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# A Systemic Approach to Evaluate Maturity in Data-Driven Human Resource Analytics: The Multi-Level Perspective Framework

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**ABSTRACT**

Many maturity models for Human Resource Analytics (HRA) do not capture how capabilities evolve across levels within and outside the organization. We use a systems-thinking framework to assess HRA maturity across five stages, from Initial to Optimized. The study combines the Fuzzy Analytic Hierarchy Process (FAHP) to weight nine key performance indicators (KPIs) and the Multi-Level Perspective (MLP) to interpret how change is shaped by outside pressures, current routines, and local innovations. The nine KPIs cover training, data security, system integration, budgeting, and related enablers. Results show a clear shift in priorities: early stages focus on funding, training, and basic safeguards, while later stages emphasize full integration and continuous improvement. MLP helps connect these internal shifts to wider forces of digitalization and policy. The work offers practical guidance for organizations in Iran that aim to build HRA in resource-constrained settings. We also outline next steps, including simple simulation tools and adaptive roadmaps, so leaders can test "what if" choices and plan long-term alignment between HR strategy and changing socio-technical conditions.

***Keywords***

Human resource analytics maturity model; Multi-level perspective; Systems thinking; Data-Driven human resource management.

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## 1. Introduction

Over the past two decades, organizations have faced increasingly volatile environments and complex, dynamic workforces (Khazaei et al., 2025a). These conditions have compelled organizations to adapt rapidly to external changes, exposing them to new challenges (Haseli, 2018; Bakhteri et al., 2022). In parallel, human resource departments have undergone significant transformation. They no longer serve merely administrative functions but are progressively taking on strategic and value-generating roles within organizations (Vargas et al., 2018; Levenson, 2018; Larsen and Edwards, 2021a). This evolution has been largely driven by the widespread adoption of digital technologies and the acceleration of digital transformation (Ghaedi et al, 2024), which have fundamentally altered how employees are managed and have provided managers with greater access to employee-related data and information (Gholian-Jouybari et al, 2024). Such data enables employers not only to better understand employee behavior and psychology but also to design more effective management strategies (Giermindl et al., 2022; Fernandez and Gallardo-Gallardo, 2020; McIver et al., 2018; McCartney and Fu, 2021; Huang et al., 2023).

These transformations, coupled with the growing emphasis on data-driven analysis, have created a need for new strategic decision-making capabilities within human resource management (HRM) (Ridgway et al, 2025), aimed at enhancing organizational competitiveness (Haseli, 2018; Levenson, 2018; Minbaeva, 2018). In particular, Human Resource Analytics (HRA) has gained traction as a tool for evidence-based decision-making, offering an alternative to intuition-based approaches (Lansford, 2019; Lushero and Bader, 2023). HRA facilitates performance improvement and reduces the risk of poor decisions, which is why many organizations are increasingly interested in developing these capabilities across their operations.

Despite this rising interest, many organizations continue to face serious challenges in the systematic implementation of HR analytics. These challenges include a shortage of specialized expertise, technological limitations, information management issues, and a lack of coordination among organizational units. Consequently, a significant proportion of HRA initiatives fail during early implementation stages, with approximately 42% of projects reported as unsuccessful (Bersin, 2021). Scholars have also warned that HR functions may struggle to successfully navigate the era of big data, risking failure to leverage its full potential for strategic decision-making if critical challenges are not addressed (Angrave et al., 2016). Organizations frequently cite a substantial gap between their current capabilities and the resources truly

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required to fully leverage data-driven HR analytics, commonly referred to as the "capability gap" (Minbaeva, 2018). Much of this failure can be attributed to weak control over internal performance indicators; however, the growing need for clearly defined success and performance metrics in organizations is evident.

Figure 1 illustrates the global growth trajectory of the HRA market (in billion USD) across various regions, including North America, Europe, Asia-Pacific, the Middle East, and Latin America, from 2017 to 2024. While North America and Europe have seen dominant market shares, the Middle East has also shown stable and notable growth, signaling the increasing relevance of HRA in that region.

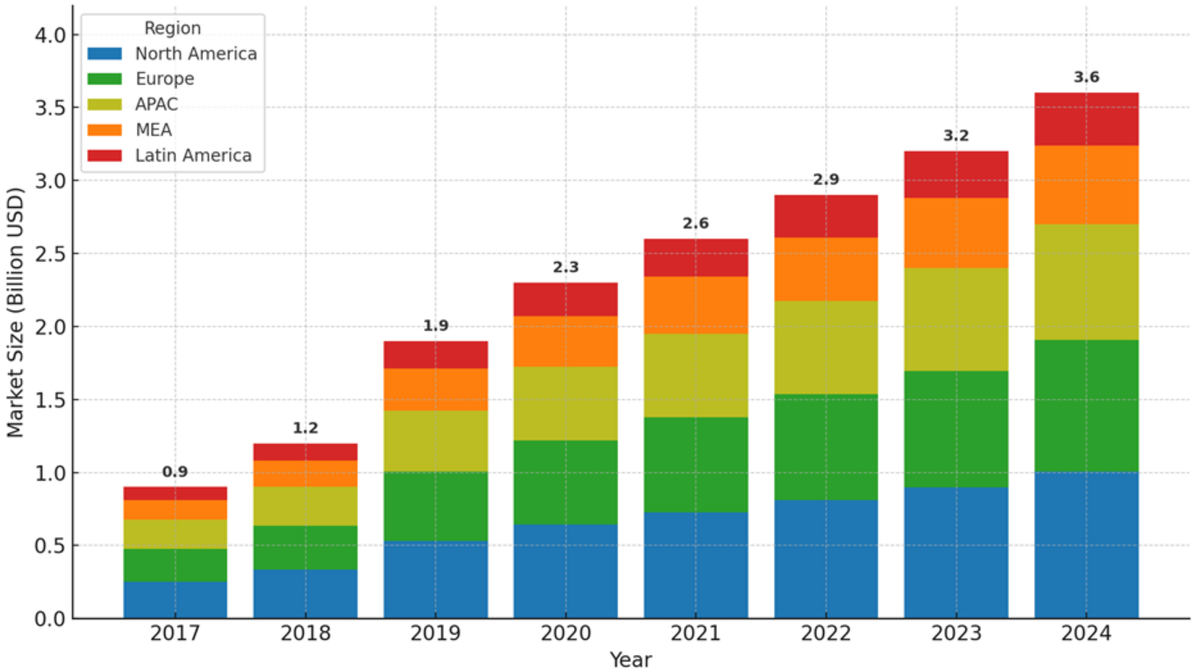


Figure 1. Market share of HRA by global regions over the past eight years (in Billion USD, Source: Global market insights, 2024).

In the Middle East, Iran, one of the region's largest and most populous countries, holds substantial potential to expand the HRA market. With the continued growth of diverse industries and the increasing need to optimize human resource processes, Iran is well positioned to play a significant role in advancing this market. The availability of an educated workforce and the increasing emphasis on optimizing organizational performance have positioned Iran as a key player in the Middle East's HRA landscape.

In this context, researchers view Human Resource Analytics as a multidimensional and multifaceted organizational capability, whose successful development requires coordination and integration of resources, skills, and technologies (Ramachandran et al., 2023; Wang et al., 2024; Wirges and Nair, 2022; Cullen et al., 2023). Previous studies have shown that developing HRA in a way that enables integrated operation across all organizational dimensions is challenging, but essential for maximizing the value of data-driven insights (Marler and Boudreau, 2017; Levenson, 2018).

One of the most suitable tools to support the development and assessment of these capabilities is the Maturity Model (MM), which has been widely used in scientific research as a framework for evaluating the maturity of business analytics, business intelligence, and data analytics processes (Chen and Nath, 2018; Arunachalam et al., 2018). Research indicates that such models can help organizations systematically progress from initial to more advanced maturity levels, thereby enhancing their overall capabilities (Marks et al., 2012; Gokalp et al., 2021). However, the current academic literature lacks a dedicated maturity model tailored specifically to HRA, revealing a clear research gap (Bahuguna et al., 2023; Wang et al., 2024). Moreover, most existing models are static and overlook interdependencies across dimensions, which can adversely affect investment planning and prioritization (Meyer et al., 2009).

This study develops and evaluates a Human Resource Analytics Maturity Model (HRAMM) to guide progress in data-driven HR practices. The model defines five maturity levels and assigns weights to a focused set of KPIs at each stage. By considering the links among technology, organizational processes, and culture, the model provides a more comprehensive and practical picture of analytical capability. The framework is designed for use in Iranian organizations and similar contexts, helping decision makers improve strategy and day to day performance through structured use of HR data.

## 2. Literature review

In the theoretical background of the HRA maturity model, the literature is divided into three main sections. The first focuses on studies related to HRA, the second examines maturity model approaches, and the third synthesizes previous research in business analytics, business intelligence, and data analytics maturity frameworks.

In the academic literature, HRA has been defined in various ways (Marler and Boudreau, 2017; Margherita, 2021; Thakral et al., 2023). These definitions commonly refer to the use of statistical and mathematical techniques to support decisions related to an organization's people (Larsen and Edwards, 2021; Edwards et al., 2022; Cullen et al., 2023). In recent years, HRA has been conceptualized as an organizational capability (Levenson, 2018; Minbaeva, 2018; Falletta and Combs, 2021; Samson and Bhanugopan, 2022), reflecting its multidimensional nature and its reliance on various internal resources and organizational factors (Minbaeva, 2018; Wirges and Nair, 2022). Organizational capability refers to the way an organization combines its resources, knowledge, and skills to systematically perform activities and generate specific outcomes (Salvato and Rerup, 2010). These capabilities should be developed using both internal and external assets and must be continuously maintained and enhanced (Helfat and Peteraf, 2003). Recent studies emphasize the need for integration across organizational assets and departments to develop HRA capabilities (Shet et al., 2021; Ramachandran et al., 2023; Wang et al., 2024), especially given that they operate across organizational boundaries and at multiple levels (Howell and Bondarouk, 2017; Minbaeva, 2018). Therefore, companies aiming to advance their HRA capabilities should transition from a purely HR-centric approach toward more integrated, organization-wide strategies (Andersen, 2017).

An MM is defined as "a structured collection of elements that describe characteristics of effective processes at different stages of development" (Pullen, 2007). Originally developed in software engineering, this approach significantly reduced development costs and improved process quality and efficiency (Gokalp et al., 2021). In recent years, management and operations research has increasingly adopted maturity models, as they offer a simple yet effective method for assessing the quality of organizational capabilities and systems (Lismont et al., 2017; Doctor et al., 2023) and for developing actionable improvement pathways (Wendler, 2012).

HR analytics has received increasing attention as organizations seek to make more evidence-based HR decisions. However, despite its growing popularity, many organizations still struggle to realize its full value due to limitations in organizational structure, analytical capabilities, and system support (Heuvel and Bondarouk, 2017).The key purpose of a maturity model is to identify gaps between a capability's current and desired states, thereby helping organizations build an effective roadmap for enhancing their maturity level (Becker et al., 2009; Stueber et al., 2023). Since the concept of maturity aligns with a stage-based development approach (Monteiro et al., 2020), the models typically propose incremental improvements through a series of intermediate stages (Sen et al., 2012). The main components of a maturity model include maturity levels, model dimensions, and evaluation tools (de Bruin et al., 2005). Each maturity level represents a stage to which the model's constituent dimensions can progress (Monteiro et al., 2020). These levels should be distinct, measurable, and logically connected to the previous and next levels (Becker et al., 2009).

Over the past few decades, researchers have proposed hundreds of maturity models for various organizational capabilities (Doctor et al., 2023), including business analytics (e.g., Cosic et al., 2012), data analytics (e.g., Carvalho et al., 2019), and business intelligence (e.g., Lahrmann et al., 2011; Lismont et al., 2017b). These terms are often used interchangeably in the literature (Arunachalam et al., 2018) to describe the organizational capability for the broad use of data, advanced analytics, and evidence-based management to support strategic decisions and actions (Davenport and Harris, 2007; Chen and Nath, 2018) (see Table 1).

Table 1. Categorized summary of prior studies.

| Area | Study | Topic | Key findings |
|---|---|---|---|
| HRA | Marler and Boudreau (2017) | Definitions and terminology in HRA | HRA involves statistical techniques for decision-making related to people. |
| | Minbaeva (2018) | HRA as an organizational capability | HRA is defined as a multidimensional capability that requires the integration of resources and skills. |
| | Shet et al. (2021) | Role of integration across assets in HRA development | Successful HRA implementation requires collaboration across organizational units. |
| Maturity Model Approach | Pullen (2007) | Definition and components of maturity models | A maturity model is a structured framework describing the characteristics of process stages. |
| | Gokalp et al. (2021) | Maturity models for process cost efficiency | Maturity models improve productivity and quality by reducing process development costs. |
| | Boon et al. (2025) | Core elements of maturity models | Maturity levels, model dimensions, and evaluation tools are the foundational components. |
| Analytics and Maturity Models | Cosic et al. (2012) | Maturity models in business analytics | Maturity models contribute to higher-quality business analytics. |
| | Carvalho et al. (2019) | Maturity models in data analytics | These models support wide-ranging use of data for informed decision-making. |
| | Lismont et al. (2017) | Evidence-based management in business intelligence | Business intelligence is identified as a core component of data-driven decision-making maturity. |

Although HR analytics enables organizations to utilize big data in human resource decision-making, scholars argue that organizations should not rely exclusively on date-driveninsights, and strategicHR decisions should also incorporate managerialexperience and contextual considerations (Opatha,2021). The literature reveals that while maturity models have been widely developed across domains such as data analytics, business intelligence, and HRA, they often treat organizational development as a linear, compartmentalized process. This overlooks the interdependent and dynamic nature of socio-technical systems, where progress in one area (e.g., data integration) is closely influenced by shifts in culture, policy, or technological infrastructure. Most existing models emphasize discrete elements such as standardization, security, or integration but fail to capture the feedback loops, cross-level interactions, and emergent behaviors that characterize real-world transitions.

To address this gap, the present study adopts the Fuzzy Analytic Hierarchy Process (FAHP) as a methodological foundation within a systems thinking framework. By systematically evaluating and weighting KPIs across five maturity levels, the model accounts for uncertainty, interconnection, and contextual variability. It is particularly tailored to the unique organizational and cultural structures of developing countries such as Iran, offering a more nuanced, adaptive, and systemic approach to assessing and enhancing HRA maturity. This enables organizations to better align their transformation strategies with both internal readiness and evolving external pressures.

## 3. Methodology

To conduct the research using a scoping review methodology, we followed the guidelines proposed by Arksey and O'Malley (2005) and later expanded by Levac et al. (2010). These methods were designed to ensure high levels of transparency and systematic rigor, thereby enhancing the accuracy, reliability, and credibility of the research process (Paré et al., 2016). Although scoping reviews are highly systematic, they should not be confused with traditional systematic reviews. Generally, systematic reviews, such as meta-analyses, aim to synthesize prior empirical findings in order to answer questions like "what works best?". In contrast, scoping reviews are more exploratory, aiming to provide an initial assessment of the volume and types of literature available on an emerging topic, identify existing gaps, and suggest directions for future research.

Our framework for conducting this scoping review aligns with the standards endorsed by systematic review advocates, emphasizing that each step of the process must be carried out with precision and transparency (Mays et al., 2001). The scoping review process should be sufficiently documented to allow for replication by other researchers. This level of clarity not only enhances the credibility of the findings but also protects the methodology from criticism of a lack of rigor (Mays et al., 2001) (see Figure 2).

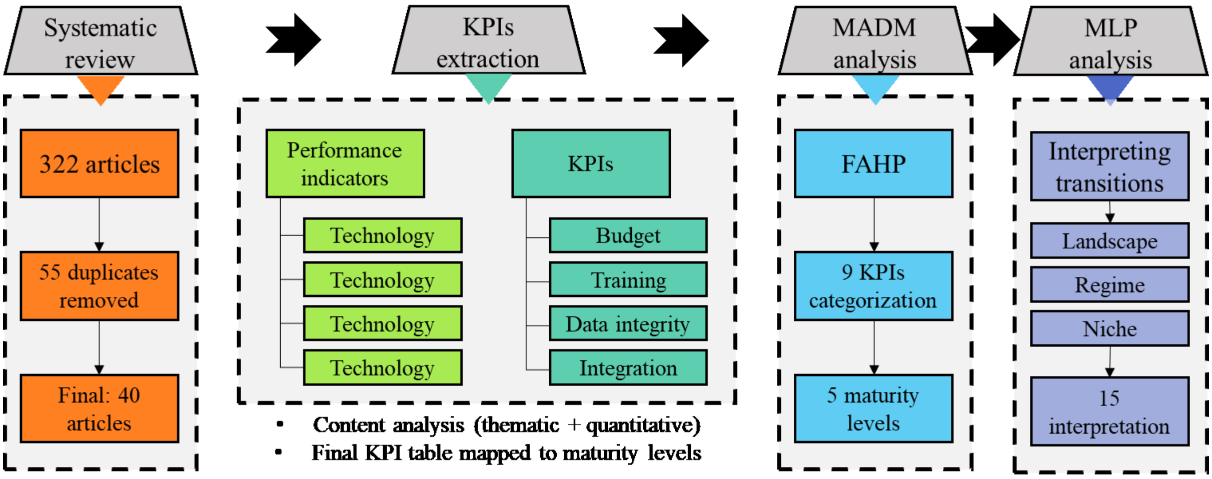


Figure 2. A five-phase research methodology framework integrating systematic review, KPI extraction, FAHP-based MADM analysis, and MLP interpretation.

The method used for identifying sources in this scoping review needed to provide both breadth and depth to comprehensively capture the domain. Unlike a narrowly focused research question that limits the investigator to a predefined set of studies (as in traditional systematic reviews), scoping reviews are not confined to a rigid protocol. This flexibility allows researchers to refine search terms and adjust sensitivity throughout the review process as their understanding of the literature evolves. At the outset, researchers may refrain from applying strict limitations on keywords, study identification, or source selection. The process is iterative and reflexive, allowing adjustments to ensure thorough coverage of the relevant literature.

Given these distinctions, the framework adopted in this study consists of five distinct phases: 1) Clear and focused research questions were formulated to define the scope and objectives of the review. These questions were designed to elicit a comprehensive perspective on the topic under investigation. 2) A wide-ranging search was conducted to identify all potentially relevant studies. This stage aimed to ensure inclusivity and diversity of viewpoints across the literature. 3) Identified studies were filtered to retain only those that directly addressed the research questions and met quality and methodological criteria. This ensured that only reliable and relevant studies proceeded to the analysis phase. 4) The selected studies were organized and categorized to extract key findings and structure them effectively. This helped streamline the data for deeper analysis. 5) The extracted data were synthesized and presented in a structured manner, offering a unified and in-depth understanding of the scoping review outcomes. This stage facilitates better comprehension for both researchers and practitioners (Oliver, 2001).

### *3.1. Protocol development*

As a foundational step, a detailed research protocol was designed to guide the scoping review process. This included defining core research questions, search strategies, inclusion/exclusion criteria, and data extraction procedures. Additionally, the protocol specified team responsibilities, the conceptual framework, data analysis techniques, and a project timeline. Aligned with best-practice recommendations from methodological experts, the protocol served as a systematic yet flexible roadmap that could be updated as needed (Ebrahimi et al., 2025). The guiding research questions were:

- What key indicators and metrics are used to measure data-driven HRM maturity?
- What maturity levels are typically proposed for assessing HRM analytics?
- What are the promising and practical research directions for future studies in HRM maturity assessment?

These questions were designed to provide a comprehensive understanding of performance measurement indicators in data-driven human resource maturity and to highlight future research opportunities in this evolving domain.

### *3.2. Systematic review and screening*

To ensure comprehensive coverage of performance indicators and maturity assessment in data-driven HRM, six major databases were searched: Emerald, Springer, ProQuest, Taylor and Francis, ScienceDirect, WILEY, and Web of Science. Additionally, one article was manually added from Scopus. These databases were chosen for their diverse collections and broad publisher coverage, minimizing selection bias. Each team member independently performed trial searches to refine the keywords. After multiple rounds of discussion, a final set of keywords was agreed upon (see Table 2). No publication-year restriction was applied; only articles in English or Persian were included. Searches were conducted uniformly across all databases, and results were cross-validated among team members. The process took place in Fall 2024, yielding 322 articles.

Table 2. Summary of literature search results

| Database | Keywords | Articles |
|---|---|---|
| Taylor and Francis | Data-driven HRM maturity; HR performance indicators | 22 |
| Emerald | Data-driven HR analytics; HR performance | 34 |
| WILEY | Data analytics maturity models; HRM and analytics maturity | 37 |
| Springer | HR analytics and competitive advantage; data capabilities | 68 |
| Web of Science | Data-driven analysis and HRM; analytical capabilities | 87 |
| ProQuest | Maturity measurement and human data management; employee performance | 11 |
| ScienceDirect | HR analytics and optimization; maturity and efficiency indicators | 73 |

A multi-stage screening process was conducted to ensure relevance. Of the 322 initial articles, 55 duplicates were removed. Subsequently, 237 articles were excluded for lacking a focus on KPI-based maturity assessment in HR analytics, according to predefined inclusion/exclusion criteria. One manually identified article from Scopus was added, bringing the total to 40 final articles, as shown in Figure 2. A structured coding form was developed to extract data from each article, including publication year, journal name, article title, type, authors, research questions, key findings, and future research directions. This step aimed to map out the intellectual landscape of KPI-based maturity assessment in HRM. Key concepts were also extracted to develop a conceptual map of relevant performance indicators. This map supports a comprehensive understanding of how data-driven HR maturity has evolved and highlights gaps for future research.

### *3.3. Fuzzy analytic hierarchy process*

The FAHP used in this study is based on Chang's method (1992), which integrates classical AHP with fuzzy logic to handle multi-criteria decision-making (MCDM) under uncertainty. In modern complex and uncertain environments, especially in HR contexts where subjective judgments are common, traditional decision-making tools like cost-benefit analysis are often insufficient. FAHP offers a flexible and robust framework that improves decision accuracy by incorporating triangular fuzzy numbers to model expert opinions.

This method was applied to evaluate the relative importance of KPIs in data-driven HRM maturity models. FAHP is particularly useful for incorporating diverse stakeholder perspectives and addressing ambiguities in HR assessment. Triangular fuzzy numbers convert linguistic terms (e.g., "more important," "much more important") into numerical values, enabling structured pairwise comparisons (see Table 3).

Table 3. Triangular fuzzy numbers and their reciprocals

| **Linguistic term** | **Fuzzy number ($l, m, u$)** | **Reciprocal ($l^{-1}, m^{-1}, u^{-1}$)** |
|---|---|---|
| Equal importance | (1.0, 1.0, 1.0) | (1.0, 1.0, 1.0) |
| Slightly more important | (0.5, 1.0, 1.5) | (1.5, 1.0, 2.0) |
| More important | (1.0, 1.5, 2.0) | (0.5, 1.5, 1.0) |
| Strongly more important | (1.5, 2.0, 2.5) | (0.4, 0.5, 1.5) |
| Very strongly important | (2.0, 2.5, 3.0) | (0.3, 1.5, 0.5) |
| Absolutely more important | (2.5, 3.0, 3.5) | (0.3, 0.3, 1.5) |

Pairwise comparisons were conducted using expert judgments aligned with the KPI hierarchy. Consistency of the fuzzy pairwise matrices was verified using Gogus and Boucher's inconsistency index. While Chang's FAHP is simpler and easier to compute (based on arithmetic means), Buckley's FAHP offers more accuracy in resolving inconsistency using geometric means but requires advanced software tools. In this study, Chang's method was selected for its simplicity and interpretability, making it suitable for initial modeling and practical implementation in data-driven HR environments (Kubler et al, 2016).

If $M_1 = (a_1, b_1, c_1)$ and $M_2 = (a_2, b_2, c_2)$ are two triangular fuzzy numbers, the arithmetic operations on them are defined as follows:

$$\begin{aligned} M_1 \oplus M_2 &= (a_1, b_1, c_1) \oplus (a_2, b_2, c_3) = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \\ M_1 \otimes M_2 &= (a_1, b_1, c_1) \otimes (a_2, b_2, c_2) = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2) \end{aligned} \quad (1)$$

Various FAHP methods have been proposed by researchers. However, they all share a common foundation: combining fuzzy theory with hierarchical structure analysis. Most studies have applied the method introduced by Chang (1992). The steps of implementing and computing FAHP from Chang's perspective are as follows:

**Step 1:** Construct the pairwise comparison matrix based on triangular fuzzy numbers $M_{g_i}^j$, where i=1,2,…,n, refers to the row number and j=1,2,…,m, refers to the column number.

$$(M_{gi}^j)_{m*n} = \begin{bmatrix} M_{g1}^1 & \cdots & M_{g1}^m \\ \vdots & \ddots & \vdots \\ M_{gn}^1 & \cdots & M_{gn}^m \end{bmatrix} = \begin{bmatrix} (1,1,1) & (a_{12}, b_{12}, c_{12}) & \cdots & (a_{1m}, b_{1m}, c_{1m}) \\ \vdots & \cdots & \ddots & \vdots \\ (a_{n1}, b_{n1}, c_{n1}) & (a_{n2}, b_{n2}, c_{n2}) & \cdots & (1,1,1) \end{bmatrix} \quad (2)$$

**Step 2:** Calculate the fuzzy synthetic extent value $(S_i)$ for each row of the pairwise comparison matrix.

$$S_i = \sum_{j=1}^{m} M_{gi}^j \otimes \left(\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j\right)^{-1} \quad (3)$$

**Step 3:** Determine the degree of possibility that $s_i$ is greater than $s_k$, using a defined formula based on the comparison of fuzzy numbers.

$$V(S_i > S_k) = \begin{cases} 1 & m_i \geq m_k \\ 0 & l_k \geq u_i \\ (\dfrac{l_k - u_i}{(m_i - u_i) - (m_k - l_k)} & othermise \end{cases} \quad (4)$$

**Step 4:** Calculate the degree of possibility for each S being greater than the rest of the fuzzy numbers (n−1), by taking the minimum value among them.

$$V(S \geq S_1, S_2, \ldots \ , S_k) = V[(S \geq S_1), (S \geq S_2), \ldots, (S \geq S_k)] = Min\, V(S \geq S_i) \ , \qquad i = , \ldots \ , k \quad (5)$$

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**Step 5:** Compute the weight vector $W = (W_1, W_2, \dots, W_n)^T$ of the pairwise comparison matrix using the minimum degrees of possibility. Normalize the resulting weights using a normalization formula to determine the relative importance of each criterion.

$$W_i' = Min\, V(S_i \geq S_j \mid \mathrm{j} = 1, \dots, \mathrm{m} \;, \mathrm{i} \neq \mathrm{j})$$

$$W_i = \frac{W_i'}{\sum_{i=1}^{n} W_i'} \tag{6}$$

### *3.4. Multi-Level perspective: A systemic method*

The Multi-Level Perspective (MLP) is a systems thinking methodology designed to understand complex, long-term transitions in socio-technical systems. It conceptualizes change not as a linear or isolated process, but as the outcome of dynamic interactions across different structural levels. This holistic view aligns with systems thinking principles, in which elements are interrelated (Khazaei et al., 2025b) and feedback loops play a critical role in shaping system behavior over time (Safaie et al., 2023). In this study, MLP is used to examine how KPIs evolve within the broader maturity of data-driven HRA (Geels, 2019) (see Figure 3).

At the niche level (the foundation of the system), innovations and experimental practices emerge in protected environments. These may include pilot programs, start-ups, or research-driven initiatives in HR analytics, such as predictive modeling for employee engagement or machine learning in recruitment. Niches represent the seeds of systemic change, nurtured by supportive actors who shield them from immediate competitive pressures. They serve as testbeds for new ideas, enabling trial-and-error learning that might not be possible within mainstream settings (Geels, 2002).

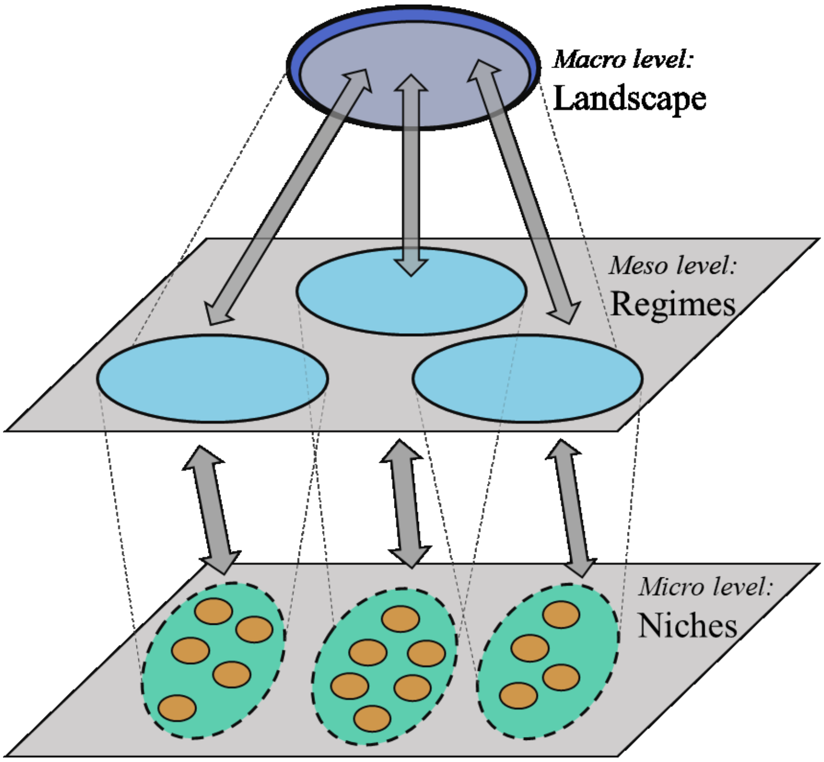


Figure 3. The MLP framework as a systems thinking approach, illustrating the interplay between three levels of socio-technical systems (Geels, 2002, 2019).

The regime level encompasses dominant organizational structures, norms, and policies that guide current practices. In the HRA context, this includes established HR processes, legal frameworks, and cultural expectations. Regimes tend to be stable and self-reinforcing, making them resistant to abrupt transformation. However, as niche innovations mature and gain legitimacy, they begin to challenge the regime, particularly when existing structures face performance gaps or external pressures. Understanding the regime's rigidity and its potential levers for change is essential in systems thinking to identify where interventions can be most effective (Genus and Coles, 2008).

At the top of the framework lies the landscape level, representing external macro-trends such as demographic shifts, technological advancements, regulatory changes, or global crises. These factors evolve independently of actors at the regime or niche levels but exert significant influence on them. For instance, increasing global emphasis on data governance or digital transformation creates landscape pressure that accelerates the need for mature HRA capabilities. Systems thinking highlights how these pressures cascade through the system, creating windows of opportunity for innovation to scale up (Shahroodi et al., 2024).

By applying MLP as a systems-thinking tool, this study identifies 15 distinct transition patterns across the three levels. These patterns help interpret how organizations progress through different stages of maturity in adopting data-driven HR practices. Rather than viewing KPI evolution as a series of isolated upgrades, the MLP perspective frames it as an emergent property of systemic interactions in which innovation, institutional inertia, and contextual pressures intersect. This approach not only explains the past trajectory of HRA development but also guides strategic planning for future transformation.

## 4. Results

To build a comprehensive maturity model for HRA, clear research questions and objectives were first established. These questions aimed to identify the key dimensions and performance indicators across different maturity levels, focusing on technology, organizational structure, performance, and data-driven culture. The goals included identifying existing technological standards, organizational capabilities, and performance attributes essential for successful HRA implementation. In addition, an empirical expert validation was conducted to ground the KPI weights and maturity transitions in practice. We recruited nine experts using purposive sampling, including five senior HR practitioners from large Iranian organizations, two data and HRIS specialists, and two academics with publications in HRA and analytics. All experts had at least seven years of relevant experience. Evidence was collected in two steps. First, each expert completed a structured FAHP instrument, in which pairwise comparisons were made for the nine KPIs across the five maturity levels, using triangular fuzzy numbers. Second, a 90-minute online workshop was held to clarify definitions and resolve outliers. Individual judgments were aggregated using the fuzzy arithmetic mean consistent with Chang's FAHP procedure. Consistency was examined with the Gogus and Boucher inconsistency index. Kendall's W was also computed to assess agreement among experts. All responses were anonymized, participation was voluntary, and consent was obtained prior to data collection.

The literature search was then conducted using a range of academic sources, including peer-reviewed articles, books, and theses. Databases such as Web of Science, ScienceDirect, and others were searched to identify relevant materials on HR analytics, organizational maturity models, and key performance indicators. Sources were selected based on their relevance to topics like system integration, data management, organizational support structures, and data-driven decision-making. These materials provided both conceptual and empirical foundations for identifying HRA maturity dimensions.

Following this, key data were extracted and coded from the selected studies. Core components and performance indicators were identified across four categories: technological architecture, organizational processes, performance characteristics, and cultural alignment. Data were coded separately for each dimension to ensure structured, consistent integration into the final maturity model. This process enabled the development of a well-defined framework, offering specific indicators for each maturity level within data-driven HR analytics. Table 4 summarizes the domains, dimensions, and KPI definitions of the proposed data-driven HRA maturity model.

Table 4. Domains, dimensions, and KPI definitions in data-driven HRA.

| Domain | Dimension | Definition | Components | Component definition | KPIs |
|---|---|---|---|---|---|
| Technology | HRA Architecture | Describes the technological architecture of HRA | Technology Standards | Reference standards for system interoperability and data modeling | % Compliance with technology standards |
| | | | System Integration | Description of internal and external HRA integration | % of system integration |
| | Data Management | Managing data collection elements | Data Storage | Capacity to store and retain essential data | Volume of stored data |
| | | | Data Modeling | Structuring data for analysis and access | Quality of data structuring |
| Organizational | HRA Strategy | Long-term planning for HRA | Allocated Budget | Organizational budget allocated to HRA | % of allocated budget |
| | | | Executive Support | Level of executive support for HRA initiatives | % of managerial support |
| Functional | Data Governance | Ensuring input data quality | Data Completeness | Validation of data integrity and completeness | % of complete data |
| | | | Data Security | Ensuring authorized access and privacy | Number of security incidents |
| Dissemination | Analytical Culture | Promoting an analytical mindset within the organization | Analytical Awareness | Fostering a data-driven decision-making culture | Number of training sessions |

In the data analysis phase, findings extracted from the reviewed articles were assigned to specific KPIs. For example, under the technology dimension, indicators such as alignment with technology standards and system integration were identified as key performance metrics. For each KPI, five maturity levels were defined, ranging from "Initial" to "Optimized." These levels indicate an organization’s progress in adopting HRA and its organizational maturity in this area. Each level is associated with specific characteristics and benchmarks that help determine the current stage of maturity and the targets the organization should aim to achieve. Table 5 presents the key performance indicators and their corresponding maturity levels in data-driven HR analytics.

Table 5. Key performance indicators and maturity levels in data-driven HR analytics

| # | KPI | Level 1: Initial | Level 2: Repeatable | Level 3: Defined | Level 4: Managed | Level 5: Optimized |
|---|---|---|---|---|---|---|
| A | % Compliance with technology standards | No standards applied | Partial compliance with some standards | Compliance with common standards | Full compliance with global standards | Optimized and updated use of standards |
| B | % of system integration | Systems work independently | Limited integration | Full internal integration | Full internal and external integration | Integration with automated interactions |
| C | Volume of stored data | Limited and manual storage | Partial data storage | Systematic data storage | Effective data storage methods | Continuous and optimized storage |
| D | Quality of data structuring | Unstructured data | Limited structuring for some data | Fully structured for basic analytics | Optimized structuring and accessibility | Highest quality data structuring |
| E | % of allocated budget | No specific budget | Limited budget for specific areas | Adequate budget for HRA strategies | Budget aligned with management priorities | Flexible and optimized budgeting |
| F | % of managerial support for HRA | Limited and partial support | Support for some objectives | Systematic support in decision-making | Strategic executive support | Full and strategic top-level support |
| G | % of complete data | Data is incomplete | Partial data completion | Systematic data completion | Completion with validation | Full data completeness guaranteed |
| H | Number of security incidents | Security breaches not identified | Partial security monitoring | Systematic security oversight | Reduced number of incidents | Maximum and continuous security |
| I | Number of training sessions | Limited and sporadic training | Training for select teams | Broad training across departments | Continuous and systematic training | Extensive training and cultural integration |

### *4.1. Fuzzy-AHP analysis of KPI importance across maturity levels*

To make the FAHP procedure transparent and reproducible, we provide a brief example of how linguistic inputs were encoded. During elicitation, experts compared KPI pairs using a six-point linguistic scale: equal, slightly more important, more important, strongly more important, very strongly important, and absolutely more important. Each phrase corresponds to a triangular fuzzy number listed in Table 3. For instance, when comparing System integration with Budget allocation at the Managed level, seven of nine experts rated integration as strongly more important, and two rated it more important. We converted these selections to the corresponding fuzzy numbers from Table 3, averaged the resulting triples to obtain the group judgment for that pair, and recorded the reciprocal term for the reverse comparison. As a second illustration, at the Initial level, most experts rated Training over Data structuring as very strongly important, given the need to build basic literacy before technical refinement. All pairwise judgments were then synthesized using Chang's FAHP steps, and matrix quality was checked using the Gogus and Boucher inconsistency index along with Kendall's W for agreement. This example reflects the typical workflow used across all maturity levels and KPI pairs.

Table 6 illustrates the evolution of KPI importance weights across five maturity levels, as assessed using the FAHP. This integrated table offers a consolidated view of how each KPI's relative weight changes as organizations progress through different stages of data-driven HR maturity, from Initial (Level 1) to Optimizing (Level 5).

Table 6. Consolidated FAHP results showing the relative importance (BNP and normalized weights) of nine KPIs across five maturity levels in data-driven human resource analytics.

| **KPIs** | **Level 1** | | **Level 2** | | **Level 3** | | **Level 4** | | **Level 5** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | BNP | Weights | BNP | Weights | BNP | Weights | BNP | Weights | BNP | Weights |
| **A** | 0.101 | 0.0968 | 0.135 | 0.1296 | 0.13 | 0.1245 | 0.116 | 0.1105 | 0.116 | 0.1105 |
| **B** | 0.109 | 0.1039 | 0.117 | 0.1121 | 0.099 | 0.0944 | 0.148 | 0.1409 | 0.137 | 0.1306 |
| **C** | 0.127 | 0.1213 | 0.093 | 0.089 | 0.163 | 0.1556 | 0.105 | 0.1003 | 0.119 | 0.1138 |
| **D** | 0.077 | 0.0732 | 0.075 | 0.0715 | 0.085 | 0.0811 | 0.073 | 0.0691 | 0.075 | 0.0715 |
| **E** | 0.132 | 0.1257 | 0.12 | 0.1153 | 0.095 | 0.0911 | 0.125 | 0.1191 | 0.143 | 0.1364 |
| **F** | 0.114 | 0.1089 | 0.106 | 0.1014 | 0.11 | 0.1052 | 0.087 | 0.0834 | 0.109 | 0.1037 |
| **G** | 0.125 | 0.1195 | 0.124 | 0.1185 | 0.133 | 0.1273 | 0.127 | 0.121 | 0.125 | 0.1195 |
| **H** | 0.129 | 0.1231 | 0.135 | 0.1299 | 0.111 | 0.1062 | 0.146 | 0.1392 | 0.123 | 0.117 |
| **I** | 0.133 | 0.1276 | 0.138 | 0.1327 | 0.12 | 0.1145 | 0.122 | 0.1163 | 0.101 | 0.0968 |

At the Initial level (Level 1), the highest weights are assigned to KPIs such as budget allocation (E), training efforts (I), and data security (H) (see Figure 4). These priorities reflect the foundational needs of organizations initiating a data-driven transformation, in which establishing a secure, well-funded, and well-educated environment is crucial. Conversely, lower weights for indicators such as data structure quality (D) and technical standard alignment (A) suggest that technical refinement and integration are not yet a major concern at this early stage.

At the Repeatable level (Level 2), training (I) and security (H) remain dominant, indicating a focus on process stabilization through consistent learning and protective measures. Notably, the weight of the budget (E) slightly declines, suggesting that financial structure is now more established, while low emphasis continues on technical quality (C, D).

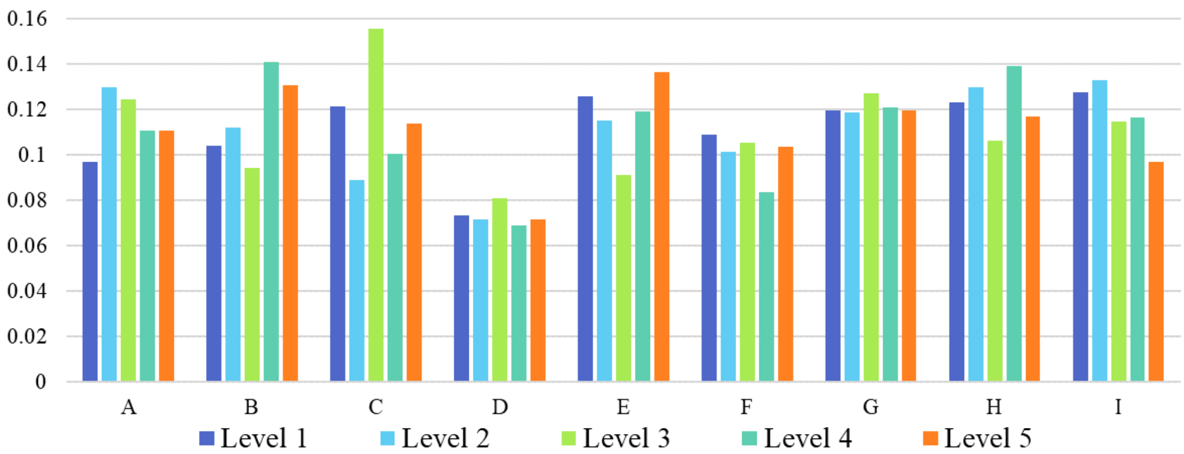

Figure 4. Comparison of normalized weights for nine KPIs across five organizational maturity levels in HRA.

At the Defined level (Level 3), KPIs related to data structure (C) and data modeling (A) receive the highest weights, indicating a transition toward the development of systematic, optimized data architectures. This indicates that organizations at this level are consolidating their infrastructure to support future scalability, thereby shifting focus from governance and training to core data readiness.

The Managed level (Level 4) represents a peak in integration (B) and security (H), underscoring the need for full-system coordination and strict control of data access as organizational complexity increases. In contrast, the importance of managerial support (F) and data structure quality (D) declines, indicating they have likely reached a satisfactory baseline relative to prior levels.

Finally, in the Optimizing level (Level 5), budget flexibility (E) and system integration (B) become the most critical KPIs. These reflect the organization's shift toward strategic refinement, efficient resource allocation, and continuous optimization of inter-system functionality. Meanwhile, early-stage enablers such as training (I) and basic data structuring (D) are de-prioritized, signaling maturity in foundational capabilities.

In summary, the FAHP analysis reveals a logical and sequential shift in KPI importance, beginning with foundational enablers such as funding and training and progressing to system integration and optimization. This pattern underscores the need for organizations to align their maturity journey with evolving performance priorities at each stage.

Transition analysis of HRA systems using MLP

As organizations progress from initial stages toward full maturity in data-driven human resource analytics, merely identifying and weighting key performance indicators is insufficient. To gain a deeper understanding of the barriers and enablers of this transformation, the MLP framework can be employed. MLP analyzes the transformation of socio-technical systems across three analytical layers: the macro level (landscape), the meso level (regimes), and the micro level (niches). This framework enables a dynamic, multidimensional interpretation of the maturity transition, rather than treating it as a linear process.

In this study, the use of MLP helps contextualize the FAHP results within a broader socio-technical framework, allowing us to interpret why certain indicators are prioritized in lower maturity levels and how shifts in policy, technology, or organizational culture influence changes in priority at more advanced stages. According to this framework, external drivers such as global pressures toward digitalization (landscape), the current administrative and structural setup of organizations (regimes), and emerging pilot innovations or successful experimental projects (niches) simultaneously shape the organizational maturity journey. The following MLP-based interpretation for each maturity level explores the dynamics of transition and systematically identifies barriers and enablers of transformation.

*Level 1 – Initial: MLP-based analysis*

At the initial level of HRA maturity, organizations are in the early stages of adopting data-driven practices. From an MLP lens, transformation is minimal because the pressures from the broader landscape remain weak or unrecognized. External factors such as national digital transformation policies or global data governance standards may exist, but are often not internalized by the organization. At the regime level, traditional HR practices dominate, characterized by manual data entry, fragmented reporting, and a lack of digital integration. Institutional resistance, limited digital competencies, and the absence of strategic support act as strong barriers. At the niche level, however, small-scale initiatives may emerge: isolated training sessions on HR analytics, pilot dashboards for monitoring simple KPIs, or individual efforts to digitize HR records. These niches, while not yet structurally disruptive, can serve as seeds for systemic transition, but only if they are supported by policy incentives and aligned with broader regime reforms. Table 7 provides an MLP-based analysis of Level 1 (Initial) maturity in HRA.

Table 7. MLP-based analysis of Level 1 (Initial) maturity in HRA.

| MLP# | Observed state at level 1 | Examples in Iranian organizations | Barriers and leverage points |
|---|---|---|---|
| Landscape | Weak external pressure for transformation; digitalization not fully enforced | National documents on IT modernization exist, but lack enforcement mechanisms | Opportunity: leverage public-sector digitalization plans or regulatory frameworks to stimulate movement |
| Regime | Manual, isolated, and reactive HR processes; no integrated systems | Paper-based employee files, non-standardized reports, and fragmented HR systems | Barrier: Institutional inertia, limited budget, cultural resistance to technology |
| Niche | Sporadic pilot efforts with limited institutional impact | HR managers using Excel-based KPI dashboards; ad hoc training in HR analytics | Potential: Early adopters can become champions of change if connected to a formal strategy or policy-level encouragement |

*Level 2 – Repeatable: MLP-based analysis*

At the repeatable level, organizations begin to systematize certain HR processes and embed them into organizational routines. From an MLP perspective, the landscape pressure becomes slightly more visible: governmental calls for digital reporting, industry benchmarks, and increasing regional competition create a soft but growing push for modernization. However, these forces are often perceived as optional rather than imperative. At the regime level,

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organizations start to codify processes, but systemic inertia remains strong. Most changes are operational rather than structural; for example, HR units may automate attendance tracking or introduce performance monitoring tools, but these remain loosely connected. At the niche level, we observe clearer experimentation: internal training modules on data literacy, the use of KPI dashboards by select departments, or the implementation of pilot digital HR systems without full institutional integration. The regime still isolates these efforts rather than scaling them, but the shift toward repeatability shows that some niches are gaining traction. The organization stands at a tipping point where landscape forces and niche innovation must converge to overcome regime rigidity. Table 8 presents the MLP-based analysis of Level 2 maturity in HRA.

Table 8. MLP-based analysis of Level 2 maturity in HRA.

| MLP# | Observed state at level 2 | Examples in Iranian organizations | Barriers and leverage points |
|---|---|---|---|
| Landscape | Emerging pressure from policymakers and market dynamics | Ministry-level reporting requirements, regional competitors adopting HR tech | Leverage point: Frame compliance and modernization as strategic imperatives rather than optional upgrades |
| Regime | Early automation and formalization of HR tasks without systemic integration | Attendance tracking systems, isolated HR analytics tools | Barrier: Siloed digitalization, lack of cross-functional alignment, short-term thinking |
| Niche | Training programs and pilot technologies are tested by mid-level HR professionals | Departmental-level KPI dashboards, Excel-to-web migration of HR records | Potential: Institutionalize successful pilots through HR strategy alignment and budgeted expansion plans |

*Level 3 – Defined: MLP-based analysis*

At the defined level of HRA maturity, organizations exhibit a noticeable shift from isolated experimentation toward structured, organization-wide practices. From the MLP lens, pressures at the landscape level, such as national digital transformation roadmaps, cross-sector success stories, and investor expectations for transparency, are now more actively acknowledged. Organizations begin to align internal goals with external expectations. At the regime level, formal frameworks and digital standards are introduced across departments: organizations adopt organization-wide KPI systems, develop centralized data repositories, and integrate multiple data sources. However, legacy systems and cultural inertia may still constrain full harmonization. At the niche level, we see advanced experimentation: predictive analytics pilots, cross-functional HR analytics teams, and early use of AI in candidate screening or workforce planning. These innovations are increasingly aligned with regime goals and, if nurtured properly, can form the basis for regime transformation. At this point, the organization is in a critical phase, sophisticated enough to define and test, but still fragile if external pressure or leadership support wavers. Table 9 presents the MLP-based analysis of Level 3 maturity in HRA.

Table 9. MLP-based analysis of Level 3 maturity in HRA.

| MLP# | Observed state at level 3 | Examples in Iranian organizations | Barriers and leverage points |
|---|---|---|---|
| Landscape | Institutional pressure for modernization and accountability is growing | Digital governance guidelines, data ethics codes, and stakeholder demand for reporting | Leverage point: Use landscape shifts to justify strategic data integration and system investment |
| Regime | Organization-wide frameworks for HR analytics begin forming | Centralized HRIS systems, integrated KPI dashboards, and defined analytic workflows | Barrier: Resistance to de-siloing, inconsistent data quality, and lack of interdepartmental coordination |
| Niche | Advanced pilot initiatives are increasingly structured and aligned with strategy | Predictive models for attrition, talent analytics platforms, and internal HR data science labs | Potential: Embed niche teams into core HR functions; align their success with regime KPIs and long-term strategic planning |

*Level 4 – Managed: MLP-based analysis*

At the managed level of HRA maturity, organizations move beyond defining analytics processes to controlling and optimizing them across departments. From an MLP standpoint, landscape pressures become more directive: legal compliance mandates, investor scrutiny, regional benchmarking, and competitive positioning drive organizations to formalize data-driven practices. The regime begins to transform: digital infrastructures are not only established but governed through policies, performance standards, and integrated platforms. HR systems are connected to finance, operations, and strategic planning. Cultural alignment improves, though resistance may persist when automation challenges power structures or entrenched norms. At the niche level, experimentation gives rise to institutional capability. What were once test pilots (e.g., data dashboards or predictive tools) have now become embedded systems, maintained by trained analysts or internal data teams. The boundary between niche and regime begins to blur. However, sustaining this transition demands leadership commitment, real-time feedback mechanisms, and alignment with changing landscape expectations. Table 10 presents the MLP-based analysis of Level 4 maturity in HRA.

Table 10. MLP-based analysis of Level 4 maturity in HRA.

| MLP# | Observed state at level 4 | Examples in Iranian organizations | Barriers and leverage points |
|---|---|---|---|
| Landscape | External forces increasingly prescriptive and measurable | HR technology adoption KPIs in national plans, ESG reporting standards, and sector-wide audits | Leverage point: Position HR analytics as a strategic enabler of compliance and competitiveness |
| Regime | Formalized governance and cross-functional integration of HRA systems | Integration of HRIS with ERP, automated reporting dashboards, and performance governance layers | Barrier: Mid-level resistance to analytics-based decision-making; challenges in maintaining interoperability and data governance |
| Niche | Embedded capabilities; pilots become routine, sustained by trained personnel | Internal HR analytics units, HR-data fusion with BI tools, and AI-enhanced recruitment platforms | Potential: Niche teams can drive continuous improvement loops; potential for feedback systems and adaptive HR decision support models |

*Level 5 – Optimized: MLP-based analysis*

At the optimized level, the organization has achieved full integration and strategic alignment of its HR analytics systems. Through the MLP lens, the relationship between landscape, regime, and niche is no longer one-directional; the organization begins to shape its environment rather than merely adapt to it. At the landscape level, the organization participates in shaping national and sectoral standards, contributes to data governance discussions, and positions itself as a digital leader in HR transformation. At the regime level, systems are agile, continuously learning, and equipped for real-time optimization. Processes are data-driven, automated, and deeply embedded across all organizational functions. HR analytics informs strategic forecasting, workforce modeling, and cross-organizational decision-making. At the niche level, the distinction with the regime effectively disappears. Innovation becomes an ongoing, institutionalized process, with internal R&D, AI-enhanced models, and predictive simulations constantly refining operations. The organization not only responds to external pressures but also co-creates future expectations, serving as a benchmark for others. Table 11 presents the MLP-based analysis of Level 5 maturity in HRA.

Table 11. MLP-based analysis of Level 5 maturity in HRA.

| MLP# | Observed state at level 5 | Examples in Iranian organizations | Barriers and leverage points |
|---|---|---|---|
| Landscape | Organization becomes an active shaper of external expectations | Participation in HR-tech policymaking forums; exporting best practices to peer institutions | Leverage point: Institutional legitimacy allows shaping national standards and influencing regulatory evolution |
| Regime | Fully adaptive, data-driven HR architecture integrated with strategic management | Real-time dashboards, simulation-based workforce planning, and AI-supported decision environments | Barrier: Sustaining innovation pace; risk of stagnation if feedback systems are not maintained; need for strong ethical governance around employee data usage |
| Niche | Continuous, embedded innovation as part of daily operations | HR innovation labs; embedded AI models for retention, wellbeing, inclusion | Potential: Niche thinking institutionalized as a permanent innovation engine; agile experimentation accelerates long-term resilience and strategic foresight capability |

The layered interpretation offered by the MLP highlights that organizational transformation toward advanced HRA maturity is neither linear nor internally driven alone. Rather, it emerges from a dynamic interplay between external macro pressures, entrenched internal practices, and bottom-up innovations. The alignment, or misalignment, among these levels fundamentally shapes the speed and depth of organizational change. With this in mind, the following discussion synthesizes the FAHP-based findings within this socio-technical transition framework and identifies practical implications for HR leaders, policymakers, and system designers seeking to foster sustainable, data-driven HR ecosystems.

## 5. Discussion

The evolution of HR analytics maturity is not only a matter of weighted KPIs across five levels but also a reflection of dynamic socio-technical transitions across landscape, regime, and niche layers. Figure 5 illustrates the maturity of HR analytics through the multi-level perspective (MLP), highlighting the interaction between macro-level pressures (landscape), organizational structures (regimes), and innovations (niches) across five maturity levels. This systems-thinking approach reveals how innovation scales and embeds within an organization over time.

At the initial stage, key priorities include training initiatives, budget allocation, and basic data security measures. These reflect the organization's need to build foundational capabilities. In the MLP framework, this aligns with isolated, experimental efforts (niches) and minimal pressure from the landscape. In contexts such as Iran, this suggests the necessity of investing in employee training for basic tech and data awareness, alongside minimal infrastructure funding to initiate digital transformation.

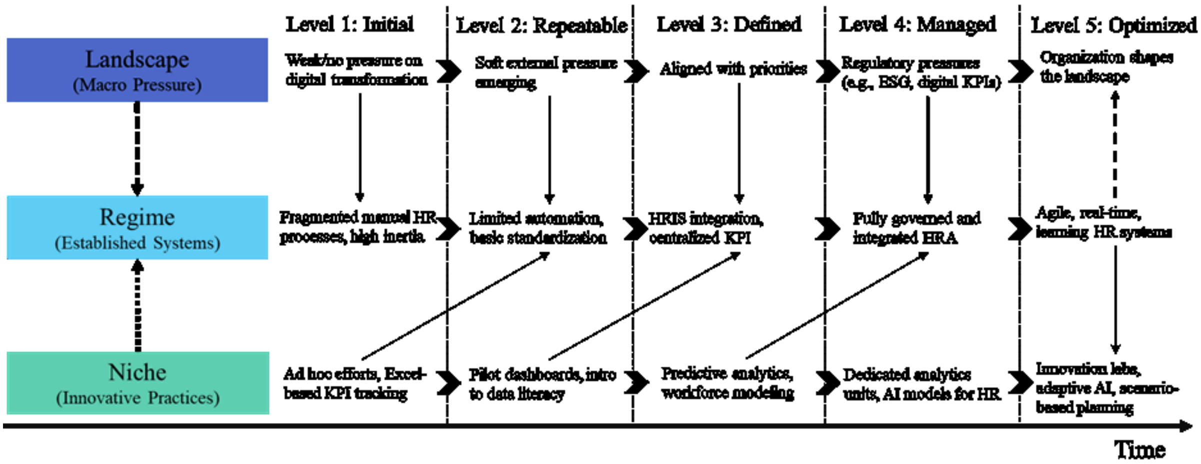


Figure 5. Multi-level perspective (MLP) of HR analytics maturity across five levels.

In the repeatable level, integration becomes essential. Regimes, partially automated systems, basic KPI tracking, and managerial support evolve from pilot innovations. Increasing budget flexibility and standardized training help overcome systemic inertia. For large Iranian organizations with siloed structures, developing integrated data systems is crucial to improve efficiency and coordination.

By the defined level, data systems are formalized. Organizations begin to develop centralized storage and structured access. Regimes stabilize, and predictive capabilities emerge. This stage benefits from strong managerial sponsorship and full systematization of data architecture. Iranian firms managing fragmented data ecosystems must prioritize storage standardization and stakeholder alignment to move beyond local optimizations.

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At the managed level, pressures from the landscape (e.g., regulatory frameworks and ESG reporting standards) intensify. The regime becomes governed, and data systems are integrated across functions. Security incidents can be reduced through advanced protocols, and sustained managerial commitment is critical. In the Iranian context, attention to data protection and regulatory alignment will be key to building resilient systems.

Finally, in the optimized level, the boundary between niche and regime fades. Organizations adopt agile, real-time analytics systems and co-shape industry landscapes through innovation. Investment efficiency, standards harmonization, and a wide-scale data-driven culture become core capabilities. For organizations operating in rapidly evolving environments such as Iran, adapting to global technological standards and fostering an analytics-driven workforce can provide a critical competitive advantage.

This study underscores the critical role of HRA in shaping data-driven decision-making across various stages of organizational maturity. Through the prioritization and evaluation of KPIs, we observe that organizations transition from foundational concerns, such as training and data security, toward advanced capabilities like system integration, predictive modeling, and strategic resource allocation. Importantly, HRA maturity is not merely a technical upgrade but a strategic transformation in how human capital is understood, managed, and optimized. The shifting weight of KPIs across maturity levels reflects the evolving needs of organizations as they align HR functions with broader institutional goals. For countries like Iran and similar developing contexts, this progression offers a roadmap for scaling HRA adoption from isolated efforts to institutionalized intelligence.

Methodologically, the study adopts a systems-thinking lens, integrating the MLP to understand the nonlinear and dynamic nature of maturity transitions in HR analytics. Rather than viewing the maturity journey as a staged checklist, MLP allows us to contextualize each stage within the interaction of landscape-level pressures, regime-level organizational structures, and niche-level innovations. This layered framework highlights how external regulatory changes, internal managerial shifts, and localized pilot efforts collectively shape the path toward data-driven maturity. The use of FAHP to weight KPIs complements the MLP by quantifying priorities while acknowledging uncertainty and complexity. Ultimately, this combined approach offers both depth and structure to HRA research, enabling a more realistic, adaptive, and forward-looking assessment of organizational readiness.

## 6. Conclusion

This study demonstrates the strategic value of HRA as a maturity-building tool that enables organizations to shift from reactive HR management to integrated, predictive, and optimization-oriented practices. Through the identification and fuzzy prioritization of nine KPIs, the findings reveal a structured path from foundational capabilities, such as training and data security, to advanced dimensions, including real-time system integration and budget optimization. The distribution of KPI weights across maturity levels not only offers diagnostic insight but also highlights the evolving competencies required at each stage. For Iranian organizations operating in transitional economies, these insights provide a scalable roadmap for maturing HRA practices in alignment with resource availability and institutional readiness.

More importantly, by applying a systems-thinking lens through the MLP, the study reframes HRA development as a dynamic socio-technical transition rather than merely a set of technical upgrades. This approach clarifies how broader environmental pressures (landscape), entrenched organizational systems (regime), and bottom-up innovations (niches) interact to influence the pace and success of HRA adoption. The integration of FAHP with MLP reveals that KPI prioritization results from ongoing co-evolution across these levels, and that meaningful transformation requires alignment across strategic, operational, and experimental domains. This layered interpretation deepens our understanding of organizational maturity and serves as a practical planning framework for institutions seeking resilience amid digital transformation.

This study has several limitations that inform cautious interpretation of the results. First, the context is Iran. Institutional settings, regulatory structures, and digital readiness in Iran differ from those in many countries, which may limit generalizability. The maturity pathways and KPI priorities we report should be viewed as a context-informed baseline that requires local calibration elsewhere. Second, the evidence base for KPI identification relies on a scoping review. Scoping reviews emphasize breadth over exhaustive appraisal, which can introduce selection bias and publication bias. Although we searched multiple databases and applied explicit inclusion criteria, some relevant studies may have been missed, particularly non-indexed or practice-oriented sources. Third, expert elicitation for FAHP introduces subjectivity. Despite using structured pairwise comparisons, consensus procedures, and consistency checks, judgments reflect the perspectives of a limited panel. The FAHP variant adopted here, Chang's method, prioritizes simplicity and transparency, yet it is sensitive to the mapping of linguistic terms to triangular fuzzy numbers and to the aggregation scheme. Fourth, the design is crosssectional. We infer maturity transitions using MLP interpretation and expert knowledge rather than tracking organizations longitudinally. As a result, causal dynamics and the timing of transitions remain to be validated with panel data, case studies, or field experiments. These limitations motivate future work. Replication in other developing and developed contexts, mixed-method validation using organizational case studies, longitudinal measurement of maturity change, and comparison of FAHP variants or alternative MCDMs can strengthen external validity and methodological robustness.

Looking ahead, this study paves the way for the development of adaptive, systems-oriented decision-making tools in HR analytics. Future research should build on the MLP framework to develop simulation models that map multiple transition pathways across various policy and technological scenarios. Such models can help organizations identify leverage points, such as regulatory shifts, scaling pilot programs, or strategic reinvestment, that accelerate progress toward maturity. These simulations, embedded in system dynamics or agent-based modeling techniques, enable practitioners to test "what-if" scenarios and anticipate resistance points within their HR infrastructure. This direction holds particular promise in volatile and uncertain environments where agility and foresight are indispensable. In addition, several concrete directions can extend the model's scope and validity. First, adapt the maturity framework to sector-specific contexts, for example, healthcare, manufacturing, and financial services, with tailored KPI taxonomies and process maps. Second, conduct cross-cultural validation across developing and developed economies to examine contextual transferability and to recalibrate KPI weights where needed. Third, implement longitudinal field studies that track organizations across maturity stages and compare simulated trajectories with observed transitions. Fourth, triangulate FAHP with complementary MCDM approaches and qualitative case studies to test robustness, refine constructs, and capture socio-technical nuances. Furthermore, the methodological integration of MLP with other soft systems and MCDMs, such as DEMATEL, system dynamics, or scenario-based fuzzy cognitive mapping, can provide richer diagnostic and prescriptive capabilities. These hybrid frameworks can explore non-linear feedback loops, cross-domain interdependencies, and cultural adaptation challenges that often hinder HR transformation. Particularly in developing contexts like Iran, where institutional inertia and policy fragmentation are common, systems thinking-based approaches can bridge the gap between strategic intent and practical execution. By institutionalizing these tools within HR departments, organizations will be better equipped to design data strategies that are not only technically sound but also socially and contextually embedded.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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