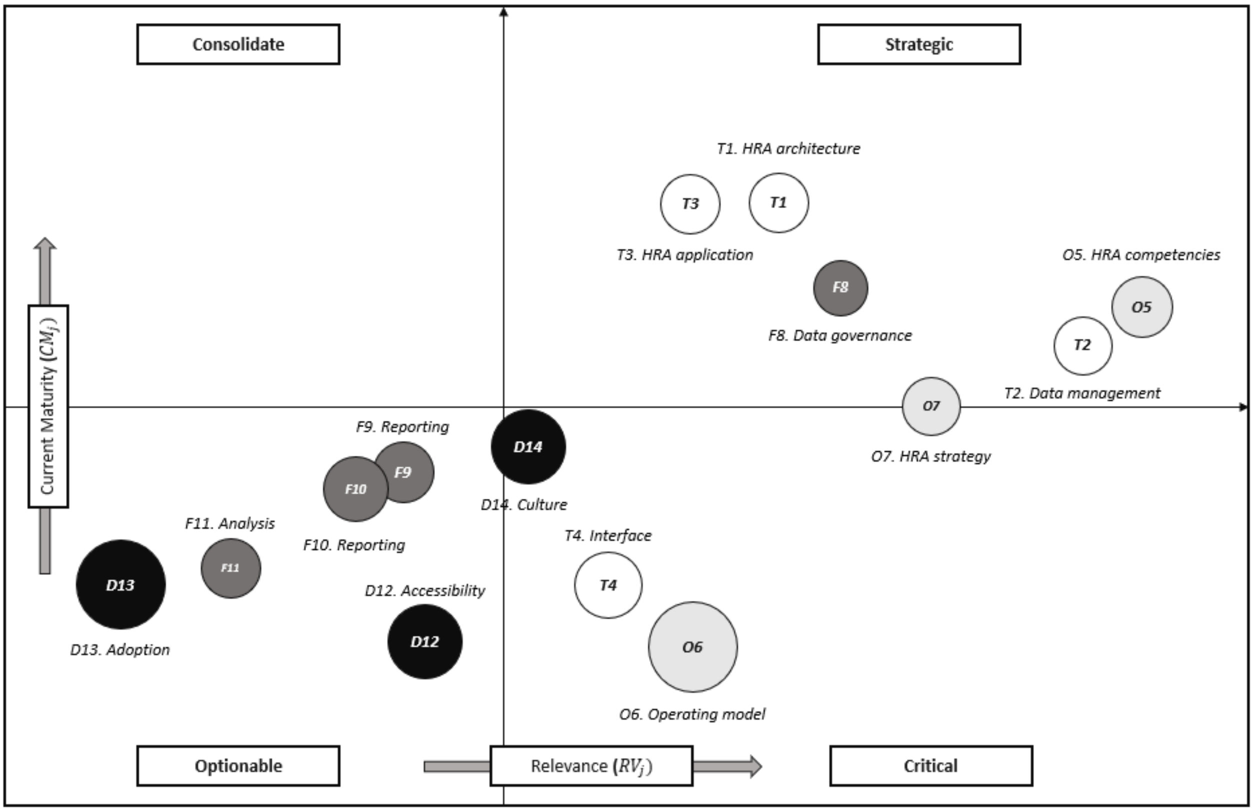

Figure 6. Relevance and current maturity scores for the HRAMM in the target company.

The figure enables the visualisation of critical and strategic dimensions, providing a map to guide investments and improvement efforts. Most critical dimensions are the technological interface (*T4. Interface*) and the analytics governance (*O6. Operating model*). It is interesting to notice that there are not dimensions to be consolidated. This is consistent with the analytics project conducted by the company, which started only one year ago. The organisation, with good foresight, first invested in strategic dimension, obtaining a sufficient level of maturity for the most relevant dimensions. This development path is visible also considering the distribution of dimensions on the graph, where relevance and maturity scores are often directly proportional.

5. Discussion

The results presented in the previous sections provides different interesting insights regarding HRA and its evolutionary path. First, the proposed HRAMM provides a comprehensive definition of HRA and an accurate description of its main constituting elements. Second, the matrix of interdependencies, supported by the results obtained in the target company, reveals the existence of specific enablers for the construction and development of analytics capabilities. Third, this research explains the fundamental role of strategic dimensions to exploit the true potential of HRA. Each of these findings is discussed in detail in the following paragraphs.

5.1. HR Analytics as organisational capability

Previous research defined HRA as a practice (Marler and Boudreau, 2017; 106), a process (Huselid, 2018) or a more generic HRM approach (Patre, 2016; Leonardi and Contractor, 2018; Chatterjee et al., 2021; Margherita, 2021) based on different principles and methods (Tursunbayeva et al., 2018; Fernandez and Gallardo-Gallardo, 2020).

Our research, however, demonstrated that analytics is a multi-dimensional construct which is developed through an evolutionary process defined by discrete stages of maturity. HRA are embedded in different individuals (e.g., see *O5. HR Analytics competencies*), processes (e.g., see *O6. Operating model – Defined processes*), and organisational structures (e.g., see *T1. HR Analytics architecture* or *O6. Operating model – Defined roles*), in line with the definition of organisational capabilities (Levenson, 2018; Minbaeva, 2018). Additionally, analytics development requires the active participation of different organisational resources (e.g., see *O6. HR Analytics competencies* or *O7. HR Analytics strategy*), revealing a complex and forked nature. In this regard, capabilities are rooted in the combination of skilled personnel, organisational resources, and processes or routines (Teece, 2019). Analysing HRA as a practice or a process, thus, provides a limited understanding of its real development, because it does not consider the individuals, resources, and organisational structures enabling its effective implementation. Practices, processes, and procedures are part of a HRA solution, but they are the repeated application of these analytics capabilities. This research, thus, confirmed that HRA, to be successfully developed, needs to be approached as an organisational capability.

More specifically, in the light of organisational capability theory (Winter, 2000; Teece et al., 2000), HRA should be understood as a dynamic capability. Dynamic capabilities enable an enterprise to successfully reconfigure resources and processes to respond to changes in business and strategic issues (Pisano and Teece, 2007), realigning assets and activities (Teece, 2007). Analytics, as dynamic capabilities, eventually enable three main procedural dimensions (Schilke et al., 2017) in talent management. First, the identification of possible threats, opportunities, or business issues related to people management (i.e., sensing). Second, the mobilisation specific resources to successfully exploit opportunities or solve business problems (i.e., seizing). Third, the continuous improvement of people management practices (i.e., transforming) (Teece, 2007). Effective dynamic capabilities must be developed gradually along a path that is unique for each organisation (Teece et al., 2019). In this regards, our research support organisations in defining their personalised development path, considering their current and desired state of maturity. The application and combination of these procedures (i.e., sensing, seizing, transforming), developing dynamic capabilities in the appropriate manner, eventually, are important to increase organisational resilience. Resilience is defined as the organisational ability to anticipate, prepare for, respond and adapt to external and internal changes in order to survive and prosper (Denyer, 2017). In this regards, HRA capability is one of the most effective way to increase organisational resilience in talent management, responding to the increasing complexity and dynamicity characterising the present workforce.

5.2. Analytics enablers – Technological and organisational factors

Interdependencies and maturity levels analysis confirmed that technological (see *Technological area*) and organisational factors (see *Organisational area*) are fundamental enablers for the development of HRA capabilities (Marler and Boudreau, Margherita, 2021; Qamar and Samad, 2021). Information technologies enable the collection, management, and analysis of employee data, providing the "raw" material to conduct any type of analytics initiatives or program. Individual competencies, governance rules, and organisational structures enable their effective application, control, and future development. These areas, indeed, have a great impact on the functionalities that HRA could provide to the organisation and its decision-makers (see *F8. Data governance, F9. Measurement, F10. Reporting, F11. Analysis*). Reports, statistical analysis, and analytics, requires high-quality data, high-quality analytics technologies, and access to a multi-disciplinary community of knowledge and competencies (Qamar and Samad, 2021). Organisations interested in building or developing their HRA capabilities, thus, should start investing in their *Technological* and *Organisational* areas, preparing the groundwork for the implementation of analytics initiatives. Additionally, it is important to remember that the success in analytics development requires an effective integration among these resources, as it possible to see in the interdependencies matrix (see Figure 5). Data without the required skills to analyse them and organise talent management practices are just worthless numbers. On the contrary, great organisational competencies without a proper technological infrastructure become a wasted opportunity. Eventually, our model suggests that HRA should be developed harmoniously focusing on all its constituting dimensions. *Technological* and *Organisational* areas are the main pillars, but investments should be made also in the other dimensions to exploit the various functionalities of analytics solutions. In this regards, our model support practitioners in defining this equilibrium and maintaining it over time, identifying and correcting possible misalignments.

These findings are consistent with the results achieved in the target company (see Figure 4). One year into their project to develop analytics capabilities, the organisation presents the highest maturity scores in the two areas described above (i.e., *Technological*: 2,65; *Organisational*: 2,31). In detail, the company reports good values for its technological (*T1. HRA architecture*: 3) and data management architecture (*T2. Data management*: 2,59). The company, indeed, has focused much of its recent investments in this area, improving their HR information systems, their human capital management software, and buying a mobile application (i.e., a people experience platform) to collect and organise employee's data in real-time. The organisation also secured all the necessary skills for reporting and basic analysis by hiring two new figures in the HR department, both characterised by an engineering background (O5. *HRA competencies*: 2,67). Additionally, the company has configured a three-year partnership with a research centre in social analytics, in order fill up possible missing competencies. The dimensions related to the operating model (*O6. Operating model*: 1,75) and the system interface (*T4. Interface:* 2) reported the lowest values and are positioned in the clusters of critical dimensions (see Figure 6). The first, it is because the HRA has still not been fully included and formalised in organisational structures. Roles, processes, and responsibilities, thus, are defined at an informal operational level. The second, it is because the low level of analytics diffusion (see *Diffusion area*) does not yet require great effort to ensure a good interface to all possible users.

5.3. Analytics impact – The strategic dimension

Technological infrastructure and organisational resources enable the initial application HRA practices, bringing to the table the first results of analytics functionalities. The later maturity stages of this capability, however, also require the development of the strategic (*O7. HRA Strategy*) and cultural dimensions (*D14. Culture*).

First, top-management interest and the dedicated budget for HRA have a strong relationship with technological infrastructure and human capital resources required for analytics development. More specifically, during HRA development path, organisational resources allocated for analytics and its weight within the HR and business strategy affect each other going through the various stages of maturity in a continuous cycle. Interest in HRA increase when the board see the results of analytics initiatives. Positive results, then, often depends on an improvement in technologies and individuals' competencies. Companies interested in improving their HRA capabilities, thus, needs to leverage these dimensions, carefully balancing investments, the launch of analytics initiatives, and the promotion of obtained results.

Second, the strategic dimension is important to exploit the true potential of analytics, and thus, generate value for the organisation. The real success of HRA is evaluated considering the strategic impact generated by managerial actions resulting from analytics results (Levenson, 2018). The effective implementation of these practices, however, depends on the credibility of analytics results (*D13. Adoption*) and the decision-makers' habit of using data to support their decisions (*D14. Culture*). Both dimensions, as reported in the interdependencies matrix, requires or present a strong synergy with analytics role in business strategy (*0.7 HRA strategy*). These findings emerged also in the meetings with the representatives of the target company. Their main project, indeed, started with econometric analyses of employee's data collected through a questionnaire administered to the entire population. Then, a new people strategy based on analytics results has been proposed to the CEO and the presidents of the various organisational divisions, who supported the proposed change programme.

Eventually, the level of diffusion (see *Diffusion area*) has no impact on most dimensions. The company-wide adoption of analytics, thus, is one of the last dimension to be approached by organisation interested in HRA. The diffusion of analytics practices, indeed, is often driven by enthusiastic employees or "innovation champions" (Vargas et al., 2018). This occurred also in the target company, where the idea of HRA development started from some "innovators" within the HR department. In this case, HRA has been developed and adopted within the HR department or specific organisational cells. The rest of the organisation only received communication of results and activities, rarely proactively participating in analytics and change management processes. This is often in line with organisational needs, which use HRA to solve specific business issues (Levenson and Fink, 2017). Analytics diffusion, thus, is not necessarily a requirement to reach the "adequate" level of maturity for a certain organisation. It is important to notice that not all organisations have a real need and advantage to reach the final stages of HRA maturity. The diffusion dimension, however, is the last required piece to complete the development of this capability. An organisation manages its talent through a data-driven approach when its related decisions are based on data, and this happen when all relevant decision-makers have the opportunity and habit to use data during their decisional processes.

6. Conclusion

Research contributions, limitations, and possible future research are discussed in the following paragraphs.

6.1. Practical and theoretical implications

This research generates interesting contributions for practitioners. First, we provide a HRAMM 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. The HRAMM could be periodically re-used to measure analytics maturity and to adjust the development path according to organisational changes. Second, this study proposes a procedure to comprehensively measure and evaluate HRA dimension, analysing their relationships. Thus, we mapped the interdependencies among analytics dimensions, depicting the different interactions in terms of prerequisites and synergies to be leveraged to successfully extend HRA capability. In this regards, we also suggested that the level of maturity should be consistent with organizational structures and business strategies, in order to ensure an effective and harmonious development. Eventually, we proposed a method to for grouping the various dimensions into four different 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 to prioritise and plan their efforts and investments. Also, clusters and priority scores can be periodically updated, adjusting the prioritisation hierarchy. Both the HRAMM and the prioritisation procedure have been applied in a specific company, demonstrating the real applicability of our research results.

From a theoretical perspective, this paper provides different contributions regarding HRA conceptualisation and definition. Our research revealed that analytics is defined through 14 dimensions and 37 further components. In this regards, we stated that HRA, during its development, needs to be conceptualised as a dynamic capability, evaluating its various intersections with the organisation. The development of this capability, in the end, increase organisational adaptability and resilience, generating a competitive advantage for the organisation. Additionally, we demonstrated that analytics are developed through an evolutionary path characterised by several discrete stages of maturity. Eventually, this research enriches the input-process-output model used to discuss HRA (Marler and Boudreau, 2017; Margherita, 2021), providing three main contributions. First, we demonstrated that technological and organisational resources are fundamental input to enable the development of HRA. Second, this study revealed the moderating role of the analytics strategic dimension, considered a key success factor for its development. Eventually, we discussed how the level of diffusion unlocks the outcomes (e.g., evidence-based decision-making, organisational resilience) related to the later stages of HRA maturity. This level of development, however, is not always necessary or convenient for the organisations, which to consciously assess their own condition and the relative room for improvement.

6.2. Limitations and future research directions

This paper contains several potentially limiting factors solvable through further research activities. First, the HRAMM has been defined using a theoretical top-down approach for both maturity dimensions and levels. This approach has been selected considering the immature stage of HRA research and that its maturity had not yet been defined. Future research could build another model using a bottom-up approach, starting their analysis from the HRAMM proposed in this paper.

Second, despite its accuracy and comprehensiveness, our model assigned equal weight to each dimension, component, metric, and maturity level. This approach made unclear how to effectively measure and evaluate both synergies and prerequisite among dimensions in relation to the stage of maturity. Additionally, the interdependencies and the findings discussed in this paper derive from a single case study. Future research, thus, should expand the implementation of the model to a larger number of companies in order to understand whether the dynamics presented in this research can be 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.

Eventually, future research streams could use the proposed model to analyse the relationship between HRA maturity (or the maturity of a specific dimension) and certain organisational level variables. 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. Eventually, our model can be applied to test the consequences of analytics maturity of different organisational performances (e.g., resilience, turnover, innovation).

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Appendix A – Final coding sheet

The Table represents the final coding sheet used to review academic literature. This sheet corresponds to the final version of the model, but represents only areas, dimensions, and components. For each dimension, then, at least one academic sentence has been provided, in order to reveal the reasoning behind the definition of our maturity model.

Area	Dimensions	Components	Sentences
Technological	*T1. HRA architecture*	1.1. Technological standards	*"Analytics is a highly resource-intensive function, including the use of technology infrastructure. HR analysts need data infrastructure to perform data analysis using different analytical techniques and computational intelligence." (Shet et al., 2021)*
		1.2. Technological integration	*"the lack of integration among many different systems […] leads to poor strategic application" (Boudreau and Cascio, 2017)* *"an integrated IT infrastructure is needed to facilitate the use of multi-source data in analyses […], the development of HR analytics will be characterized by integration, with data and IT infrastructure integrated across disciplines and across organizational boundaries" (van den Heuvel and Boundarouk, 2017).*
	T2. Data management	2.1. Data storing	*"In terms of data storage, data lakes complement data warehouses, which usually employ a pre-defined data model and therefore can support reporting activities and advanced analytics (usually requiring a data scheme)." (Nocker and Sena, 2019)*
		2.2. Data modelling	*"cloud-based data warehouses and blazing-fast computing speeds have made it possible to gather and access the data in ways that were hardly conceivable only a few years ago." (Boudreau and Cascio, 2017)*
		2.3. Data collection frequency	*"analytics developments are seen […] in automating data collection and data preparation activities, which are currently perceived as taking up considerable time by the HR analytics professionals." (van den Heuvel and Boundarouk, 2017)*
		2.4. Data granularity	*"The data collected for people analytics tend by their nature to be very sensitive, granular and personal" (Giermindl et al., 2021)*
		2.5. Data integration	*"To be sure, data management remains a significant obstacle to more widespread adoption of HR analytics. It includes issues such as disparate systems that cannot "talk" to each other, data integration, and ensuring error-free data" (Boudreau and Cascio, 2016)* *"The development of HR analytics will be characterized by integration, with data and IT infrastructure integrated across disciplines and even across organizational boundaries" (van den Heuvel and Boundarouk, 2017)*
	T3. HRA application	3.1. Software for analytics	*"Scholars need to keep working in the development of statistical and optimization models and specific software that allow predictive and prescriptions analysis" (Fernandez and Gallardo-Gallardo, 2020)* *"Furthermore, HR analytics needs IT and software like HCM software to collect, manipulate and report data." (Qamar and Samad, 2021)* *"[…] the next big thing in HR analytics is the use of business-user-friendly self-service analytical software (Coolen, 2015).*
		3.2. Software for visualization	*"[…] HR analytics results typically rely on visualization such as charts, graphs, heat maps, and dashboards on which the data is displayed with specialized graphics to better illustrate underlying relationships" (Hamilton and Sodeman, 2020).* *"Workforce analytics provide operational as well as analytical dashboards for data exploration and visualization. Dashboards can represent complex data in easy-to-understand formats such as bar charts, infographics, maps and scatter plots" (Lal, 2015)*
	T4. Interface	-	*"[…] another related element raised by several respondents was the development of analytics as a self-service for managers, […] this implies the ability to run HRA at any time, in any place, and on any device or, as one respondent put it, doing HR analytics "on the fly" (van de Heuvel and Boundarouk, 2017).*
Organizational	*O5. HRA competencies*	5.1. Team competencies	*"the majority of analytics training should ideally be cross-functional, and only a smaller part of the training should be HR specific (or specific for other functions/lines of business)" (Rasmussen and Ulrich, 2015).* *"multidimensional capabilities are needed: 1. […] develop logic models to understand relationships within variables and numbers; 2. […] include HRA within a general business intelligence department; 3. […] knowing about HR processes and variables, data, etc.; 4. […] ability to sell HRA to businesses presenting results in a convincing manner; 5. […] ability to conduct statistical analysis also with cutting edge developments such as machine learning; 6. […] ability to provide adequate solutions for warehousing; 7. […] ability to provide adequate software solutions" (Van den Heuvel and Bondarouk, 2017).* *"analytical competencies are required to build the correct causal (conceptual) model with the necessary degree of sophistication, to operationalize it, and to test it using the appropriate statistical techniques." (Minbaeva, 2018)* *"Because these competencies are difficult to find in a single individual, success often comes from forming workforce analytics teams comprised of employees from diverse backgrounds" (McIver et al., 2018)*

		5.2. Technological presidium	*"[…] important to understand where the data is, who is responsible for it, and where and how it is archived and transmitted or communicated." (Hamilton and Sodeman, 2020).*
		5.3. Organisational experience	*"[…] organizations at the aspirational stage of analytics justify actions with analytics. Organizations at the experienced stage of analytics guide actions with analytics, […] report that organizations at the transformed stage of analytics prescribe actions with analytics" (Lunsford, 2019)*
	O6. Operating model	6.1. Defined processes	*"[…] development of HRA at the processes level requires: (a) building systems and establishing work-flows to continuously support data quality, (b) linking the results of analytics projects with existing organizational processes, and (c) encouraging experimentation and enabling follow-up actions via HR Business Partners. […] In order to build analytical competencies, analytics projects must be linked with existing organizational processes, especially HR processes" (Minbaeva, 2018).*
		6.2. Dedicated resources	*"Extant literature argues that building business relevant HRA requires organizations to establish particular skills and resources at the individual and organizational level." (Elmer and Reichel, 2021)* *"They leverage resources from outside HR (and the company, if needs be) One way to accelerate progress is to leverage (beg, borrow or steal if necessary!) resources from outside HR" (Green, 2017)*
		6.3. Defined roles	*"The role of HR professionals has evolved throughout history—from "personnel administrators" and "industrial relations professionals" in the 20th century to "HR managers" and "people managers" in the 21st century" (Kryscynski et al., 2018)* *For instance, the size of PA teams ranges from one single person to several hundreds, and many companies run a team of single- or double-digit numbers. Yet, successful PA leaders share that the team started very small, usually by one visionary and dedicated individual, and still struggling in the relatively new landscape of data-rich and data-driven work environments." (Yoon, 2021)*
		6.4. Defined responsibilities	*"HR professionals are responsible for asking strategically relevant questions, framing them so the logical connections are clear, and for storytelling with data" (Boudreau and Cascio, 2016)* *"The HRA team at the very centre is responsible for overseeing current HRA projects, including the processing and delivery of analytical outputs" (Elmer and Reichel, 2021)*
	O7. HRA strategy	7.1. Dedicated budget	*"However, in many organizations, the TM is not interested in investing large amounts of money in HRA, often because they are unsure of the likely benefits" (Minbaeva, 2017; Shet et al., 2021)*
		7.2. Strategic definition	*"HRA is an area of HRM practice, research and innovation concerned with the use of information technologies, descriptive and predictive data analytics and visualisation tools for generating actionable insights about workforce dynamics, human capital, and individual and team performance that can be used strategically to optimise organisational effectiveness, efficiency and outcomes, and improve employee experience" (Tursunbayeva et al., 2018)* *"Companies that lack support from the C-suite will likely face greater practical and bureaucratic barriers to effective analysis" (Hamilton and Sodeman, 2019)*
		7.3. Strategic alignment	*"[…] analytics framework should be built highlighting connections and relationships between HR variables and business strategy as well as individual and collective behaviours" (Boudreau and Cascio, 2017).* *"when closely linked to an organization's business strategy (Huselid, 2015), the effective use of analytics may be the biggest contributor to the building of great, sustainable organizations in the future" (Beatty, 2015; Huselid, 2015; Minbaeva, 2018).*
		7.4. Board and top management support	*"gaining support and direction from the top management is crucial in order to give a long-term footprint to HR core goals and a strong expertise regarding firm's business model to HR personnel, so to contingently converge their resources towards firm's competitive advantage" (Hamilton and Sodeman, 2020).* *"Generating business relevant HRA outputs requires an HRA team having the ability to customize analytical outputs and speaking a language of numbers" (Elmer and Reichel, 2021)*
		7.5. Decision-makers analytics understanding	*"[..] HRA need to be rooted in a keen understanding of data and the context in which it is collected if it is to generate meaningful insight" (Angrave et al., 2016)* *"[…] HR executives must attain a top-level understanding of how analytics processes are conducted" (Hamilton and Sodeman, 2019)*
Functional	*F8. Data governance*	8.1. Data integrity 8.2. Data accuracy 8.3. Data completeness 8.4. Data confidentiality 8.5. Data availability	*"data quality is one of the most crucial barriers to the development of credible organizational human capital analytics" (Minbaeva, 2018)* *"Companies will seriously focus more on data quality and its validity rather than data quantity" (Patre, 2016)* *"Data quality refers to the availability and consistency of the data required for the adoption of HRA" (Shet et al., 2021)* *"when formal, centralized coordination of data collection is lacking, data duplication, wrong entries, and other problems are common" (Minbaeva, 2018)*

	F9. Measurement	-	*"standardization of measurements […] implies the development of reliable and valid measurements […] with the purpose of facilitating organizations in conducting cross-country and cross-cultural HR analytics" (Van den Heuvel and Bondarouk, 2017).* *"people involved in HR analytics currently spend the majority of their time on the basic reporting and the calculation of metrics" (Van den Heuvel and Bondarouk, 2017).*
	F10. Reporting	10.1. Report frequency 10.2. Report distribution	*"advances in real-time analysis and reporting, as well as the availability of powerful personal devices, suggests we may be entering an era where leaders can call up HCA in real-time as they face the decisions to which the analytics would contribute" (Boudreau and Cascio, 2017).* *"it was perceived that HR analytics would reach a certain level of maturity by 2025, implying higher levels of standardization, resulting in automated calculations and dashboards automatically reporting the effect-sizes of relationships." (Van den Heuvel and Bondarouk, 2017).*
		10.3. Visualisation effectiveness	*"what is striking to us is that the effectiveness of the analytics in driving decisions is often not so much a function of the statistical or methodological sophistication, but rather presenting results in a visually striking way […] turning analytical insights into concrete business actions begins with effective storytelling with data" (Boudreau and Cascio, 2017).*
	F11. Analysis	11.1. Explanatory 11.2. Predictive 11.3 Prescriptive	*"First, "descriptive" analytics, aiming to answer questions related to what happened, why it happened, and what is happening […]. Second, "predictive analytics", answering questions such as what will happen and why will it happen in the future […]. Third, "prescriptive" analytics, aimed to answer questions such as what should I do and why should I do it" (Margherita, 2021)* *"[…] with progress mainly in terms of more advanced reporting solutions, the respondents predicted a shift in focus to analytical solutions with visualization capabilities and the statistical power to, for example, develop predictive models" (Van den Heuvel and Bondarouk, 2017).*
Diffusion	*D12. Accessibility*	-	*"HRA promises to help organisations understand their workforce as a whole, as departments or work groups, and as individuals, by making data about employee attributes, behaviour and performance more accessible, interpretable and actionable" (Pape, 2016)* *"In HRA […] quality and accessibility of data appeared as a theme that the HR professionals of our case organizations were deeply concerned about" (Dahlbom et al., 2019)*
	D13. Adoption	13.1. Objectives' support	*a fundamental requirement is that HCA address key strategic issues that affect the ability of senior leaders to achieve their operating and strategic objectives" (Boudreau and Cascio, 2016)* *initiatives will be driven by the C-suite in support of overall corporate objectives as HR big data analytics are instrumental in gaining long-term competitive advantage in the marketplace" (Hamilton and Sodeman, 2019)* *"HR managers use analytics to set concrete objectives for the employees" (Gaur et al., 2019)*
		13.2. Decisional support	*"The term, "data-driven," is common in the literature, reflecting the role of data as well as the remaining elements of the DIKW continuum, in supporting decision making in organizations today" (Lunsford, 2019)* *"The key output from workforce analytics is not a dashboard or an attrition number, but the actions that decision makers and companies take that alter the business to add value" (McIver et al., 2018)*
	D14. Culture	14.1. Analytics credibility	*"[…] analytics users must believe the analytics (familiar in the logic, reasonable variances, limited outlying results), […] must believe that the analytics suggest effects that are large and compelling enough to merit attention or action […], muse see must see implications for their actions or decisions" (Boudreau and Cascio, 2017).*
		14.2. Analytics dictionary	*"Additionally, they [HR professionals] are also more likely to understand and appreciate analytical insights that come from HR professionals who can speak the language of analytics and put HR issues into these analytical terms." (Kryscynski et al., 2018)*
		14.3. Analytics culture	*"The development of HCA as an organizational capability requires the development of social structures and an organizational culture conducive to analytics." (Minbaeva, 2018)* *"Culture is considered another top barrier to HR analytics adoption" (Fernandez and Gallardo-Gallardo, 2020)* *"As such, the establishment of an evidence-based culture will likely directly influence the effectiveness and added value of people analytics teams" (Peeters et al., 2020)*