Measuring HR Analytics Maturity: Supporting the Development of a Roadmap for Data-driven Human Resources Management

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Purpose: Despite increasing interest, firms are struggling in developing HR Analytics (HRA) capabilities. Furthermore, academic literature is immature and lacks practical guidance and comprehensive models that could support practitioners in developing analytics capability. Thus, this paper aims at providing a maturity model – i.e. HRAMM - and an interdependency matrix through which: (i) operationalizing HRA capability and assessing its organisational maturity; (ii) generating harmonious development roadmaps for capability improvement; (iii) enabling benchmarking and continuous improvement.

Method: The research is based on the integration of the popular methodology of Becker *et al.*, (2009) and the procedure for maturity evaluation of Gastaldi *et al.,* (2018). This method combines academic rigor and analytics field expertise through 8 main phases, including literature review and knowledge creation techniques.

Findings: We define HRA maturity through 4 areas and 14 dimensions, providing a comprehensive model to operationalize HRA capability. Additionally, we argue that HRA maturity develops through an evolutionary path described by four discrete stages of maturity that go beyond traditional analytics maturity. Eventually, the interdependency matrix reveals the existence of specific enablers for the development of HRA.

Originality: This paper is the first providing a model to evaluate HRA maturity and an interdependency matrix to systematically evaluate the prerequisites and synergies among its constituting dimensions.

Practical implications: This paper provides practitioners with useful tools to monitor, evaluate, and plan their HRA development path. Additionally, our research support practitioners in prioritizing their efforts and investments, generating an effective roadmap to develop and improve HRA capability.

Keywords: *HR Analytics; Workforce analytics; People analytics; Human capital analytics; Maturity model; Organisational capability; Development path; Decision-making.*

1. Introduction

In the last two decades organisations have been forced to operate in an increasingly volatile environment, handling a dynamic and complex workforce (Huselid 2018; Bechter *et al.* 2022). HR departments experienced a transformation from a purely administrative to a more strategic and business-oriented role (Vargas *et al.* 2018) which aims at proactively contributing to organizational value creation (Levenson 2018; Larsson and Edwards 2021). Additionally, the diffusion of digital technologies transformed the traditional ways of managing employees (Giermindl *et al.* 2022; Fernandez and Gallardo-Gallardo 2020) providing data and information to better understand personnel's psychology and behaviours (McIver *et al.* 2018; McCartney and Fu 2022). In this context, organisations have been increasingly interested in HR Analytics (HRA), willing to replace traditional intuition-based procedures with evidence-based decisional processes (Lunsford 2019). Despite the mounting interest (Ramachandran *et al.*, 2023; Bahuguna et al., 2023; Thakral et al., 2023), companies still face several difficulties in developing HRA (Angrave *et al.* 2016; Shet *et al.* 2021; Edwards *et al.* 2022; Ramachandran *et al.*, 2023). Most organisations, indeed, are still in their early stages of development, focused on solving specific problems (e.g. turnover) (Kiran *et al.* 2023) with isolated analytics techniques (Wirges and Neyer 2022).

HRA is increasingly conceived as an organisational capability to nurture (Minbaeva, 2018) but we have scant knowledge on how to successfully develop this capability (Marler and Boudreau 2017; Levenson 2018; Ramachandran *et al.*, 2023). In this regard, academic research provided conceptual and promotional contributions (Marler and Boudreau 2017; Qamar and Samad 2021), revealing its immaturity (Margherita 2021; Bahuguna *et al.*, 2023). This paper aims at filling this gap by not only providing a HRA Maturity Model (HRAMM), but also systematically evaluating the prerequisites and synergies among capability constituting dimensions. The model provides researchers with a comprehensive definition of HRA capability, described through 4 areas, 14 dimensions, and 37 further components. Additionally, we highlight that the development of HRA capability depends on different organisational dimensions (e.g. technologies, individual competencies, strategic relevance, analytics diffusion, etc.) and their effective integration, suggesting an organisational and interdisciplinary approach for future research. Eventually, we provide useful methods that can support practitioners in evaluating the current maturity of their HRA capabilities and planning a harmonised path for their development.

2. Theoretical background

The theoretical background has been organised into two main paragraphs. The first one focuses on HRA literature. The second one focus on maturity models.

2.1. HR Analytics

Academic literature discussed HRA using different labels and definitions (Marler and Boudreau 2017; Margherita 2021; Thakral et al. 2023), which share the usage of statistical and mathematical techniques to support people-related decisions (Larsson and Edwards 2021; Edwards et al. 2022). Recently, scholars defined HRA as an organisational capability (Levenson 2018; Minbaeva 2018; Falletta and Combs 2021; Samson and Bhanugopan 2022), stressing its nature rooted in different organisational levels and dimensions (Minbaeva 2018; Wirges and Neyer 2022). Organisational capabilities refer to the way in which organisational resources, knowledge, and competencies are combined to perform and extend output actions (Salvato and Rerup 2010). They need to be built, developed, and maintained over time, integrating and reconfiguring internal and external resources (Helfat and Peteraf, 2003). In this regard, recent research argued that also HRA development requires integration among different resources and areas (Shet *et al.*, 2021; Ramachandran *et al.*, 2023), operating across organisational levels and boundaries (van den Heuvel and Boundarouk, 2017; Minbaeva, 2018). Firms interested in its development, thus, should move from an individual- and HR-centred approach to one that considers the composite and organisational nature of HRA (Andersen, 2017). If HRA is treated and developed as an organisational capability, indeed, it will "stay" in the organisation even if HR analysts and analytics responsible would leave (Minbaeva 2018).

The discussion on the emergence and development of HRA becomes particularly relevant considering its current state of maturity among organisations. Recent research (Falletta and Combs 2021; Shet *et al.* 2021; Wirges and Neyer 2022) showed that most of the firms are still in a start-up phase, characterised by descriptive analyses and isolated predictive analytics applications (Lismont *et al.* 2017; Wirges and Neyer, 2022). The systematic use of descriptive (32%) or predictive (5%) analytics is very limited, even if most HR decisions are now made considering factual data and information (Wirges and Neyer 2022). Previous studies deepened the main barriers and challenges that firms tackle in establishing and developing HRA capabilities. The main difficulties are related to data management, the technical and analytical skills required for new HR professionals, and the integration between different information systems (Fernandez and Gallardo-Gallardo 2020; Peeters et al. 2020). Scholars also discussed the problems in bringing strategic value to the organisation, including the difficulties in communicating with top-management (Ellmer and Reichel 2021; Jörden *et al.* 2022) and in converting HRA results into practical actions (Levenson and Fink 2017). Eventually, recent academic research noted that most of the complexities associated to HRA maturity are related to the required technical integration and interdepartmental collaboration (Fernandez and Gallardo-Gallardo 2020). HRA successful development, thus, does not solely depend on the application of sophisticated (but often isolated) analytics techniques, but rather on the effective interaction, integration, and consistency of its various socio-technical dimensions (Shet *et al.*, 2021; Wirges and Neyer 2022; Ramachandran *et al.*, 2023).

These findings conflict with the traditional definition of HRA maturity. Previous studies, indeed, often defined HRA maturity through the three levels of analytics sophistication, i.e. descriptive, predictive, and prescriptive (Marler and Boudreau 2017; Margherita 2021). The adoption of more advanced analytics techniques, however, does not fully reflect the maturity of an organization in terms of HRA (Shet *et al.*, 2021; Wirges and Neyer 2022). Isolated predictive projects, focused on specific HR issues (e.g. turnover) or processes (e.g. recruitment), have been also found in firms in their early stages of analytics development (Lismont *et al.* 2017; Wirges and Neyer 2022). A firm can be said to "possess" a capability only when it enables a repeated and reliable execution of specific practices and processes (Helfat and Peteraf, 2003). The HRA capability of a firm, thus, refers to its organisational ability to systematically and continuously use data and analytics to support people related decisions (Lismont *et al.*, 2017; Shet *et al.*, 2021), generating value and competitive advantage for the whole organisation (McCartney and Fu 2021). HRA maturity, then, depends on the correct integration, management, and strategic exploitation of different organisational dimensions, which enable the repeated and reliable execution of analytics activities on different people-related practices.

In this regard, academic research on HRA is still in an embryonic state (Margherita, 2021; Bahuguna *et al.*, 2023; Thakral *et al.* 2023), with several underdeveloped research areas and research gaps (Hamilton and Sodeman 2019; Qamar and Samad 2021). More specifically, there is very limited research on how to successfully build, develop, and maintain HRA capabilities over time (Marler and Boudreau 2017; Qamar and Samad 2021). First, scholars have still to reach a consensus on which resources, processes, and dimensions needs to be considered during HRA development (Angrave *et al.*, 2016), with several works that use a silos approach and consider analytics practices as isolated initiatives or projects (Falletta and Combs, 2021).

Second, only a limited number of studies analysed the relationships and interactions between organisational areas and dimensions (Wirges and Neyer 2022), often using an approach focused on HR departments and their professionals (Andersen, 2017). Third, current research lacks comprehensive models and frameworks enabling the assessment, evaluation, and improvement of HRA capability maturity (Bahuguna *et al.,* 2023). These gaps generate a lack of practical research and guidance to support practitioners in defining and planning their evolutionary paths, prioritising efforts and activities (Levenson 2018; Fernandez and Gallardo-Gallardo 2020; Greasley and Thomas 2020).

2.2. Maturity models

A Maturity Model (MM) is defined as a "structured collection of elements that describe the characteristics of effective processes at different stages of development" and provides "points of demarcation between stages and methods of transitioning from one stage to another" (Pullen 2007). Managerial research and practice become increasingly interested in MMs since they offer a simple but effective method to assess the quality of organisational capabilities and systems (e.g. Lismont *et al.,* 2017; Gastaldi *et al.,* 2018; Doctor et *al.,* 2023), developing effective path for improvements (Wendler 2012).

The key objective of a MM is to reveal the gaps between the initial and the desired state of a certain capability, providing support to generate an effective development path for maturity improvement (Becker *et al.,* 2009; Stoiber *et al.,* 2023). 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). Levels are the different maturity stages that each constituting dimension could assume during its 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 (Becker *et al.,* 2009). Dimensions represent specific areas of mutually exclusive capabilities (de Bruin *et al.,* 2005), further represented by a number of sub-components (e.g., activities, practices, or objectives). Assessment instruments are qualitative or quantitative tools (e.g., questionnaires, scoring models) enabling the evaluation of the maturity levels for each dimension (Monteiro *et al.,* 2020).

Literature proposes three types of MMs, differentiated by their purpose of use (de Bruin *et al.* 2005; Maier *et al.,* 2009). Descriptive models assess the as-is maturity state of a certain organisational capability, considering specific dimension and evaluation criteria (Becker *et al.*, 2009; Maier *et al.,* 2009). 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). Comparative models enable internal and external benchmarking across companies, using data from a large number of participants (Becker *et al.,* 2009). Additionally, MMs can be specified through two different approaches, according to how dimension and levels are determined. On the one hand, using a top-down approach, a fixed number of maturity levels and dimensions are theoretically specified (Marx *et al.,* 2012). On the other hand, using a bottom-up approach, the requirements and measures are initially determined, and then clustered into maturity levels (Lahrmann *et al.,* 2011).

In the last decades, scholars proposed hundreds of MMs for multiple organisational capabilities, (e.g. Cosic *et al.*, 2015; Doctor *et al.*, 2023) and systems (e.g. Gastaldi *et al.*, 2018), including business analytics and intelligence systems (e.g. Lahrmann *et al.,* 2011; Lismont *et al.,* 2017). However, most MMs in the literature are fixed and static (Lahrmann *et al.,* 2011), neglecting the interdependencies between their dimensions and components (de Bruin *et al.,* 2005; Maier *et al.,* 2009). These models fail in providing comprehensive and effective guidelines for prioritising interventions during the potential improvement path. Additionally, the importance of interdependencies increases in complex and branched organisational systems (Gastaldi *et al.*, 2018). For complex systems, such as HRA, it is fundamental to evaluate and analyse the interdependencies among the dimensions constituting the organisational capability (Ramachandran *et al.,* 2023).

3. Method

The research has been conducted within a collaborative project (Shani *et al.,* 2008) that includes the 3 authors, 2 companies, and 4 HRA experts, integrating academic research rigour and HRA practical expertise. The different actors and their roles are discussed in the various stages of the research. The MM has been developed following the methodology by Becker *et al.* (2009). Despite being acknowledged as one of the most rigorous, accurate, and comprehensive method for MM development (Pöppelbuß and Röglinger 2011; Cosic *et al.* 2015; Brooks *et al.* 2015), the methodology does not explain how measuring and evaluating dimensional interdependencies and, thus, how prioritising efforts and activities. Consequently, we integrated the original framework with the methodological procedure proposed by Gastaldi *et al.* (2018). The entire methodology, composed by 8 main phases, is summarised in Figure 1.

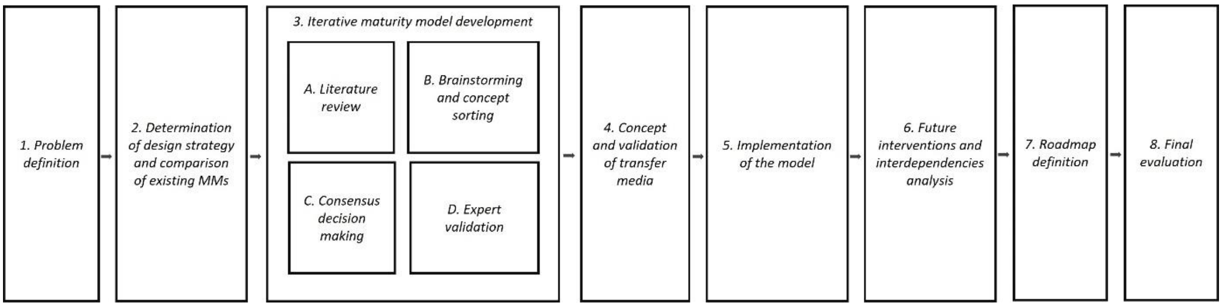

Figure 1. Research methodology
Source: Authors' own work.

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) are the result of their continuous iteration and interaction. In the next paragraphs each stage and its output will be described in detail.

3.1. Problem definition

The first stage of the process is the problem definition, which concerns: (i) the identification of the targeted domain and the target group; (ii) the discussion of problem relevance and intended benefits; (iii) the determination of the conditions for model application (Becker *et al.*, 2009). Thus, we determined HRA capability as targeted domain and organizations as target group. Then, we defined our research objectives and questions. Eventually, model completeness, optimisation, and comprehensibility have been searched 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). However, there are not MMs on HRA into the literature. Thus, a strategy to design a completely new MM has been followed.

3.3. Iterative maturity model development

The third stage aims at defining the fundamental structure of our MM, selecting the best development approach, designing its main elements and, finally, validating its effectiveness (Becker *et al.*, 2009). First, we decided to build a prescriptive model (de Bruin *et al.*, 2005; Lavalle *et al.*, 2011), in line with our objectives. Second, a multi-dimensional structure has been selected due to HRA complex and articulated nature. Third, we decided to adopt a top-down approach, considering that HRA maturity has not been clearly defined. Once the structure and the approach were determined, model levels and dimensions were defined and validated through 4 sub-phases: (3.3.1) two content-based literature reviews to build a preliminary version of the HRAMM; (3.3.2) five sessions of brainstorming and four sessions of concept-sorting to define model structure; (3.3.3) six sessions of consensus decision-making to refine the model; and (3.3.4) a set of meetings with HRA experts to validate the model.

3.3.1. Literature review

First, we conducted a review on data analytics, business analytics, and business intelligence MMs, in order to understand how these solutions have been modelled and assessed by previous research. The search strategy has been performed on Scopus on 1st February 2023, and updated on 1st July 2023, obtaining 40 papers. Appendix 1 represents the systematic search process. These documents

Second, we conducted another extensive content-based review on HRA. As aforementioned, indeed, researchers have not yet provided a shared definition of HRA capability and maturity (Margherita 2021; McCartney and Fu 2021). Thus, in this second review, we wanted developing a comprehensive understanding of constituting dimensions, success factors, and relevant criteria determining the maturity of HRA. Additionally, we assessed whether the metrics used to assess the maturity of business analytics and business intelligence systems (as well as their grouping logics), identified and selected in the first review, could be applied to HRA. Our search was conducted again on Scopus on 1st February 2023, and updated on 1st July 2023, extrapolating at the end 187 papers. Appendix 2 presents the systematic search process and final sample of reviewed articles.

The first sample of documents has been used to extrapolate relevant areas, dimensions, components, metrics, and maturity levels previously used. The second sample of articles 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 3 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.

3.3.2. Brainstorming and concept-sorting

HRA literature is still in its early stages of development (Fernandez and Gallardo-Gallardo 2020; Bahuguna *et al.*, 2023). 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) of at least 2 hours have been organised with 4 managers operating for a global consultancy firm with over 25,000 employees specialising in HR digitalization, HR controlling, and HRA development. The firm has been selected because it has been active in the HRA field for over 5 years, supporting organizations from different industries through a dedicated team of HR professionals and data scientists. The objective of the first 2 brainstorming sessions was to identify all possible areas and dimensions characterising HRA. 2 further sessions, then, were used to discuss and determine the possible stages of HRA maturity.

Concept-sorting technique, then, has been used to: (i) subdivide each dimension into more granular components and sub-components (e.g., metrics and sub-metrics); (ii) decline each possible dimension, components, and sub-components into the possible 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, 4 sessions of at least 2 hours each have been organised, one for each area of the maturity model (e.g., Organisational one, see Section 4 for further details). In each session, the team worked on the set of components and metrics generated during the brainstorming sessions. Finally, for each metric or sub-metric, the team generated and discussed a set of alternative indicators to assess maturity at different levels.

3.3.3. 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). Thus, 6 sessions have been organised to evaluate the evolving model and converge on its various areas, dimensions, components, metrics, indicators, and levels. Specifically, 4 sessions have been used to discuss model dimensions and components (one for each area), while 2 further sessions have been used to refine model levels and their maturity indicators. Each session lasted at least 2 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 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.

3.3.4. Expert validation

In the last phase, we discussed the model with 4 HRA experts operating in different firms. Appendix 4 provides a brief description of their organizations, role, and expertise in HRA. More specifically, 2 meetings of 1 our each have been organised with each expert. In the first one, the model has been presented to facilitate and solicit their opinions on the model structure. In the second one, organised after at least five days, each expert provided comments and suggestions for improvement. Eventually, the HRAMM has been validated organizing a meeting with all HRA experts in order to converge on a single model. 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 designing the MM, we defined our transfer media for academic and practitioner communities (Becker *et al.,* 2009), selecting an interactive questionnaire to be administered through an online platform. For each metrics and/or sub-metric of the model, the team produced a question with 4 possible answers (indicators) reflecting the different levels of maturity. According to our objectives, each question 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 (Gastaldi *et al.,* 2018).

The initial questionnaire has been sent to the same HRA experts involved in the previous phase, asking them to read it and indicate possible unclear elements. Then, 2 virtual meetings were scheduled with each expert to discuss their 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 the second meeting, possible corrections or changes to the questionnaire were discussed with the expert and the project team. The output of this phase is the final validated questionnaire.

3.5. Implementation of the HRAMM

After the validation phase, the model has been applied in a firm with over 20,000 employees operating in the tourism sector, referred as *Ebe* from now on for privacy reasons. *Ebe* has been selected for three main reasons. First, the firm went through a project led by the HR department for the development of HRA capabilities, starting from scratch in 2021. Second, its technological infrastructure is based on different information systems that need to be integrated to sustain HRA activities. Third, the firm is spread over different departments and geographical areas, and thus, requires different granularities of data and analytics. *Ebe* characteristics make the firm an interesting and representative case of the typical organization interested in the implementation of HRA, as confirmed also by the managers involved in the development and implementation of the HRAMM.

The questionnaire has been sent to the corporate team responsible for HRA to give them the time to scan and preliminary answer each question. Then, a virtual meeting has been organised to solve unclear questions or inconsistent answers. Finally, the maturity of each dimension has been calculated by averaging over the components, metrics, and sub-metrics forming the dimension, and then, discussed with company representatives to ensure that results corresponded to the real organisational conditions. The assessment of the maturity level laid the foundation for the next phases (3.6 and 3.7).

3.6. Future intervention and interdependency analysis

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

First, the team scheduled 4 virtual meetings with *Ebe*'s representatives to understand the possible development path for their HRA maturity. Each meeting has been dedicated to a specific area of the model; the group initiated collective thinking on how achieving the desired maturity levels. More specifically, the dimensions to be improved, the type of required investment, and the critical issues to achieve expected maturity levels have been discussed within the project group. Second, we organised 2 meetings with the 4 managers involved in the development phase, presenting them implementation strategies. Third, all meetings have been transcribed and independently cross-analysed by the team of researchers to develop a first understanding of possible dimensional interdependencies. Then, researchers integrated their ideas proposing a preliminary version of the matrix that represents the interdependencies among HRA dimensions. The preliminary framework has been presented and discussed also with *Ebe* and HRA experts, reflecting on the different dimensional relationships. Eventually, the research team integrated all these reflections and stimuli in a final and comprehensive matrix of prerequisites, synergies, and relationships among the different dimensions of the model.

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

- *Prerequisite*: it indicates that, in order to increase the maturity of Y, it is suggested to have previously reached an acceptable maturity (at least 2) level in X.
- *Strong prerequisite*: it indicates that, in order to increase the maturity of Y, it is suggested to have previously reached a good maturity (3 or 4) level in X.
- *Synergy*: it indicates that it is suggested to simultaneously improve the maturity of X and Y.
- *Strong synergy*: it indicates that it is necessary to simultaneously improve the maturity of X and Y.

The final interdependency matrix is reported in paragraph 4.2.2.

3.7. Roadmap definition

The objective of this phase was to define a roadmap for HRA maturity improvement, integrating the HRAMM and the interdependency matrix. More specifically, we associated the current (and expected) maturity levels with the interdependency matrix to determine 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 (CMj) and desired (DMj) maturity score for each dimension, averaging the current maturity levels of its constituting sub-dimensions (CMij; DMij). Second, we associated to each prerequisite or synergy a predefined set of scores (PSxyij). 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 (RVj) for each dimension by summing the scores on the row (X) corresponding to that specific dimension (Y).

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

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

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

Finally, each dimension was assigned to one of the previously described clusters. The four clusters are presented 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 HRAMM (Becker et al. 2009). In this phase, usefulness, quality, and effectiveness have been used as evaluation criteria. In this regard, 2 further meetings have been organised with *Ebe*'s representatives to discuss the results and the limitations related to the implementation of the HRAMM and the interdependency matrix. In these meetings, the target company also provided some suggestions for improving the overall procedure. The usefulness and practical contributions of the model are discussed in Section 6, together with its limitations.

4. Results

The results of this research process are reported in three main paragraphs. In paragraph 4.1, the HRAMM and its main constituting dimensions are reported. In paragraph 4.2, we introduce the results obtained through the implementation of the model in *Ebe*, presenting its maturity scores (Section 4.2.1), interdependency matrix (Section 4.2.2), and cluster analysis (Section 4.2.3).

4.1. HR Analytics Maturity Model

The final HRAMM is reported in Table I. The model encompassed 14 dimensions and 37 components. The dimensions are grouped in four main areas:

- *Technological*: it describes the technological architecture required to develop reliable HRA capabilities (e.g., technological infrastructure that enable data collection and management activities);
- *Organizational*: 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 predictive analytics);
- *Diffusion*: it evaluates the pervasiveness of HRA in the organisation (e.g. diffusion of an analytics mindset).

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 levels and dimensions, provides a detailed and simple way to assess current and desired HRA maturity.

4.2. Implementation results

The following paragraphs reports the results achieved through the implementation of the HRAMM and interdependency matrix.

4.2.1. Maturity levels

Figure 2 describe *Ebe*'s positioning 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.

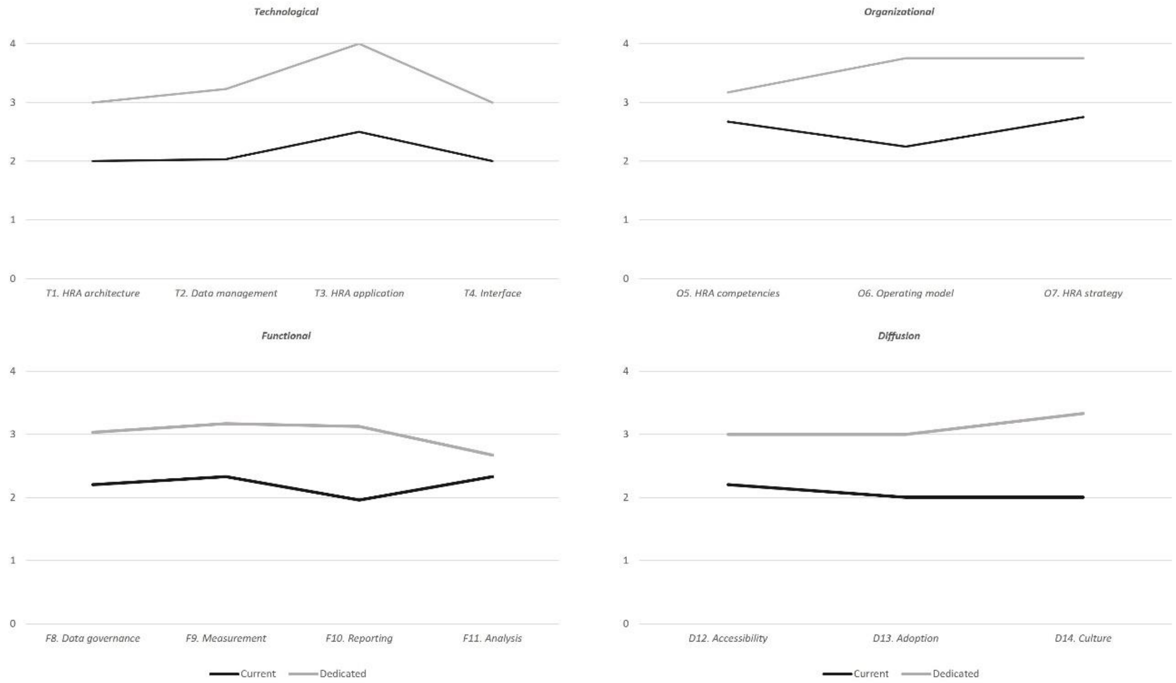

Figure 2. *Ebe* position on the different dimensions of the HR Analytics Maturity Model.
Source: Authors' own work.

4.2.2. Interdependency matrix

Figure 3 shows the final framework representing the interdependencies between the dimensions of the HRAMM. The matrix enables two different types of analysis. First, through a vertical analysis 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 it is possible to detect the impact that a specific dimension produces on the others. For instance, an improvement in the competencies of HRA responsible could enable more sophisticated reporting activities and/or statistical analysis.

		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 3. Prerequisites and synergies among the dimensions of the HR Analytics maturity.
Source: Authors' own work.

4.2.3. Cluster analysis

Figure 4 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 CMj and RVj. The size of the circles, representing the various dimensions of the HRAMM, is proportional to the difference between the current state of maturity CMj and the desired state (DMj) in 3 years. Larger circles represent the maturity dimensions that *Ebe* is more interested to improve. The figure enables the visualisation of critical and strategic dimensions, providing a map to guide investments and improvement efforts.

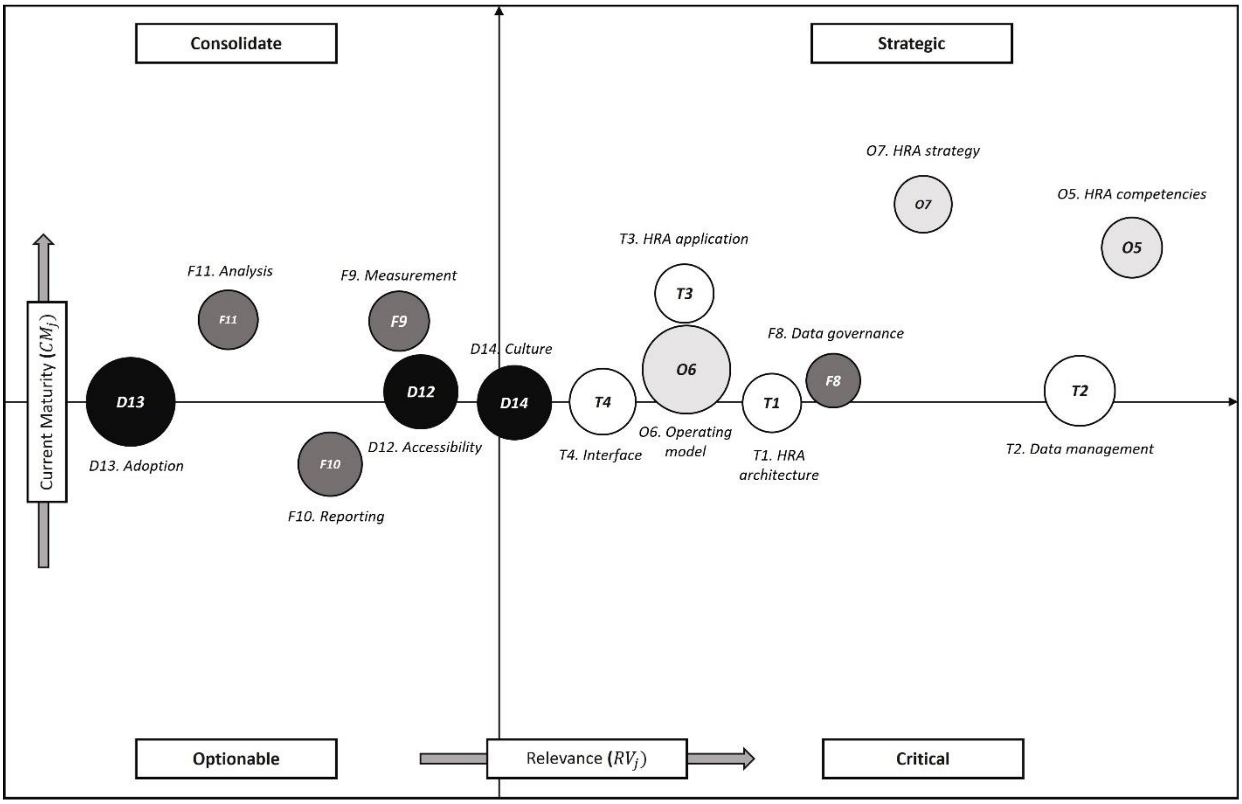

Figure 4. Relevance and maturity for HR Analytics at *Ebe*
Source: Authors' own work.

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 capability maturity and its dimensions. Second, the interdependency matrix reveals the existence of specific enablers for the emergence and development of HRA capability. Third, the 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

Academics conceptualised HRA as a HR practice (Marler and Boudreau 2017), HR process (Huselid 2018) or a more generic HRM approach (Larsson and Edwards 2021) based on different statistical principles and methods (Margherita, 2021). Additionally, previous studies defined HRA maturity through the three levels of sophistication of analytics techniques, i.e. descriptive, predictive, and prescriptive analytics (Marler and Boudreau 2017; Margherita 2021). Recent research, however, argued the adoption of sophisticated analytics techniques is often related to isolated projects, and thus, does not fully represent the real HRA maturity of a firm (Shet *et al.*, 2021; Wirges and Neyer 2022).

In this paper, HRA capability is defined as the organisational ability to systematically implement, manage, and strategic exploit data and analytics to support people-related processes and decisions. More specifically, this research provides for the first time a comprehensive operationalisation of HRA capability, described through 4 areas, 14 dimensions, and 37 further components. The HRAMM reveals which organisational resources, processes, and structures are involved in the emergence and development of this capability, aligning and enriching previous studies on analytics and organisational capabilities (e.g. Minbaeva, 2018). The interdependency matrix, then, emphasises the importance of the dimensional interaction and integration in the improvement of HRA maturity, which develops through an evolutionary path defined by 4 discrete stages of maturity. As stated by previous research (e.g. Minbaeva, 2018; Levenson, 2018; Wirges and Neyer, 2022), we suggest future research to approach HRA as an organisational capability. Analysing HRA as a practice, initiative, or isolate project provides a limited understanding of its organisational emergence and development since it does not consider all socio-technical interactions occurring during its evolutionary path (Falletta and Combs, 2021; Wirges and Neyer 2022). In this regard, we suggest that future research could investigate whether the development and outcomes of analytics initiatives (e.g. turnover prediction, algorithmic recruitment) are affected by the maturity of different HRA capability dimensions (e.g. HRA competencies, analytics credibility). Additionally, future research could analyse the interaction between HRA and other organisational capabilities, defining which ones facilitate and/or hinder its development.

5.2. HR Analytics enablers: Technological and organizational factors

The maturity and interdependency analysis confirmed that technological and organisational factors are fundamental enablers for the development of HRA capability (Heuvel and Bondarouk 2017; Marler and Boudreau 2017; McCartney and Fu 2021). Information technologies enable the collection, management, and analysis of employee data, providing the “raw” material to conduct any type of analytics practice or project. Individual competencies, governance rules, and organisational structures enable their effective application, control, and future development. These areas 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, adequate analytics technologies, and access to a multi-disciplinary community of knowledge and competencies (Qamar and Samad 2021).

Firms interested in building HRA capability, thus, should start investing in their technological and organisational areas, preparing the groundwork for the application of analytics practices. 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 interdependency matrix (see Figure 3). 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. Additionally, our model suggests that HRA should be developed harmoniously, focusing synergistically on all its constituting dimensions. The technological and organisational areas are the main pillars, but investments should be made also in the other dimensions. In this regard, our model support practitioners in defining this equilibrium and maintaining it over time, identifying and correcting possible misalignments. Eventually, our findings provide useful contributions to academics, mapping and evaluating the foundational interactions and dynamics occurring during the development of HRA.

5.3. HR Analytics outcome: The strategic dimension

Technological infrastructure and organisational resources enable the emergence and initial implementation of HRA initiatives, bringing to the business table the first results of HRA functionalities. The later maturity stages of this capability, however, also require the development of strategic and cultural dimensions.

First, top-management interest and dedicated budget for HRA have a strong relationship with technological infrastructures and human capital resources dedicated to analytics development. More specifically, during the HRA development, 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 HRA projects. 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 and the decision- makers' habit of using data to support their decisions. Both dimensions, as reported in the interdependencies matrix, requires or present a strong synergy with analytics role in business strategy. These findings emerged also during the meetings with *Ebe's* representatives. Their main project started with econometric analyses of employee's data collected through an online questionnaire administered to the entire organizational 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 program. This legitimisation process (Belizòn and Kieran, 2021) was facilitated by the analytics culture already present in the organisation.

Eventually, it is interesting to notice that the level of diffusion has no impact on most dimensions. The company-wide adoption of analytics, thus, is one of the last dimensions to be approached by organisations 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 *Ebe*, where the idea of HRA development started from two "innovators" within the HR department. In this case, HRA has been developed and adopted within the HR department or specific organisational cells. Additionally, analytics diffusion must be oriented towards the creation and sustainment of strategic value (Shet *et al.*, 2021).

6. Conclusion

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

6.1. Theoretical and practical implications

This research generates interesting contributions for both academics and practitioners.

From a theoretical perspective, this paper provides different contributions regarding HRA conceptualisation and definition. Our research defined HRA maturity through 4 areas, 14 dimensions and 37 further components. In this regard, we stated that HRA needs to be conceptualised as an organizational capability, evaluating its various intersections with organisational dimensions and levels. Additionally, we argue that HRA maturity develops through an evolutionary path characterised by four discrete stages of maturity that go beyond traditional analytics maturity. Eventually, this research enriches the input-process-output model used to discuss HRA (Margherita 2021), providing three main contributions. First, we argued that technological and organisational resources are fundamental input to enable the development of HRA. Second, we revealed the moderating role of the analytics strategic dimension, considered as a key success factor for its development. Eventually, we discussed how the level of analytics culture, adoption, and diffusion unlocks the outcomes (e.g., evidence-based decision-making, change management practices) related to the later stages of HRA maturity. It is important to remember, however, that the relationship between analytics maturity and generated value is not linear. HRA maturity, instead, needs to be consisted with organisational resources, challenges, and objectives (Shet *et al.,* 2021).

From a managerial perspective, we firstly 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 dimensions, analysing their interdependencies. More specifically, we mapped the relationships among analytics dimensions, depicting the different interactions in terms of prerequisites and synergies to be leveraged to successfully extend HRA capability. In this regard, 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 *Ebe*, demonstrating the actual applicability of our research results.

6.2. Limitations and future research directions

This paper contains 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 design or improve our 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 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 further generalised or whether there are contextual (e.g., industry, geographical area) or organisational factors (e.g., number of employees, organisational structure) that alter our findings. Eventually, future research could use the proposed model to analyse the relationship between HRA maturity (or the maturity of a specific dimension) and 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., employees' wellbeing, innovation, performance, etc.

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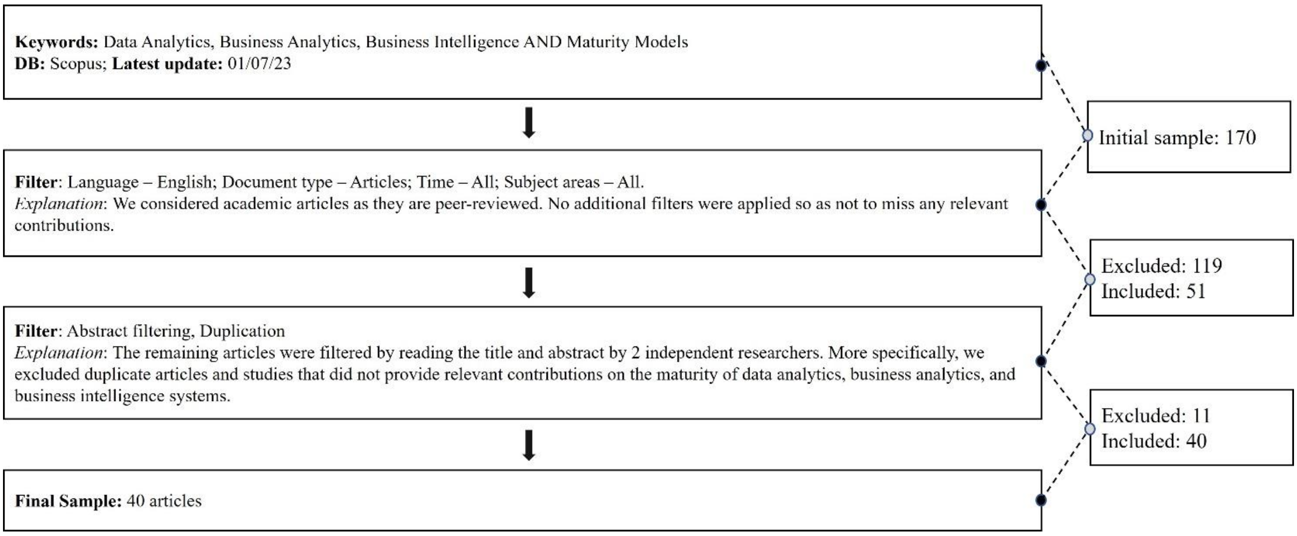
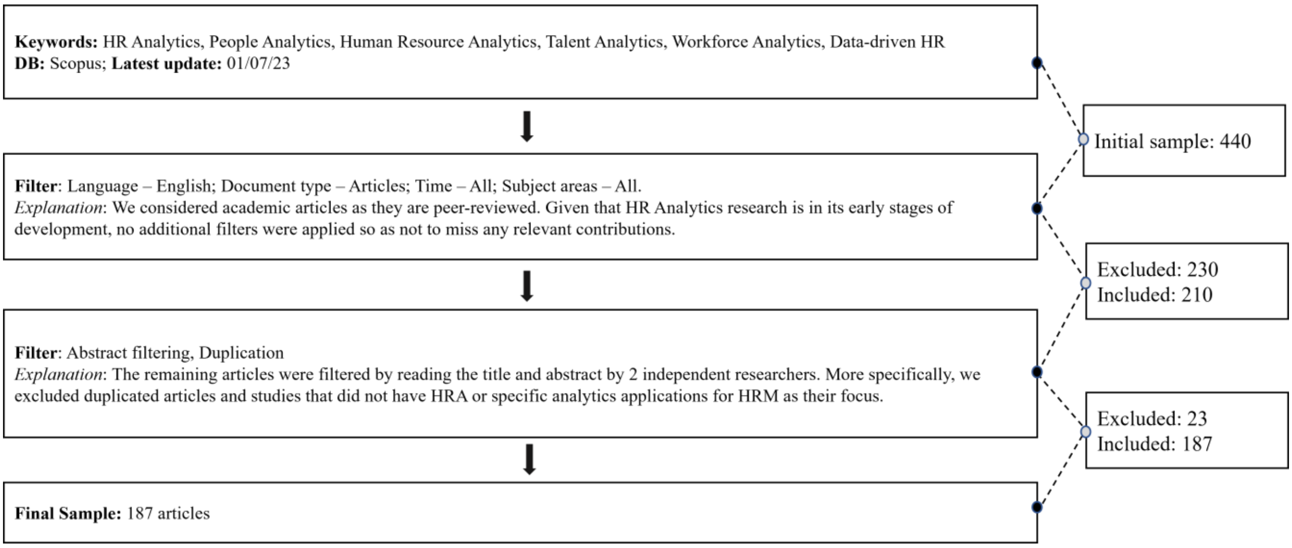
Appendix

Appendix 1. Figure: Search process for the literature review on data analytics, business analytics, and business intelligence maturity models. Source: Authors' own work.



Appendix 2. Figure: Search process for the literature review on HR Analytics. Source: Authors' own work.



Appendix 3. Final coding sheet.

The final coding sheet is represented in Table II.

Appendix 4. HR Analytics experts description.

Table III provides a description of the 4 HRA experts collaborating in the development of the HRAMM, including their organisations, roles, and expertise in the HRA field.