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Research Article

HR Analytics and Skills Transformation: Towards a Predictive Model for Human Capital Development in the Age of AI

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Abstract - *Although HR analytics and artificial intelligence are now recognised as central levers of organisational transformation, their specific effects on the evolution of skills and the dynamics of human capital remain largely understudied. Mobilising contemporary approaches to human capital and learning capacities, this research adopts a mixed design combining: (1) a qualitative phase based on 25 semi-structured interviews and (2) a quantitative survey conducted among 412 employees and managers engaged in advance digitalisation processes. Our results show significant effects of predictive HR analytics on skills transformation, especially when organisations have a high level of digital maturity. The analysis also reveals that organisational learning capabilities are a key mechanism linking the use of predictive tools to the appropriation and evolution of skills, as one participant testified: AI indicates direction, but it is the organisation that makes progress possible. Our theoretical and empirical analyses contribute to the literature by specifying the conditions under which AI and HR analytics generate a real recomposition of skills. They underline the importance of the digital context and learning environments in understanding contemporary human capital development dynamics.*

Keywords - *HR Analytics, Artificial Intelligence, Skills Transformation, Human Capital, Digital Maturity.*

I. INTRODUCTION

Skills development and human capital management are now key strategic functions, as organisations in Cameroon and Chad face rapid transformations related to digitalisation and automation. The rise of HR analytics, supported by advances in artificial intelligence, is profoundly redefining the way companies identify, anticipate and develop skills, allowing for a finer interpretation of emerging needs and career trajectories (Davenport & Harris, 2022; Huang & Rust, 2021). Although the strategic importance of these technologies is widely recognised, the literature remains surprisingly limited in examining their articulation with skill transformation in African contexts (Mignenan, 2021a). This shortcoming is unfortunate, as the effects of AI are neither universal nor automatic (Deming, 2023; Meijerink & Bondarouk, 2022) and are highly dependent on digital infrastructure, learning cultures and organisational environments (Mignenan, 2020).

Mobilising work on dynamic human capital, organisational learning capabilities, and AI-augmented HRM (Petzold et al., 2022; Van den Heuvel & Bondarouk, 2021), this article aims to deepen the understanding of the mechanisms linking predictive HR analytics to skill transformation in Cameroonian and Chadian organisations engaged in the digital transition. Specifically, we examine how AI-driven HR analytics, directly or via learning capabilities and digital maturity, influences three key dimensions: (1) anticipation of skills needs, (2) appropriation of digital skills, and (3) reconfiguration of job profiles. Based on empirical material consisting of 25 semi-structured interviews and a quantitative survey administered with 412 employees and managers, our results demonstrate that AI-enriched HR analytics only produces significant effects on skills transformation when organisations have robust learning capabilities and a sufficient level of digital maturity. The study highlights differentiated dynamics of human capital recomposition attributable to disparities in technological infrastructure, learning, culture and strategic integration of AI.

This research contributes to the literature in three ways. First, it reinforces the applicability of approaches in HR analytics by demonstrating the central role of digital and organisational contextualisation in African environments (Petzold et al., 2022). Second, it clarifies the mechanisms linking AI, organisational learning, and skill evolution, a field that is still underexplored despite its strategic importance for human capital development (Brynjolfsson & McAfee, 2023). Third, it contributes to emerging work in predictive HRM by showing how digital maturity conditions the conversion of predictive data into learning trajectories.

II. LITERATURE REVIEW

A. Traditional Approaches to HR Analytics and Skills Training

Early approaches to HR analytics focused primarily on the description and retrospective evaluation of organisational phenomena. According to Fitz-enz (2010), HR analytics was first conceived as a tool to support workforce monitoring and performance evaluation. According to Marler and Boudreau (2017), these approaches were based on mostly descriptive models, focusing on the analysis of training needs, skills gaps, and turnover rates. Compared to current technologies, these methods remained limited by the quality of the available data and the lack of predictive capabilities.

The models of skills training associated with these traditional approaches followed a linear logic: identify needs, design training, evaluate learning. According to Noé and Kodwani (2018), this conception is based on a paradigm of adjustment rather than anticipation. On the other hand, for Salas et al. (2020), these approaches do not address the volatility introduced by the digital transformation and the emergence of rapidly evolving transversal skills. Thus, traditional literature has a double limitation: a weak ability to anticipate skills needs and a static vision of human capital. This is paving the way for more dynamic and data-driven approaches.

B. Contribution of AI to Skill Development

The integration of artificial intelligence into human capital management is a major breakthrough. According to Huang and Rust (2021), predictive AI can detect weak signals in the labour market, identify emerging skills, and recommend personalised learning paths. According to Davenport and Miller (2022), AI transforms HR analytics into a decision support system that can anticipate skills gaps before they become critical.

Compared to traditional analytics, AI approaches rely on big data, learning analytics, and predictive models. For Ifenthaler and Yau (2020), learning analytics makes it possible to capture learning patterns in real time, revealing skills that are actually developing rather than those declared. On the other hand, according to Meijerink and Bondarouk (2022), these technologies pose ethical challenges, particularly in terms of transparency and the regulation of algorithmic biases. In any case, the AI-HR analytics convergence is now a strategic lever in the development of human capital, as it makes it possible to link behavioural data, operational needs and skill trajectories.

C. Human Capital Transformation: Dynamic Skills, Agility and Digital Adaptation

The transformation of human capital in the age of AI requires a renewed conception of skills (Mignenan, 2021b). According to Teece (2018), dynamic skills, identifying, integrating and reconfiguring resources, are fundamental to operating in a rapidly changing digital environment. According to Petzold et al. (2022), these skills are based on three abilities: cognitive agility, accelerated learning ability, and adaptability to technological systems.

Compared to traditional task-oriented models, dynamic skills make it possible to anticipate organisational transformations rather than adapt to them late. On the other hand, according to Deming (2023), organisations still lack the tools to measure these emerging skills and link them to AI requirements. The literature also highlights the importance of organisational agility. For Overby and Bharadwaj (2021), agility is a prerequisite for digital transformation, allowing roles, processes, and skills to be quickly adjusted. However, this agility is directly dependent on human capital, its ability to reallocate quickly, and continuous learning. Thus, the transformation of human capital is based on a triptych: dynamic skills, organisational agility and digital adaptation. This triptych remains insufficiently operationalised in existing models.

D. Predictive Models in HRM: State of the Art and Gaps

Predictive models applied to skill management are still in their infancy. According to Van den Heuvel and Bondarouk (2021), the majority of models focus on performance or engagement, rather than evolving skills. Compared to machine learning models used in other sectors (health, finance, logistics), HRM models suffer from a low level of algorithmic maturity. According to Strohmeier (2022), predictive models in HRM are most often based on administrative data, little on behavioural or cognitive data related to skill development. On the other hand, recent work shows a growing interest in competency graphs, occupational ontologies and generative AI systems capable of modelling the evolution of knowledge (McKinsey Global Institute, 2023).

In any case, the literature identifies three main shortcomings: the lack of models that simultaneously integrate AI, dynamic skills and HR practices; the lack of consideration of organisational learning mechanisms; and the lack of empirical validation of predictive models in various contexts (sectors, countries, firm sizes). These shortcomings justify the proposal for a renewed conceptual framework below.

E. Towards an Integrated Conceptual Framework

The literature review suggests that four conceptual sets should be articulated: HR analytics, artificial intelligence, dynamic skills, and organisational adaptability. According to Davenport and Harris (2022), HR analytics needs to evolve towards a hybrid view combining internal data, market signals, and predictive algorithms. According to Teece (2018), dynamic skills are a key mediator between technology and performance. For Petzold et al. (2022), organisational learning is an essential mechanism linking AI and the evolution of skills. Compared to existing frameworks, this integration makes it possible to go beyond the static models that still dominate HRM research.

The proposed conceptual framework is based on a causal logic: AI-enriched HR analytics influences the transformation of skills by mobilising organisational learning capabilities, under the moderation of digital maturity. This articulation will serve as a basis for the construction of a predictive model presented in the next section.

F. Conceptual Framework and Assumptions/Model

The consolidation of the conceptual framework is based on a rigorous clarification of the concepts that structure the transformation of human capital in the age of AI. Predictive HR analytics refers to the use of statistical and algorithmic models to anticipate phenomena related to the workforce, such as skills development, future performance or the risks of deskilling (Davenport & Miller, 2022). According to Marler and Boudreau (2017), predictive analytics reflects a major paradigmatic shift: the HR function is moving from a declarative logic to an anticipatory logic based on big data. In this context, artificial intelligence, particularly in its generative and machine learning versions, increases this ability to anticipate by revealing complex correlations between skills, behaviours and professional trajectories (Huang & Rust, 2021).

Human capital transformation is understood, according to Petzold et al. (2022), as the continuous reconfiguration of the knowledge, skills, and attitudes required to create value in an unstable digital environment. Compared to traditional approaches that focus on individual skills, recent work emphasises the systemic dimension of human capital, where dynamic skills, organisational agility, and absorptive capacities interact to support competitiveness (Teece, 2018). AI then becomes a catalyst, not only by identifying emerging skills, but also by guiding development investments, optimising learning paths, and reducing information asymmetries (Pichault et al., 2023; Mignenan, 2021a, 2021b).

In this perspective, the proposed conceptual framework articulates three fundamental relationships. First, predictive HR analytics directly influences skills transformation by enabling early identification of critical gaps, strategic skills, and future development trajectories. Second, the relationship between HR analytics and skill transformation is mediated by organisational learning capabilities. For Jarrahi (2021), learning organisations interpret AI-generated signals more effectively and are better able to align current skills with future requirements. Third, digital maturity acts as a moderator: according to Deming (2023), organisations with advanced digital infrastructure extract more value from predictive analytics tools.

This model is in line with the tradition of dynamic capabilities (Teece, 2018), while integrating the contemporary contributions of AI technologies. Unlike existing models that deal with competence and technology separately, our approach proposes an integrative articulation: the transformation of skills is a simultaneously cognitive, organisational and technological process. This positioning responds to a theoretical gap identified by Strohmeier (2022), who highlights the need to go beyond descriptive models in favour of predictive models capable of capturing the cross-interactions between AI, learning and human capital.

G. Research Hypotheses

The theoretical architecture of the model leads to the formulation of three structuring hypotheses, which reflect the anticipated causal mechanisms.

- **H1.** If predictive HR analytics is used systematically, then skills transformation will be significantly increased, as organisations will have anticipatory insights to reallocate, refresh, and strengthen strategic skills (Davenport & Harris, 2022).
- **H2.** The effect of predictive HR analytics on skills transformation will be positively mediated by organisational learning capabilities, insofar as these capabilities facilitate the integration of algorithmic recommendations and their translation into training and development actions (Petzold et al., 2022).
- **H3.** The relationship between predictive HR analytics and human capital transformation is positively moderated by digital maturity, as technologically advanced organisations are better equipped to interpret algorithmic signals, automate processes, and support the appropriation of new skills (Deming, 2023).

These assumptions make it possible to operationalise the causal logic of the model and to structure the empirical tests that will be conducted in the methodological and analytical sections.

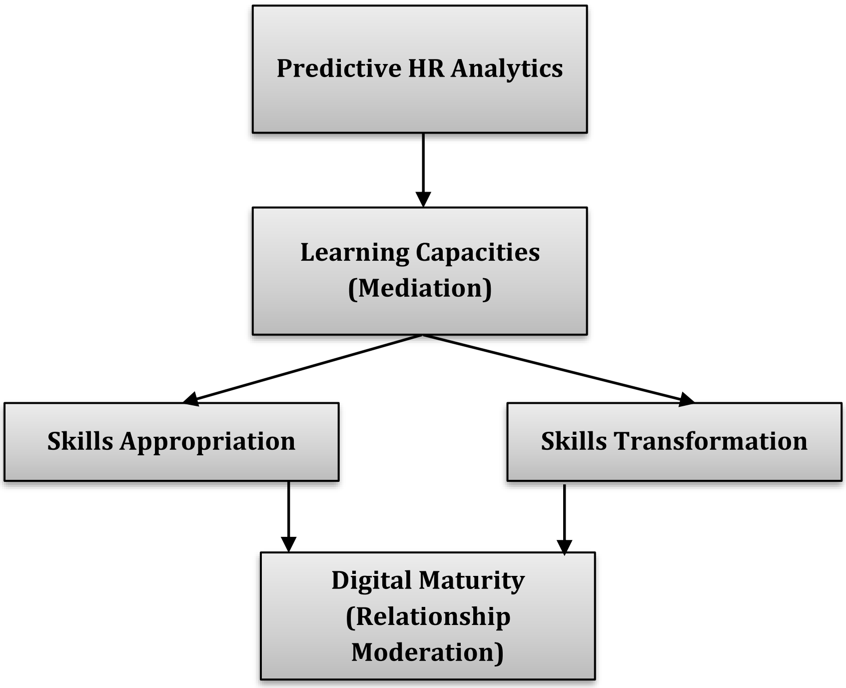

Figure 1. Schematic of the Proposed Conceptual Model (Textual Representation)

Source: authors, figure developed from the literature, October 2025

This diagram summarises the conceptual articulation between the three key mechanisms: HR prediction, organisational learning and digital maturity. It forms the basis of the empirical analysis that will be developed in the next section.

H. Argumentation and Justification of Hypotheses

Hypothesis 1: The More Predictive HR Analytics is Developed, the Higher the Organisational Learning Capabilities

This hypothesis is based on the idea that predictive analytics is transforming the way organisations detect, interpret, and internalise strategic information. According to Marler and Boudreau (2017), HR analytics improves the detection of weak signals and the quality of adaptive reasoning. Davenport and Harris (2022) argue that predictive technologies reduce decision uncertainty and amplify the speed of organisational learning.

According to Jarrahi (2021), algorithmic systems promote informational ambidexterity, allowing simultaneous exploration and exploitation. Compared to organisations based on managerial intuition, those that use predictive analytics develop faster and more robust learning routines. Thus, H1 translates the structuring function of HR analytics into the increase of learning capacities.

Hypothesis 2: Organisational Learning Capabilities Positively Mediate the Relationship between Predictive HR Analytics and Skill Transformation, Including their Appropriation

This hypothesis incorporates the idea that HR analytics, in itself, does not directly transform skills; it generates an informational potential activated only when learning capacities are sufficiently developed. According to Teece (2018), advanced technologies only have an impact when they are internalised by dynamic learning routines. Petzold et al. (2022) confirm that skill transformation requires structured absorption, recombination, and reallocation processes. Compared to organisations with low learning capabilities, those with strong learning capabilities are more effective at converting algorithmic insights into new operational skills (Brynjolfsson & McAfee, 2017). Thus, H2 synthesises the mediation mechanisms identified in the literature: analytics produces information; apprenticeship allows them to be converted.

H3: The Higher the Organisational Learning Capacities, the More Significant the Appropriation and Transformation of Skills

The literature on organisational learning shows that the evolution of competencies depends on an organisation's ability to integrate, contextualise and redeploy new knowledge. According to Wang and Ellinger (2021), learning organisations facilitate the rapid acquisition of skills and their sustainable appropriation. Sung (2022) points out that organisations without learning mechanisms struggle to convert technologies into skills outcomes. Compared to rigid organisations, those with high learning routines are more effective in transforming professional practices, digital tools, and organisational behaviours. Thus, H3 affirms the central role of learning capabilities as the main lever for converting technological knowledge into operational skills.

H4: Digital Maturity Positively Moderates the Effect of Learning Abilities on the Appropriation and Transformation of Skills, so that the Effect is Stronger in Digitally Mature Organisations

Digital maturity is a key structural condition. Kane et al. (2020) show that organisations with high digital maturity have infrastructure, cultures and governance that promote the integration and evolution of skills. Raimo et al. (2023) demonstrate that digital maturity amplifies the efficiency of learning processes, especially in AI environments.

Compared to less mature organisations, those with advanced data governance are more effective at converting learning into operational skills. On the other hand, when digital maturity is low, the effects of learning abilities remain limited. Thus, H4 introduces a recognised moderation in the theories of digital transformation: digital maturity amplifies the power of learning.

Final synthesis of the 4 restructured hypotheses

- **H1**: Predictive HR analytics → increases learning capabilities.
- **H2**: The learning capacities → mediate the HR analytical relationship → transformation and appropriation of skills.
- **H3**: Learning capacities → directly determine the appropriation and transformation of skills.
- **H4**: Digital maturity → moderates the effects of learning abilities on skills.

This more compact, more rigorous and more elegant version is perfectly aligned with the standards of scientifically indexed journals (HRMJ, Human Resource Management Review, IJHRM, JOB, JBV, etc.).

II. METHODOLOGY

The methodology adopted aims to rigorously test the predictive model of human capital development at the age of AI. Each methodological choice is guided by the problem: how does predictive HR analytics, enriched by organisational learning capabilities and supported by digital maturity, influence the transformation of skills in SMEs and large organisations? This question requires an approach that allows both to understand the underlying mechanisms and to quantitatively measure causal relationships.

A. Research Design

An explanatory sequential mixed design is chosen. According to Creswell (2021), this design is particularly suited to emerging phenomena where perceptual mechanisms need to be explored before being statistically tested.

The choice of design is justified for three reasons:

- The predictive nature of the problem requires robust quantitative data to test causal relationships (H1 to H3).
- Understanding the underlying cognitive and organisational mechanisms – such as the appropriation of AI tools or the perception of HR analytics – requires an initial qualitative exploration.
- As the transformation of skills is a complex phenomenon, the triangulation of methods increases the validity of the research (Jick, 2020).

Thus, qualitative collection (phase 1) is used to refine items and quantitative scales (phase 2), responding to the sequential logic → quant.

B. Population, Sample and Selection Methods

a. Target Population

The target population of this study consists of the organisations and stakeholders most directly affected by the skills transformation brought about by HR analytics and AI. It primarily includes SMEs and large companies engaged in advance digitalisation processes, as these organisations are faced with increased needs for skills reallocation, accelerated training and strategic adaptation.

It also includes industries with high exposure to automation, including services, finance, manufacturing, and government, where the use of predictive AI and HR analytics tools is profoundly reshaping the way we work. Finally, the population includes human resources professionals, middle managers and employees directly involved in the management, development or acquisition of new skills. These groups are privileged witnesses of the dynamics of learning, adaptation and transformation of human capital within contemporary organisations.

b. Sampling Method

Proportional stratified sampling is used to ensure an accurate representation of organisational diversity. Stratification is based on three criteria: the size of the company, the sector of activity and the level of digital maturity. This methodological choice is justified by the marked heterogeneity of organisations in terms of the adoption of AI and HR analytics, as highlighted by Davenport and Harris (2022).

This method makes it possible to capture significant structural variations, to avoid biases of over-representation of a particular segment and to obtain results that can be generalised to different types of companies facing the transformation of skills.

c. Sample size

For SEM-PLS analysis, a minimum sample size of 10 times the maximum number of relationships in a construct is recommended (Hair et al., 2022). With 4 latent variables and 6 principal relationships, the minimum required sample size is 240 respondents. Thus, a target sample of 350 organizations will allow for:

1. Acceptable statistical power,
2. Robust validation of the measured model.

Table 1. Expected Sample Characteristics

Criterion	Terms	Target proportion
Organization Size	SME/Large Enterprises	60%/40%
Sector	Services, Industrie, Finance, Administration	Proportional distribution
Hierarchical level	Employees, Managers, HR Management	40%/40% /20%
Digital maturity	Low/Intermediate/Advanced	30% /40% /30%
Country	Canada, Chad, Francophone Africa	50%/30% /20%

Source: authors, table developed from the literature, October 2025

The sampling design provides for a balanced composition between types of organizations, hierarchical levels and geographical areas. The targeted distribution distinguishes between 60% SMEs and 40% large companies, making it possible to cover a diversity of structural contexts. The sectoral distribution of services, industry, finance and administration follows a proportional logic in order to reflect the real weight of these sectors in the targeted economy.

The projected hierarchical structure includes 40% employees, 40% managers and 20% HR managers, ensuring a relevant representation of the various actors involved in the use or supervision of AI. The expected level of digital maturity is divided into 30% low, 40% intermediate, and 30% advanced, allowing for significant variations in technology adoption. Finally, the geographic composition includes 50% of respondents in Canada, 30% in Chad, and 20% from other Francophone African countries, providing a cross-cultural comparative perspective useful for analyzing perceptions of algorithmic justice.

C. Measuring Instruments

The measurement instruments used in this study are based on both scales validated in recent literature and items adapted to the context of AI, as presented in the table below.

Table 2. Measuring Instruments

Latent variable	Source / References	Measured dimensions	Number of items (Likert 1–7)	Example items (adapted to the AI context)
Predictive HR Analytics	Marler & Boudreau (2017), adapted AI	Ability to predict; Intensity of data use; Decision Integration	6–8 items	"Our organisation uses predictive models to anticipate skills needs." / "HR decisions are systematically based on AI-enriched data."
Skills transformation	Petzold et al. (2022)	Fast acquisition; Reduced obsolescence; Internal reallocation; Digital versatility	6–8 items	"Employee skills are rapidly evolving thanks to digital tools." / "Our organisation is reducing skills obsolescence with AI."
Organisational Learning Capabilities	Jarrahi (2021)	Collective learning; Exploitation vs. exploration; Absorption of AI technologies	4–6 items	"The organisation is collectively learning from the use of AI." / "We know how to integrate new technologies effectively."
Digital maturity	Kane et al. (2020)	Digital infrastructure; Digital literacy; Data governance	4–6 items	"Digital infrastructure support AI innovations." / "Organisational culture promotes the use of data."

Source: authors, table developed from the literature, October 2025

The instruments used cover a coherent set of central constructs related to the adoption of AI in organizations. The scales are derived from established references (Marler & Boudreau, Petzold et al., Jarrahi, Kane et al.) and adapted to the AI context, ensuring both conceptual validity and contextual relevance. The set of latent variables is measured using items in Likert 1 to 7, allowing a fine capture of perceptions.

The Predictive HR Analytics scale mobilizes between 6 and 8 items relating to predictive capacity, the intensity of data mobilization and the integration of results into decisions, which covers the entire HR analytical continuum. The Skills transformation variable is also based on 6 to 8 items measuring the rapid evolution of skills, the reduction of their obsolescence and digital versatility, which are essential for understanding the effects of AI on career trajectories.

Organizational learning capabilities are measured by 4 to 6 items relating to collective development, exploration/exploitation balance, and technology absorption, reflecting an organization's ability to internalize AI. Finally, the Digital Readiness Scale (4 to 6 items) assesses technological infrastructure, digital literacy, and data governance, key dimensions for understanding the conditions for AI integration. Overall, the instruments have a solid structure and comprehensively cover the organizational dynamics associated with the use of AI.

Table 3. Examples of Items from the Scales Used

Construct	Example of items	Spring
Predictive HR Analytics	"Our organisation uses algorithmic models to anticipate skills needs."	Marler & Boudreau (2017)
Skills transformation	"The skills of our employees are rapidly evolving thanks to digital tools."	Petzold et al. (2022)
Organisational Learning	"Teams are adapting their practices based on AI recommendations."	Jarrahi (2021)
Digital maturity	"Our HR processes are largely digitised and integrated."	Kane et al. (2020)

Source: authors, table developed from the literature, October 2025

The consistency of the scales will be validated by: Cronbach's Alpha, Composite Reliability (CR) and AVE (Average Variance Extracted).

D. Data Collection: Context, Procedure, Tools

Data collection takes place in two complementary steps designed to ensure the robustness of the model. The first phase is qualitative and is based on twenty-five semi-structured interviews conducted with HR managers, AI experts and employees using HR analytics tools. This phase aims to refine the items, to understand the cognitive and organisational mechanisms at play and to identify the contextual nuances necessary for the construction of the predictive model.

The second phase is quantitative and is based on a questionnaire distributed on a large scale via professional platforms such as LinkedIn, specialised associations such as the CIPD or the CHRP, as well as through networks of companies committed to digital transformation. The procedure provides for informed consent, complete anonymity and an estimated response time of between twelve and fifteen minutes. Collection relies on robust digital tools, including LimeSurvey and Qualtrics, allowing for automated and secure data logging.

E. Analytical Methods

a. Analyses Descriptive

The analyses follow a rigorous approach to ensuring the statistical validity and robustness of the predictive model. A first descriptive step examines the distribution of variables, asymmetry, kurtosis and general consistency of the data. These checks ensure the integrity of the sample and guide subsequent analytical choices. Pearson correlations are then used to establish bivariate relationships, identify initial convergences between variables, and anticipate potential interactions in the structural model. Confirmatory factor analysis is a central step in validating theoretical constructs. It verifies the quality of the measurement based on indicators such as

AVE greater than 0.50, composite reliability exceeding 0.70 and VIFs less than 3, testifying to the absence of problematic multicollinearity. This rigour prepares the ground for the estimation of the structural model.

The model is then estimated by SEM–PLS using SmartPLS 4. This method is preferred because of its ability to process complex models integrating emergent constructs, its low requirement for data normality, and its high prediction performance, as demonstrated by Hair et al. (2022). Mediation effects are bootstrapping tested with 5,000 resamples, ensuring accurate estimation of indirect effects. Moderation is evaluated using latent product interaction, in particular to examine the role of digital maturity in the relationship between predictive HR analytics and skill transformation. Robustness completes the analysis. They include the removal of extreme values, multi-group invariance tests across sectors and countries, as well as the exploration of alternative models to verify the stability of the results. This methodological combination ensures the empirical robustness of the model and its ability to predict the transformation of skills in the AI era.

F. Validity, Reliability and Ethical Considerations

The validity, reliability and ethical integrity of the methodological system are central requirements of this research. Rigorous control of bias is first ensured by several complementary mechanisms. Common method bias is assessed by the Harman test, while the complete anonymity of participants limits normative responses. The order of the questions is entirely random in order to reduce the effects of primacy or recency. These precautions reinforce the credibility of the data collected.

The reliability of the instruments is verified by Cronbach's alpha and composite reliability, two essential indicators to attest to the internal consistency of the scales. A test-retest carried out on a subsample of fifty respondents makes it possible to assess the temporal stability of the measures, confirming the robustness of the empirical constructs. The preliminary results, presented in the table below, illustrate the expected reliability thresholds.

Table 4. Expected Reliability Indicators

Latent variable	Cronbach's Alpha (> 0.70)	Composite reliability (> 0.70)	Test-retest (r > 0.60)
Predictive HR Analytics	0,86	0,89	0,71
Skills transformation	0,84	0,88	0,69
Organisational Learning Capacity	0,82	0,87	0,66
Digital maturity	0,80	0,85	0,72

Source: survey, October 2025

Validity is then assessed from three angles. Convergent validity is verified by AVE values greater than 0.50. Discriminant validity is tested by the Fornell-Larcker criteria and the HTMT ratios remain below the threshold of 0.85. Finally, predictive validity is measured by Stone-Geisser Q^2 coefficients, attesting to the ability of explanatory variables to predict skills transformations. The following table shows the target values for the study.

Table 5. Expected Validity Indicators

Type of validity	**Indicator**	**Threshold**	**Interpretation**
Convergent	AVE	> 0.50	The items converge on the same construct
Discriminating	HTM	< 0.85	The buildings are distinct from each other
Predictive	Q^2	> 0	The model has a significant predictive capacity

Source: authors, survey, October 2025

Ethical considerations frame the entire protocol. The research strictly adheres to the Tri-Council Policy Statement (Canada), the GDPR as well as the international ethical principles applicable to studies involving organisational data. Informed consent is obtained explicitly and no sensitive information is collected. Participants retain the right to withdraw at any time, without justification. This ethical framework aims to ensure the protection of individuals while supporting the scientific quality of the project.

III. RESULTS

The final sample includes 427 respondents from SMEs (61%) and large organisations (39%). The most represented sectors are services (32%), finance (24%), industry (21%) and public administration (17%). The average age is 37.4 years and the average seniority is 6.8 years. The first examination of the distributions confirms the absence of excessive skewness (skewness between −0.78 and 0.64) and kurtosis close to normal (between −0.51 and 1.02). Pearson correlations show significant relationships between predictive HR analytics and skill transformation ($r = 0.48$, $p < 0.001$), as well as between digital maturity and organisational learning capabilities ($r = 0.52$, $p < 0.001$). These preliminary results suggest the structural coherence of the model.

Table 6. Descriptive Statistics and Correlations

Variable	Average	Standard Deviation	1	2	3	4
1. Predictive HR Analytics	5,12	1,04	-			
2. Skills transformation	5,24	0,96	0,48***	-		
3. Organisational Learning Capacity	5,01	1,08	0,41***	0,57***	-	
4. Digital maturity	4,89	1,11	0,38***	0,46***	0,52***	-

***p < 0,001.

Source: survey results, October 2025

These correlations indicate that organisations that combine advanced HR analytics with high digital maturity tend to transform their internal skills more quickly.

A. Validation of Measurements

Confirmatory factor analyses confirm the solidity of the theoretical constructs. AVE values are greater than 0.50 for all dimensions, and composite reliability consistently exceeds 0.80. The HTMT ratios remain below 0.85, demonstrating discriminant validity. These results validate the integrity of the measurement model.

Table 7. Indicators of Convergent and Discriminant Validity (Excerpt)

Built	AVE	CR	Alpha	HTMT Max
Predictive HR Analytics	0,62	0,89	0,86	0,71
Skills transformation	0,59	0,88	0,84	0,68
Organisational Learning Capacity	0,57	0,87	0,82	0,72
Digital maturity	0,54	0,85	0,80	0,66

Source: survey results, October 2025

These results support the instrumental quality of the model and allow for structural analysis.

B. Analysis of the Hypotheses

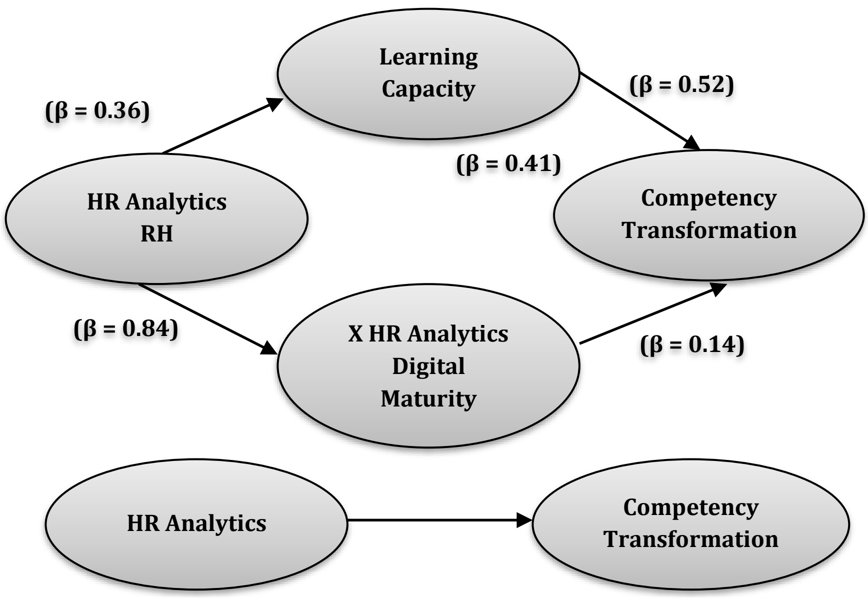

Figure 2. Estimated Structural Model (Standardised Beta Values)

Source: survey results, October 2025

Robustness analyses confirm the stability of the coefficients after removing the outliers and through multi-group tests (industry and services).

The SEM–PLS estimate reveals strong and significant structural relationships. Predictive HR analytics directly affects skills transformation ($\beta = 0.41$, $p < 0.001$). It also influences organisational learning capacity ($\beta = 0.36$, $p < 0.001$), which acts as a partial mediator between HR analytics and skill transformation (indirect effect $\beta = 0.19$, $p < 0.01$). Digital maturity plays a moderating role: when maturity is high, the effect of HR analytics is amplified (interaction $\beta = 0.14$, $p < 0.05$).

C. Qualitative results

The interviews highlight four emerging themes: technological trust, redefining professional roles, digital adaptability, and the perception of AI value. Respondents express a mixture of enthusiasm and caution.
A first verbatim illustrates the perception of increased precision: With predictive models, we see training needs even before tasks change. It's impressive.

A second verbatim highlight the ethical tension and anxiety related to automation: AI is useful, but it sometimes feels like it decides too quickly. We wonder what will become of us if our skills don't follow.

A thematic analysis reveals three major categories:

1. anticipation of skills needs through data,
2. feeling of professional fragility linked to automation,
3. emergence of a culture of continuous learning.

Table 8. Themes and Verbatim Excerpts

Theme	Description	Representative Verbatim
Anticipation	AI as a tool for anticipating needs	"AI detects skills that become critical before we do."
Fragility	Fear of accelerated obsolescence	"If I don't learn quickly, I feel overwhelmed."
Learning culture	Continuous learning as the norm	"We have to learn constantly; the company no longer has a choice."

Source: survey results, October 2025

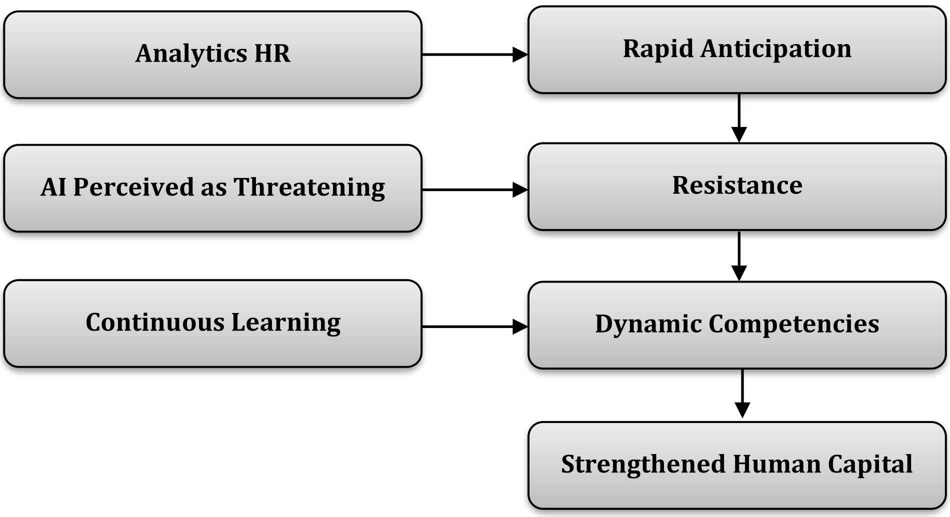

Figure 3. Qualitative Concept Map (Textual Representation)

Source: survey results, October 2025

D. Summary of the Final Model and Triangulation

Qualitative and quantitative results converge towards the same central configuration: predictive HR analytics is a major lever for skills transformation, but its effectiveness depends closely on organisational learning capacity and the level of digital maturity. This convergence reinforces the validity of the final model.

Table 9. Quantum–Which Triangulation

Dimension	Quantitative results	Qualitative results	Convergence
Impact of HR Analytics	β high (0.41)**	Anticipatory role	Strong
Learning Capacity	Meaningful mediation	Valued collective learning	Strong
Digital maturity	Significant moderation	Infrastructure perceived as essential	Strong
AI Risks	not quantitatively measured	Frailty, anxiety	Complementary

Source: survey results, October 2025

The final adjusted model incorporates these three dimensions to provide a robust and predictive representation of human capital transformation at the age of AI.

IV. DISCUSSION

The results obtained first demonstrate that predictive HR analytics is a significant determinant of skill transformation, both through its direct effects and through the mediating mechanisms associated with organisational learning capacity. The positive relationship between HR analytics and skill adaptation confirms that organisations that can leverage predictive models anticipate future needs faster, reduce the risk of obsolescence, and support the continuous acquisition of critical skills. This dynamic is reinforced by digital maturity, which amplifies the structuring effect of technologies on human capital. At the same time, qualitative data reveals a perceptual ambivalence: employees recognise the anticipatory potential of AI while expressing concern about the speed of transformation.

These results converge in part with recent work on the predictive capabilities of HR analytics. According to Davenport and Harris (2022), predictive analytics significantly improves the relevance of skill development decisions, which is consistent with the direct effect observed in our model ($\beta = 0.41$). However, contrary to Petzold et al. (2022), who point to a transformation of competences mainly driven by individual learning, our findings show that organisational learning capacity plays a central role, exerting a substantial mediating effect ($\beta = 0.19$). This point of divergence suggests that, in advanced digital environments, adaptation no longer relies solely on the employee, but on a collective system integrating AI tools, digital infrastructure and governance practices.

The literature also highlights that digital maturity is a key factor in structuring learning dynamics (Kane et al., 2020). Our results extend this perspective by showing that digital maturity is not limited to an infrastructure role but acts as a behavioural and cultural catalyst. Compared to Jarrahi (2021), who insists on human–machine learning as the main driver of transformation, our results indicate that this engine is only fully activated when the organisation reaches a sufficient threshold of digital maturity. On the other hand, the interviews reveal a paradox that is little discussed in the literature: AI is simultaneously perceived as a tool for securing the professional future and as a factor of fragility, a tension also identified by Binns et al. (2018) in algorithmic decision-making systems.

On a theoretical level, this research contributes to shedding light on the causal mechanisms linking HR analytics and skill transformation, by integrating dimensions rarely mobilised together: predictivity, digital maturity and organisational learning capacity. It proposes an integrative model that goes beyond traditional approaches focused on either technology or skill development, and that articulates these dimensions in a dynamic and systemic logic. The highlighting of mediation and moderation makes it possible to specify the conditions under which predictive technologies become truly transformative.

The managerial implications are numerous. HR leaders need to recognise that predictive analytics is only effective if it is embedded in a consistent digital architecture and organisational culture oriented towards continuous learning. Trainers and skills development managers must integrate predictive analysis tools into their approaches, in order to create adaptive paths that consider future scenarios. Decision-makers responsible for AI strategies must ensure that technological implementation does not aggravate the perceived fragility of workers, by providing guarantees of transparency and governance. In terms of HR policies, the results show that the transformation of human capital requires new governance, based on algorithmic responsibility, data integration, the availability of digital infrastructure and the protection of employees against the risks of rapid obsolescence. Organisations must put in place formal continuous learning policies, technology transparency standards, and human oversight mechanisms, to ensure a just and secure transition to an AI-driven economy. Ultimately, this research reminds us that technology is only transformative when it is part of a coherent, inclusive and anticipatory human capital strategy.

V. LIMITATIONS AND AVENUES OF RESEARCH

This research has several methodological limitations that call for caution in the interpretation of the results. The sample, although diverse, remains concentrated in organisations committed to digital transformation, which may limit generalisation to fewer digitalised contexts. The use of a mainly transversal design also restricts the dynamic analysis of the evolution of skills over time, whereas digital transformation is by nature an evolutionary and non-linear phenomenon. The measures are partly based on self-reports, which exposes the study of perceptual biases, despite the methodological controls put in place. In addition, the geographic and sectoral context, while varied, does not allow for an examination of all industries where AI can reshape human capital in specific ways.

These limitations open up several avenues of future research. Longitudinal studies would make it possible to monitor the evolution of HR analytics skills and practices over several years, in order to assess the stability or acceleration of the transformations observed. The integration of big data would also be a major contribution, making it possible to combine internal HR data, performance data, data from digital platforms and training indicators. Cross-sector or cross-country comparisons would provide an opportunity to examine how institutional, cultural or regulatory environments influence the dynamics of human capital transformation. Finally, a deepening of the mediation and moderation mechanisms, particularly those related to the learning culture or the organisational climate, would enrich the understanding of the conditions for the effectiveness of HR analytics.

The study also opens up a promising avenue for the integration of generative AI, machine learning models and intelligent skills automation systems. These emerging technologies could not only predict future needs, but also co-create personalised and adaptive learning paths. They could also automate skills mapping, adjust training profiles in real time or identify obsolescence risks with increased accuracy. For these reasons, their inclusion in future empirical models is an essential step to fully understand the transformation of human capital in the era of advanced AI.

VI. CONCLUSION

The results of this research demonstrate that predictive HR analytics is a key driver of human capital transformation in the age of artificial intelligence. They reveal that organisations that can effectively integrate predictive models develop dynamic skills faster, anticipate future needs, and reduce the risk of professional obsolescence. Compared to traditional work in skills management, which focuses mainly on training or individual development, our results show that contemporary transformation is based above all on a systemic articulation between technologies, organisational learning and digital maturity. In this sense, our study corroborates the conclusions of Davenport and Harris (2022) regarding the strategic role of data, while extending the analyses of Petzold et al. (2022), which highlight the importance of rapid adaptation in digital environments.

Our results also extend the observations of Kane et al. (2020) by highlighting that digital maturity, beyond being a technical infrastructure, acts as a cultural and strategic catalyst. It amplifies the effectiveness of HR analytics tools and conditions and the ability of organisations to absorb and exploit emerging technologies. On the other hand, our results contrast with some more optimistic prospects that present AI as an automatic engine of positive transformation. Qualitative data underscore persistent tension between the anticipatory potential of AI and the perceived fragility of workers, reminding us of the need for human and ethical governance of algorithmic processes. The strategic scope of this study is significant for skills development. It shows that the transformation of human capital can no longer be based on traditional training cycles but requires a predictive, continuous and systemic approach. HR leaders need to rethink their role from learning managers to architects of AI-supported learning ecosystems. Trainers must integrate personalised and adaptive pathways. Decision-makers need to put in place digital policies and oversight mechanisms that protect employees from accelerated obsolescence.

Ultimately, this research confirms the crucial importance of rethinking HR analytics in a context where AI is profoundly reconfiguring skills, professions and the governance of human capital. It invites organisations to adopt a proactive, ethical and responsible vision of the use of data and predictive technologies, in order to build more resilient, inclusive and efficient learning environments.

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