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Defining analytical skills for human resources analytics: A call for standardization

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Abstract

PURPOSE: *Human resources (HR) analytics systems, powered by big data, AI algorithms, and information technology, are increasingly adopted by organizations to enhance HR's impact on business performance. However, despite the widespread acknowledgment of the importance of "analytical skills" among HR practitioners in successfully implementing HR analytics systems, the specific nature of these skills remains unclear. This paper aims to address this ambiguity by firstly clarifying the concept of "analytical skills," secondly identifying skill gaps that may hinder the effective utilization of computer-assisted analytics among HR practitioners, and thirdly advocating for standardization in the understanding of "analytical skills" within the business context, particularly within HR.* ***METHODOLOGY:*** *We examine business "analytical skills" through the theoretical framework of the knowledge, skills, and abilities (KSA) included in the Occupational Information Network (O*NET) content model. Using data from the O*NET database, occupations were classified into Human Resource Management (HRM) and Analytical occupations. Then, we identified the top highly required KSAs in analytical occupations and compared their levels with those of HRM occupations to pinpoint potential gaps hindering the effective utilization of HR analytics.* ***FINDINGS:*** *Using the O*NET database, which describes work and worker characteristics, we establish the highly required analytical KSAs in the business analytics context that might be labeled "analytical skills". Then, the gap analyses reveal that important analytical KSAs, such as knowledge of sales and marketing, skills in operations analysis, and abilities in mathematical and inductive reasoning, are not expected from HR occupations, creating serious barriers to HR analytics development. In general, we have found that while HR practitioners possess some of the necessary analytical KSAs, they often lack in areas such as mathematics, computers, and complex problem-solving.* ***IMPLICATIONS:*** *Our findings underscore the need for standardization in HR analytics definitions, advocating for the adoption of the O*NET content model as a universal framework for understanding HR analytical knowledge, skills, and abilities (KSAs). By identifying critical analytical KSAs, our research can assist HR departments in improving training, recruitment, and development processes to better integrate HR analytics. Furthermore, we identify significant gaps in analytical skills among HR practitioners, offering potential solutions to bridge these gaps. From a theoretical perspective, our precise definition of HR "analytical skills" in terms of analytic KSAs can enhance research on the effects of HR analytics on organizational performance. This refined understanding can lead to more nuanced and impactful studies, providing deeper insights into how HR analytics contributes to achieving strategic business goals.* ***ORIGINALITY AND VALUE:*** *Our research offers three original insights. First, we establish a standard for HR analyst skills based on the O*NET content model, providing a clear framework for the essential knowledge, skills, and abilities required in HR analytics. Second, we identify significant analytical gaps among HR professionals, highlighting areas that need development and attention. Third, we recognize the necessity for closer cooperation between HR and professional analysts, emphasizing that such collaboration is crucial for maximizing the benefits of computer-assisted HR analytics. These insights ensure that HR analytics can move beyond being a management fad and have a real, lasting impact on business outcomes.*

Keywords: *analytical skills, human resources analytics, HR analytics, knowledge, skills, abilities, HRM, analysts, O*NET, big data, AI, standardization*

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INTRODUCTION

Human capital management (HCM) software (see Aral, Brynjolfsson, Wu, 2012) and human resources information systems (HRIS) (see Rasmussen & Ulrich, 2015) together with a variety of other "people analytics" (Tursunbayeva, Di Lauro, & Pagliari, 2018; McCartney & Fu 2022), continue to be implemented across business organizations with a mission to improve human resources management (HRM) impact on business performance giving birth to a new field of computer-assisted human resources (HR) analytics - in short, HR analytics. Drawing from one of the reviews of approaches to HR analytics (Marler & Boudreau, 2017 p.15), it might be defined as: "*An HR [human resources] practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making.*" The general idea behind HR analytics is to take advantage of information technology (IT) and the variety of workforce data that the HR departments possess but do not always use in the most effective ways. Employee pay levels across the organization, performance ratings, opinion survey results, sickness absences registers, recruitment process results, and exit interviews – are among many of those data which might be used for HR analytics to increase employee motivation, abilities, and opportunities and thus positively influence organisational performance (Blom, Kruyen, Van der Heijden, & Van Thiel, 2020; Marler & Boudreau 2017; Kryscynski, Reeves, Stice-Lusvardi, Ulrich, & Russell, 2018).

On the other hand, the promises of HR analytics to use technology as an enabler of evidence-based decision-making and increasing business outcomes, still lack their realization in the form of robust evidence (Boudreau & Cascio 2017, McCartney & Fu 2022), Instead, HR analytics might be seen as a modern management fashion (see e.g., Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016; Tursunbayeva, Di Lauro, & Pagliari, 2018) and like all management fashions (Abrahamson, 1996), it is driven by medial hype and naïve reasoning (just search for "HR analytics" in Google). There is a risk that HR analytics might end up as a buzzword (Rasmussen, & Ulrich, 2015) 'failing on big data challenges' (see Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016), adding nothing to the organisations' performance aside from a few marketing slogans. Moreover, there are more and more concerns that using technology in the form of HR analytics might have "dark sides" such as marginalizing human reasoning or impairing transparency with complex black-box algorithms (Giermindl, Strich, Christ, Leicht-Deobald & Redzepi, 2022) and ethical concerns related to privacy and data governance (Edwards, Charlwood, Guenole, & Marler, 2022).

From this perspective, there seems to be a consensus in the literature that to not fail in the HR analytics challenge, HR specialists must have professional "analytical skills" (Bondarouk, Parry & Furtmueller, 2017; Marler & Boudreau, 2017; Vargas, Yurova, Ruppel, Tworoger, & Greenwood, 2018; Kryscynski, Reeves, Stice-Lusvardi, Ulrich, & Russell, 2018; McCartney Murphy, & Mccarthy, 2021), and that the biggest risk factor for HR analytics to succeed in increasing business organizational performance is a lack of proper "analytical skills" across HR departments (Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016; CIPD, 2013, 2018b; Rasmussen & Ulrich, 2015; Levenson, 2011; Lawler, Levenson, & Boudreau, 2004; SHRM, 2016b). To manage and use emerging technologies introduced by digital transformation there is a need for specific skills (Kedziora, 2022). Although there is a consensus that HRM specialists need "analytical skills," there is no agreement on what these skills entail. Surprisingly, researchers and practitioners alike refer to "analytical skills" without a clear and commonly accepted definition of their content. However, how can we design effective training for HR if we do not fully understand what analytical skills are needed? How can we conduct HR analytics research that builds on previous findings if different researchers envision different constructs under the same label of analytical skills? Therefore, the main aim of this paper is to answer the research question (RQ) of what "analytical skills" are required to make sense of HR analytics. We aim to provide a comprehensive answer to this question by attaining three research goals: 1) Provide standardization to the meaning of the vague concept of "analytical skills" in terms of precisely defined knowledge, skills, and abilities (KSA), 2) Identify the top analytical KSA required to perform HR analytics, 3) Establish the gaps in "analytical skills" among HRM specialists that might create potential barriers to conducting meaningful HR analytics.

LITERATURE REVIEW

The ambiguity of HR "analytical skills"

To illustrate the importance of the questions regarding what "analytical skills" are required to make sense of HR analytics, we provide evidence of the ambiguity of HR "analytical skills" using a selective review of the current understanding of this topic in HRM literature. This analysis presents diverse perspectives on HR analytics capabilities drawn from a blend of sources, including scholarly and practical literature that provides definitions or descriptions of analytical capabilities in the context of HR. However, an extensive literature review on different perspectives on still emerging “analytical skills” needed for HR analytics exceeds the scope of this study. Rather, with our review, we would like to merely show that there is ambiguity around the meaning of “analytical skills,” empirically supporting our calls for standardization in our understanding of “analytical skills.” This is important, as some might state that as HR analytics is such a popular topic, there must be one common understanding or that the topic will not yield to such prominence without commonly accepted definitions. We suggest that even the selective review in Table 1 suggests that this is not the case. Our analysis in Table 1, by presenting various understandings of HR analytical skills, refutes the claim that one commonly accepted set of “analytics skills” is needed for HR analytics. The more nuanced analysis of the multidimensionality of HR analytics might be found in other sources, and we encourage interested readers to read the papers cited. However, we do not aim to repeat what is already available here (Bahuguna et al., 2024; Fernandez & Gallardo-Gallardo, 2021; Margherita, 2022; Shet et al., 2021; Suri & Lakhanpal, 2024).

Table 1. Illustration of ambiguity around HR analytical skill - the different approaches to HR analytical capabilities that can be found in the literature

What do HRM specialists need to make sense of HR analytics?	Source
Knowledge and skills in collecting the proper data, performing the right statistical analyses, and communicating the results in a meaningful and accessible way.	Marler and Boudreau (2017)
Human resource analytics personnel expertise includes business knowledge and analytical competency.	Thakur et al., (2024).
Analytical skills, which encompass the ability to utilize data and data-related processes to develop insights for decision-making, and storytelling skills, which involve communicating data effectively to influence decision-making, must work in synergy with each other.	McCartney & Fu (2024)
Analytical knowledge and experience to transform data into insights, and storytelling and visualization abilities to make complex data understandable to a wide audience.	Wang et al. (2024).
HR analysts' competencies should include a) storytelling and communication, b) consulting, c) technical knowledge, d) data fluency and analysis, e) HR and business acumen, and f) research and discovery.	McCartney et al. (2021)
Ask the right questions based on HR data; seek answers to these questions through longitudinal multivariate modeling; skills and knowledge to challenge the assumptions underpinning the analytical dashboards; ideally, knowledge of advanced statistical and econometrics techniques, necessary to disentangle correlation from causality through analysis of experiments and quasi-experiments.	Angrave et al. (2016)
Sufficient analytics skills and knowledge from the finance and IT domains, to be able to conduct HR analytics on both grounds.	Bassi (2011)
Business understanding, basic training in statistics and scientific methodology, skills in deploying a diagnostic framework, change management, and storytelling.	Rasmussen and Ulrich (2015)
Problem-solving, data analysis, visualization, statistics, data function and quality, business knowledge, consulting skills, cleaning data, maintaining data accuracy, and consistency across data stores.	Collins et al. (2018)
Skills in gathering, analyzing, and drawing practical conclusions from data, and communicating data findings to others.	SHRM (2016a)
Conduct root cause analysis, calculate univariate and multivariate statistics, communicate the results of statistical analyses understandably via presentation or public speaking, data preparation, survey design, qualitative data collection and analysis, obtaining data from others, and understanding what analytics to apply and when to apply them.	Levenson (2011)
Collect and store data, link different data, visualization, and presentation of the results; focus not only on reporting but also on data analysing and developing predictive models.	Heuvel and Bondarouk (2017)
Consultancy skills, skills in explaining HR analytics in a non-technical language via power points and visualization; knowledge of ANOVA, A/B testing, correlation and regression analyses, data cleaning and preparation; knowledge of analytics software and database structures. Focus on looking for insights that can help the business make a better decision not necessarily on scientific models.	Coolen and IJsselstein (2015)
Ability to understand and discover the cause-effect patterns hidden in employee-related data; understanding what HR analytics is not about; making judgments and assessments based on facts and data. The ability to benchmark how the organization is doing versus the outside world; some statistical knowledge but without seeing the lack of statistics competencies as a barrier; focus on helping executives make the right decisions.	Mondare, et al (2011)
The intellectual abilities to understand causal logic and establish causal models; ability to use appropriate analytics to test causal relationships in the data; ability to identify appropriate data, information, measures and metrics; ability to incorporate findings into processes of organizational decision-making.	Kryscynski, et al. (2018).
Critical causal thinking; understanding the principles of good measurement (psychometrics and econometrics); estimating causal relationships; communicating HR strategic performance results to senior line managers.	Becker et al. (2001). As cited in Kryscynski et al. (2018)
Knowledge of statistics and research design; skills in identifying key issues and asking valid questions; gathering and using appropriate data; setting the appropriate standards for rigour and relevance, ability to raise awareness of the analytical competencies of HR throughout the organization	Boudreau and Ramstad 2006
Ability to measure how human capital decisions affect the business and how business decisions affect human capital.	Lawler et al. (2004)
Ability to use Excel and PowerPoint; quantitative and mathematical skills, data gathering, survey design, root cause analysis, hypothesis generation and storytelling with data; data literacy - knowledge of how people data influence business data.	Zielinski (2019)

What do HRM specialists need to make sense of HR analytics?	Source
HR and Business domains knowledge; relationship management, problem specification; statistics, programming, data management; visualization, communication, web design, reporting results, data and systems awareness.	Reilly (2016)
Translating business issues into data analysis questions; ability to gather, structure, store, and manipulate data; knowledge of standard and advanced methods of data analysis; knowledge of statistics and machine learning; ability to present obtained results in a clear way.	Fairhurst (2014).
HR software expertise, statistical analysis and data mining, big data, machine learning; ability to understand data and choose the right tools to clean, extract, combine, analyse, and visualize data.	Chensoff et al. (2018)
Knowledge of database architecture, ability to generate and align people data with business data to inform strategic decision-making; applying modelling methodologies to people data; shaping research design to analyse organizational problems; understanding the value of multivariate analysis in addressing organizational problems; curiosity for innovations, knowledge of good practice in data presentation and storytelling techniques.	CIPD (2020)
Core skills - using appropriate data and metrics to address the most important issues; understanding concepts of correlation and causation; testing hypothesis to establish the root cause of workforce issues; optimization of the ROI from people programs; Communication skills - ability to effectively present analytics conclusions; Data science skills - use of scientific methods and algorithms to extract knowledge from various data structures.	CIPD (2018a)

Source: Authors own elaboration based on resources in the second column.

If we take a systematic look at the studies from Table 1, we might identify at least nine different categories of analytical capabilities, and each of these categories might consist of some more specific types. This illustrates the difficulty in capturing a single common meaning of "HR analytical skills." In the HR analytics context, "analytical skills" might include a variety of competencies such as:

a) Knowledge and abilities to understand the role of analytics in a broad business and organizational context:
- skills in asking insightful questions about key business issues and problems;
- skills in focusing on drawing practical business conclusions from data analysis;
- business understanding and business knowledge.

b) Skills in successful communication about HR analytics' findings and HR analytics itself:
- skills in communicating the results and insights via visualization and storytelling to managers and other stakeholders;
- skills in promoting HR analytics' importance and benefits throughout organization structures and levels.

c) Skills and knowledge necessary to think critically about the role and capabilities of HR analytics:
- understanding the limits of data analysis;
- knowledge necessary to challenge assumptions underlying HR analytics findings presented by someone else.

d) Skills and knowledge to use HR analytics to answer HR-specific questions with appropriate rigour and relevance:
- knowledge and skills in performing robust analyses of causes and effects, particularly of how people in the organization influence organizational business outcomes;
- knowledge and skills in calculating ROI from people programs;
- skills to conduct benchmarking based on HR analytics findings.

e) Knowledge and skills in using specific computer software:
- knowledge of analytical software;
- knowledge of HR-specific software.

f) Mathematical skills

g) Statistics - knowledge and skills in using various explanatory, descriptive, and inferential statistical procedure:
- basic statistical analyses;
- multivariate analysis;
- machine learning;
- data mining;
- predictive models;
- qualitative analysis.

h) Knowledge from the domain of research design, methods, and methodology:
- knowledge of hypothesis testing;
- knowledge of research methodology;
- knowledge of principles of good measurements.

i) Database knowledge and data manipulation skills:
- skills in collecting data;
- skills in preparing data;

- skills in storing and maintaining data;
- knowledge of database systems.

As can be seen in Table 1, the problem with current HR analytics research and practice is that there is no one common understanding of HR "analytical skills" and this poses a serious challenge for the effective use of IT in HR analytics development and implementation. HR "analytical skills" seem to be an umbrella term covering different visions of the successful application of HR analytics. This is challenging for HR analytics successful planning and adoption in organizations because decision-makers and HRM departments might be disoriented in the development of which "analytical skills" to invest in taking full advantage of HR analytics in enhancing organizational performance.

Thus, to fill this gap in the literature, we call for standardization in HR "analytics skills" by answering the question of what "analytical skills" are required to make sense of HR analytics. To make the first step in this direction and to gain more robust insights into the meaning of "analytical skills" we propose to based on the framework of the Occupational Information Network (O*NET) content model: (https://www.onetcenter.org/content.html) and split the vague "analytical skills" label into three occupational descriptors of analytical Knowledge, Skills, and Abilities (KSA) according to, i.e. knowledge – "organized sets of principles and facts applying in general domains," abilities – "enduring attributes of the individual that influence performance," and skills - basic skills "developed capacities that facilitate learning or the more rapid acquisition of knowledge" and cross-functional skills "developed capacities that facilitate performance of activities that occur across jobs (see also https://www.onetonline.org/find/descriptor/browse/).

Our attempt to provide standardization to HR analytical skills may contribute to the theory and practice of information management and human-computer interactions, helping HR analytics to realise its promises. First, by introducing clarity into an emergent but still ambiguous concept of "analytical skills" needed in the process of HR analytics. Second, our analysis might help to identify the analytical KSA lacking among HRM practitioners, and thus highlight potential barriers on the "human side" of HR analytics. Third, our elucidation on KSA needed in HR analytics might guide the debate on the training of HR analysts, and fourth, it might inspire further empirical research on the impact of HR analytics on organizational performance as precisely defined analytical KSA among HRM specialists might be important moderators of the effect of HR analytics on improvements in organizational performance.

METHODS

Data

In this study, we use the data from the Occupational Information Network (O*NET) database (O*NET® 24.3 Database is licensed under a Creative Commons Attribution 4.0 International License, the database source is: https://www.onetcenter.org/database.html; license terms: https://creativecommons.org/licenses/by/4.0/) developed under the sponsorship of the US Department of Labor, Employment and Training Administration. Although there are other occupation taxonomies e.g. European Skills, Competences, and Occupations the ESCO (see Popov, Snelson, & Baily, 2022 for review and comparison), we choose O*NET for several reasons. O*NET (2020) database contains occupation-specific descriptions of almost 1000 occupations and for each occupation, the data on the required level of specific knowledge, skills, and abilities are provided (for details see: https://www.onetcenter.org/overview.html and also Handel (2016) for discussion on the O*NET content model strengths and limitations). O*NET database is widely used in HRM scientific research. The wide use of the O*NET database and content model in scientific research is best illustrated by the high visibility of O*NET in academic journals. The O*NET homepage lists> 200 publications in career and vocational research, > 120 in education research, > 200 in health research, > 400 in industrial and organizational research and >600 in labor market research (see: https://www.onetcenter.org/references.html), the numbers that, according to our knowledge are unmatched by any other occupational taxonomy. What is more, the O*NET database not only describes skills, abilities and knowledge in occupations but also provides numerical estimates of levels of skills, abilities and knowledge, needed in those occupations. So in summary, although other occupation taxonomies exist and choices like this are always arbitrary to some degree we decided to use O* NET because of its comprehensive occupational data, it is widely used in HRM scientific research, its robustness is supported by the presence in peer-reviewed academic journals and it provides numerical estimates of skills, abilities, and knowledge allowing for quantitive calculations.

Strategy of analysis

To find out what analytical KSA (knowledge, skills, abilities) the HRM specialists might need to take full advantage of HR analytics, we adopted the following strategy. First, based on the occupations list from the O*NET database (see https://www.onetonline.org/find/career?c=0&g=Go), we created two separate categories of occupations: the HRM specialists' occupations and analytical occupations. Second, based on the O*NET database of KSA levels required in each occupation, we identified the top KSA required in analytical occupations. This approach allowed us to establish detailed lists of highly required analytical KSA clearly and objectively without subjective judgments. In the third step, we compared the level of the highly required analytical KSA to the required level of those KSA in HRM occupations to look for analytical KSA gaps that might constitute the barriers to the meaningful use of HR analytics (the visualization of our research strategy is presented in Figure 1). This strategy allowed us to attain the goals of this paper i.e.: 1) disentangle the vague "analytical skills" into precisely measured and objectively defined analytical KSA based on the O*NET content model, 2) identify the most significant analytical KSA, 3) establish gaps in analytical KSA.

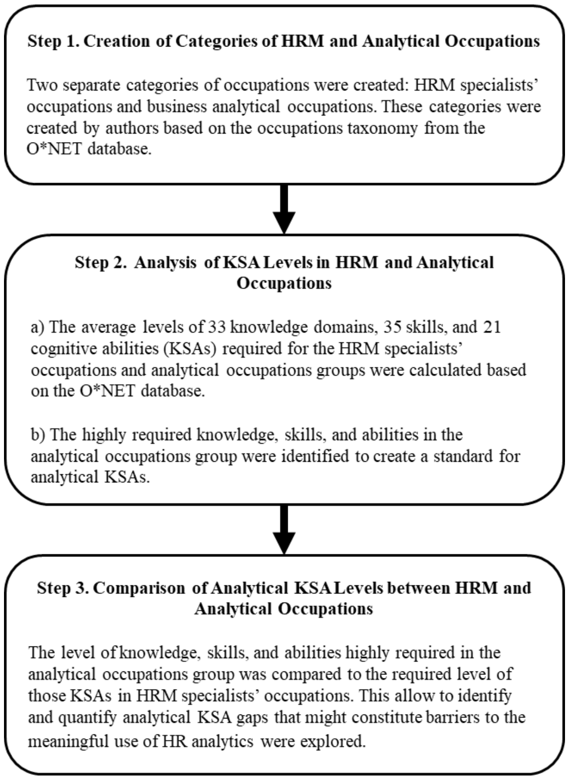

Figure 1. Visualization of the strategy of analysis

To create the HRM occupational category, we used occupations listed under the HRM career pathway in the O*NET OnLine website supplemented with the O*NET Industrial-Organizational Psychologists occupation category (https://www.onetonline.org/find/career?c=0&s=1&r=1; career clusters used in the O*NET OnLine are adapted from the National Career Clusters® Framework see: https://careertech.org/career-clusters;). We supplemented HRM occupations with IO Psychologist as this is an occupation closely related to HR Managers and HR Specialists and often its role encompasses involvement in HR analytics (see: https://www.onetonline.org/link/summary/19-3032.00). A list of eight HRM occupations from the O*NET OnLine used in this study to create a general category of HRM occupations is presented in Table 2.

Table 2. Occupations from The Occupational Information Network (O*NET) database used to create Human Resource Management (HRM) occupations category

O*NET Code	Occupation
11-3111.00	Compensation and Benefits Managers
13-1141.00	Compensation, Benefits, and Job Analysis Specialists
11-3121.00	Human Resources Managers
13-1071.00	Human Resources Specialists
13-1075.00	Labor Relations Specialists
11-3131.00	Training and Development Managers
13-1151.00	Training and Development Specialists
19-3032.00	Industrial-Organizational Psychologists

Note: The first seven occupations represent occupations from the O*NET, Human Resource Management Career Pathway.
Source: Retrieved from https://www.onetonline.org/find/career?c=4&g=Go

The creation of the analytical occupations category was more challenging. First, it is not clear what occupations are "analytical". No career pathway or job family is devoted to data analytical occupations in the O*NET OnLine. The second challenge in forming the analytical occupations for the purpose of this paper is that analytical occupations established in the search for HRM analytical KSA must perform the job in similar contexts as HRM specialists do i.e. using IT technology for analyzing data in the context of organizations, management, and business studies. Astronomers and biostatisticians are among the occupations highly involved in data analysis, but their descriptions of main work objectives do not include many tasks that deal with people management problems or issues. Thus, they might reflect analytical knowledge, skills, and abilities (KSA) not particularly relevant to HR analytics. Thus, after reviewing the lists of O*NET OnLine occupations and their descriptions, we decided to include three occupations in which incumbents have to successfully work with business and organizational data into the analytical occupations category: Business Intelligence Analysts, Management Analysts, and Operations Research Analysts. Detailed descriptions of these three analytical occupations can be found in Table 3.

Table 3. Occupations from The Occupational Information Network (O*NET) database used to create an analytical occupations category

O*NET occupational title and code	O*NET Occupation description
Business Intelligence Analysts 15-1199.08	Produce financial and market intelligence by querying data repositories and generating periodic reports. Devise methods for identifying data patterns and trends in available information sources.
Management Analysts 13-1111.00	Conduct organizational studies and evaluations, design systems and procedures, conduct work simplification and measurement studies, and prepare operations and procedures manuals to assist management in operating more efficiently and effectively. Includes program analysts and management consultants.
Operations Research Analysts 15-2031.00	Formulate and apply mathematical modeling and other optimizing methods to develop and interpret information that assists management with decision-making, policy formulation, or other managerial functions. May collect and analyze data and develop decision support software, services, or products. May develop and supply optimal time, cost, or logistics networks for program evaluation, review, or implementation.

Note: Please note that the analytical occupations category is not an official O*NET database category, it was created by the author, based on the list of occupations available in the O*NET database.
Source: Retrieved from https://www.onetonline.org/find/family?f=0

After identifying HRM and analytical occupations, we proceeded to establish the levels of knowledge, skills, and abilities (KSA) required in these occupations. Detailed data about the necessary KSA for each occupation in the Analysts and HRM categories were derived from the ONET 24.3 database levels (https://www.onetcenter.org/database.html#individual-files). In the ONET database, for each occupation, we utilized information about 21 cognitive abilities (https://www.onetonline.org/find/descriptor/browse/Abilities/), 35 specific skills (https://www.onetonline.org/find/descriptor/browse/Skills/), and 33 knowledge domains (https://www.onetonline.org/find/descriptor/browse/Knowledge/). Each occupation, knowledge domain, skill, and ability is rated on a 0 (minimum) – 7 (maximum) point scale according to the extent it is required or needed to perform the occupation successfully (for details see e.g. Tsacoumis & Willison, 2010; Handel, 2016; https://www.onetcenter.org/research.html). These raw scores are standardized into a scale from 0 to 100 for intuitive understanding, where 0 represents the lowest required level and 100 the highest (for details see https://www.onetonline.org/help/online/scales). To establish the KSA levels required for Analysts and HRM occupations, we averaged the levels of KSA required for occupations within each category. For example, for the Analysts category, consisting of three specific occupations, we computed the average levels among these occupations for each of the 21 cognitive abilities, 35 skills, and 33 knowledge domains available in the O*NET database. The same approach was applied to calculate the required levels of KSA for the HRM category, which comprises eight occupations. This procedure resulted in KSA lists for HRM and Analyst occupations, indicating the levels of KSA requirements for each of the 21 cognitive abilities, 35 skills, and 33 knowledge domains.

The procedure of creating occupation-specific ability requirements based on the O*NET database was previously adopted by Converse, Oswald, Gillespie, Field, & Bizot (2004), and this method is a cornerstone of widely used job analysis methodology (see also Sanchez and Levine, 2012; Reiter-Palmon; Brown, Sandall, Buboltz, & Nimps, 2006). Next, to identify analytical KSA, i.e., those most required for analytical types of jobs, we ranked them from highest to lowest according to their level of requirements to perform an analytical occupation. We considered as highly required those KSA with a score of 50 or higher on a 0-100 scale of O*NET database levels. Although the use of cutoff points is somewhat arbitrary, we believe that the 50 threshold for KSA levels adapted in our study is justified. This threshold represents a point above the central level on a 0-100 scale, suggesting that a given KSA is not irrelevant in a given occupation. For statistical reasons, a cutoff line of 50 allows for retaining a reasonable number of KSA. For example, adopting a slightly higher cutoff level of 60 would result in only two skills meeting this level, whereas with a slightly lower threshold of 40, 50 KSA would be considered highly required – which may be excessive for the informative presentation. While our threshold is not without limitations, it may be consistently applied, critiqued, and modified based on explicit rules, contrary to common sense reasoning around highly required “analytical skills.

Next, based on the sorted lists of the highly required KSA, we computed the percentage gaps between the KSA highly required to perform analytical occupations and levels of corresponding KSA required in the HRM occupations. These analytical gaps were computed similarly as the commonly used gender pay gap is calculated (see: https://www.gov.uk/guidance/making-your-gender-pay-gap-calculations#calculating-the-mean-average-gender-pay-gap-using-hourly-pay]), according to a formula: ((Analytical KSA – HRM KSA) / Analytical KSA) * 100%. The given KSA level for HRM occupation was subtracted from the given KSA level for analytical occupation, divided by the KSA level for analytical occupation and multiplied by 100%. In such a way, the positive gap reflects that there is a higher level of requirements for analytical occupations than HRM occupations for a given KSA. For example, the positive gap in mathematics skills = 25%, which means that, on average, analytical occupations need a 25% higher level of these skills than HRM occupations. This approach allowed for the identification of the highly required analytical KSA and the quantification of discrepancies (gaps) in the levels of analytical KSA required in analytical occupations and those required in HRM occupations.

It is important to remember that this study was not conducted on the KSA possessed by individual employees but on the level of KSA required for occupations as estimated in the O*NET database. In that context, the fact that a set of KSA is required for a given occupation does not mean that every incumbent of this occupation has this desired level of KSA. However, we assume that, on average, the O*NET database of the required level of KSA in the occupation is closely associated with the average level of KSA possessed by incumbents. First, according to the gravitational hypothesis, people generally “gravitate” toward jobs that commensurate with their abilities (Wilk, Desmarais, Sackett, 1995; Wilk, Sackett, 1996). Second, we assume that people invest in developing those professional KSAs that are required from them and neglect those KSAs that are not required from them in the workplace. Thus, investing in KSA development in one area (e.g., in human relations) improves KSA in that area but might lower KSA in competing areas (e.g., mathematics) (see Von Stumm & Ackerman, 2013). Third, the list of KSA based on the O*NET content model is a reasonably reliable estimation of KSA required in a given occupation that is used by organizations to create job descriptions and hire employees. Thus, we assume that it is reasonable to predict that if in a given occupation, there is a requirement of a specific level of KSA, then on average, the incumbents of this occupation are close to this required level of KSA, rather than have a random distribution of different levels of KSA. Thus, for example, for analytics occupations, the required level of mathematics knowledge is 70 and for HRM occupations, it is 55.8. We assume that we might expect that the HRM specialists will have a lower level of mathematics knowledge on average. People with mathematics knowledge will gravitate towards occupations other than HRM, in which a high level of mathematics is more required (and rewarded). HRM occupation incumbents will not invest time and effort in developing and maintaining mathematics knowledge as it is not the most required HRM occupation. Our nomothetic perspective adopted in this study considers the whole HRM specialists group as one entity. This approach is not perfect, as it ignores individual differences among HRM specialists, but it might help to build a general model of KSA, and thus make the first important step towards a better understanding of which type of analytical KSA might create potential barriers when introducing HR analytics into HRM departments.

RESULTS

The O*NET database provides detailed lists of knowledge domains (33), skills (35), and cognitive abilities (21). Thus, to keep clarity, we limit the presentation of our results to the most highly required analytical KSA (i.e., with the level of 50 or higher on 0-100 scale). First, Table 4 presents the lists of KSA with the highest levels required to perform the analytical types of occupations in business and organizational contexts. As we explained earlier, we suggest that those KSAs are also highly needed for HRM specialists to conduct insightful HR analytics. Second, Table 4 also contains the comparison of levels of the analytical KSA to the level of these KSAs required in HRM occupations.

As we can see in Table 4, there are seven knowledge domains highly needed for analytical occupations, and in three of them, there is a positive gap between analytical and HRM occupations (i.e. higher requirements among analytical than HRM occupations): Mathematics (20%) - "*Knowledge of arithmetic, algebra, geometry, calculus, statistics, and their applications*"(all KSA detailed descriptions in italics are quoted in this text from the O*NET database, https://www.onetonline.org/find/descriptor/browse/); Sales and Marketing (41%) "*Knowledge of principles and methods for showing, promoting, and selling products or services. This includes marketing strategy and tactics, product demonstration, sales techniques, and sales control systems*", and Computers and Electronics (14%) "*Knowledge of circuit boards, processors, chips, electronic equipment, and computer hardware and software, including applications and programming.*" In the case of skills, we have identified 13 highly required analytical skills. The gap can be observed in the case of 9 skills, with the highest gaps for Operations Analysis (31%) "*Analyzing needs and product requirements to create a design*"; Mathematics (25%) "*Using mathematics to solve problems*," and Complex Problem Solving (12%) "*Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.*" For abilities, based on the O*NET database, we have established 13 highly required analytical abilities, and for 12 of them, there were positive gaps, with the three largest gaps for Mathematical Reasoning (20%) "*The ability to choose the right mathematical methods or formulas to solve a problem.*", Number Facility (17%) "*The ability to add, subtract, multiply, or divide quickly and correctly*", and Inductive Reasoning (14%) "*The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).*"

For some KSA, we observe a negative gap, meaning that a higher level of this analytical knowledge or skill is required for HRM occupation than for analytical occupation. For knowledge, the most visible negative gaps have been observed for Customer and Personal Service (-30%) – "*Knowledge of principles and processes for providing customer and personal services. This includes customer needs assessment, meeting quality standards for services, and evaluation of customer satisfaction*" and Education and Training (-21%) "*Knowledge of principles and methods for curriculum and training design, teaching and instruction for individuals and groups, and the measurement of training effects.*" For skills, the most visible negative gaps have been observed for monitoring (-9%) "*Monitoring/Assessing performance of yourself, other individuals, or organizations to make improvements or take corrective action*" and speaking (-8%) „*Talking to others to convey information effectively.*"

Table 4. Analytical Knowledge, Skills and Abilities (KSA) highly required for analytical occupations, levels of these analytical KSA required in Human Resource Management (HRM) occupations and "analytical gaps", the percentage gaps between the level of analytical KSA required for analytical occupations and those required for HRM occupations

KSA Category	Descriptor	Mean level required for analytical occupations	Mean level required for HRM occupations	% discrepancy "analytical gap"
Knowledge	Mathematics - knowledge	70	55.8	20%
	English Language	66.1	68.0	-3%
	Administration and Management	64	64.9	-1%
	Sales and Marketing	63.8	37.4	41%
	Education and Training	61.3	74.1	-21%
	Computers and Electronics	59.9	51.4	14%
	Customer and Personal Service	51.6	67.3	-30%

KSA Category	Descriptor	Mean level required for analytical occupations	Mean level required for HRM occupations	% discrepancy "analytical gap"
Skills	Critical Thinking	61.3	57.8	6%
	Reading Comprehension	61.3	59.6	3%
	Active Listening	58.3	59.1	-1%
	Complex Problem Solving	57.8	51.1	12%
	Systems Evaluation	57.8	52.3	10%
	Judgment and Decision Making	57.7	55.4	4%
	Systems Analysis	57.7	51.1	11%
	Writing	57.1	59.2	-4%
	Speaking	56.6	60.9	-8%
	Active Learning	56.5	54.9	3%
	Mathematics - skills	56	42.2	25%
	Monitoring	51.2	55.8	-9%
	Operations Analysis	50.6	34.8	31%
Abilities	Oral Comprehension	65.5	60.9	7%
	Oral Expression	65.5	61.1	7%
	Written Comprehension	64.3	60.5	6%
	Deductive Reasoning	63.7	58.0	9%
	Inductive Reasoning	61.9	53.4	14%
	Written Expression	60.1	60.5	-1%
	Problem Sensitivity	56.5	54.2	4%
	Information Ordering	56	50.3	10%
	Fluency of Ideas	54.7	51.8	5%
	Mathematical Reasoning	54.1	43.5	20%
	Number Facility	53	44.2	17%
	Category Flexibility	52.4	49.5	6%
	Originality	52.4	51.8	1%

Note: Table created by the author based on the O*NET database; only KSA with the average level of 50 on a 0-100 scale or more are presented; for detailed descriptions and KSA definitions please see https://www.onetonline.org/find/descriptor/browse/. Analytics occupations include Business Intelligence Analysts, Management Analysts, Operations Research Analysts; HRM occupations: Compensation and Benefits Managers; Training and Development Managers; Human Resources Managers; Compensation, Benefits, and Job Analysis Specialists; Human Resources Specialists; Industrial-Organizational Psychologists, Labor Relations Specialists, Training and Development Specialists; % discrepancy "analytical gap" = [(mean level required for analytical occupations - mean level required for HRM) / mean level required for analytical occupations] *100%.

DISCUSSION

Let's be honest — most HR professionals are not attracted to HR because of the opportunity to work with data and analytics as part of their role.
Rasmussen & Ulrich (2015, p. 239)

The first goal of this study is to provide standardization to the meaning of the vague concept of "analytical skills". Instead of relying on our subjective perception, we refer to the O*NET database, which is a reliable and widely used source of occupational information (see O*NET Reference List https://www.onetcenter.org/references.html). Based on the O*NET content model, we split the vague concept of "analytical skills" into a set of precise knowledge, skills, and abilities – KSA, and an illustrative description of this KSA is presented in Table 5. By doing this, we provide a standardization framework of "HR analytical skills" and suggest establishing a common standard by referring to the KSA description in the O*NET content model. Additionally, this multilevel approach might supplement other approaches to analytical ability by adding new layers beyond solely viewing analytical ability as the ability to analyze data or deal with organizational metrics (e.g., Kryscynski et al., 2018; Minbaeva, 2018). Moreover, the standard based on occupational taxonomy might also supplement approaches based on self-reported measures, self-evaluations, and HR practitioners' perceptions (McCartney et al., 2021; McCartney & Fu, 2024; Minbaeva, 2018).

Table 5. Descriptions of the propositions of the five most important analytical knowledge, skills and abilities (KSA) in the business context, created by authors based on the O*NET Content Model and the O*NET database

	Mathematics	"Knowledge of arithmetic, algebra, geometry, calculus, statistics, and their applications."
Knowledge	English Language	*"Knowledge of the structure and content of the English language including the meaning and spelling of words, rules of composition, and grammar."*
	Administration and Management	*"Knowledge of business and management principles involved in strategic planning, resource allocation, human resources modeling, leadership technique, production methods, and coordination of people and resources."*
	Sales and Marketing	*"Knowledge of principles and methods for showing, promoting, and selling products or services. This includes marketing strategy and tactics, product demonstration, sales techniques, and sales control systems."*
	Education and Training	*"Knowledge of principles and methods for curriculum and training design, teaching and instruction for individuals and groups, and the measurement of training effects."*
Skills	Critical Thinking	*"Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions, or approaches to problems."*
	Reading Comprehension	*"Understanding written sentences and paragraphs in work-related documents."*
	Active Listening	*"Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times."*
	Complex Problem Solving	*"Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions."*
	Systems Evaluation	*"Identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system."*
Abilities	Oral Comprehension	*"The ability to listen to and understand information and ideas presented through spoken words and sentences."*
	Oral Expression	*"The ability to communicate information and ideas in speaking so others will understand."*
	Written Comprehension	*"The ability to read and understand information and ideas presented in writing."*
	Deductive Reasoning	*"The ability to apply general rules to specific problems to produce answers that make sense."*
	Inductive Reasoning	*"The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events)."*

Note: These propositions of business analytical KSA arrangement are not present in the official O*NET Content Model, they are created by the authors of this work based on their analyses of the O*NET database, but all KSA definitions are directly cited from The O*NET Content Model.
Source: Retrieved from https://www.onetcenter.org/content.html

In connection to the second goal, identification of the top analytical capabilities required to perform HR analytics, we assume that HR analytics is performed in the contexts of organizational and business studies and one of the main aims of HR analytics is to assist management and support organizational decision making and HR policy formulation. Therefore, we suggest that referring to those KSA needed for succeeding in analytical occupations performed in the context of business settings as Business Intelligence Analysts, Management Analysts, and Operations Research Analysts (see Table 3) might provide us with a reasonable approximation of what might be the highly required analytical KSA in HR analytics. This approach allows us to create a list of analytical KSAs containing: 7 knowledge domains, 13 skills, and 13 cognitive abilities. Table 4 provides a coherent overview of those analytical KSAs that might be most highly required for HR analytics (a detailed description of the O*NET database KSA might be found at https://www.onetonline.org/find/descriptor/browse/). These findings highlight the complexity of skills, abilities, and knowledge domains needed to succeed in analytics and are in line with approaches to HR analytics competencies that underscore that analytical skills are more than just data analysis (Angrave et al., 2016; McCartney et al., 2021; Rasmussen & Ulrich, 2015; Zielinski, 2019;). Analytical knowledge and experience (Wang et al., 2024) or analytics capabilities (Minbaeva, 2018) are seen in the literature as determinants of successful HR analytics implementation and organizational factors that enable HR analytics (Margherita, 2022 Fernandez & Gallardo-Gallardo, 2021), yet, the lack of analytical capacities among HR professionals is considered one of the important challenges for HR analytics (Shet et al., 2021). Thus, having precise standards of what knowledge, skills, and abilities to expect from HR analysts might be seen as one of the cornerstones of implementing HR analytics effectively in organizations. Moreover, Wirges and Neyer (2023) suggest that there is a need for clearer clarification of the role HR plays in the process of HR analytics and a clear definition of analytical KSA might help bring more clarity here.

Concerning the third goal of this paper, establishing the gaps in "analytical skills" among HRM specialists, that might create potential barriers to conducting meaningful HR analytics, the analysis presented in Table 4 allows us to establish gaps in required analytical KSA among HRM. It seems that the important barrier for HRM in conducting HR analytics might be mathematics, as there are gaps in mathematics knowledge, mathematics skills, and mathematics abilities. Although gaps in mathematics' KSAs might not be particularly surprising, as they represent what people generally think of analytical skills, nonetheless these gaps focus our attention on the somewhat painful truth that the organizations interested in HR analytics should concentrate on providing training in mathematics for HRM departments. It seems that mathematics is an unavoidable foundation for using IT technology in HR analytics, and basic math revision will be helpful in the curriculum of every HR analytics course. However, as the other KSA gaps discussed in the next section revealed, even the sharpest "mathematical mind" alone cannot guarantee success in HR analytics. There are important analytical KSAs around such capabilities as e.g. data communication and systems and critical thinking that are necessary but might be lacking among HR. In general, these findings, showing gaps between the desired analytical KSA and the actual KSA of HR professionals, are congruent with the discussion in contemporary HR analytics literature. It suggests that to fully harness the potential of analytics, HR specialists must cooperate with professional analysts. This type of expertise cooperation might bring to the table distinct yet complementary expertise of each group and generate value and benefits for organizations (Mondare et al., 2011; Wirges & Neyer, 2023; Barbour, Treem & Kolar, 2018).

Consequently, besides maths, the noteworthy gap is in sales and marketing knowledge – "*Knowledge of principles and methods for showing, promoting, and selling products or services. This includes marketing strategy and tactics, product demonstration, sales techniques, and sales control systems*" (all KSA detailed descriptions in italics are quoted from the O*NET database https://www.onetonline.org/find/descriptor/browse/). This is a more surprising knowledge domain for HR analysts, but also, in our selective literature review (see Table 1), some authors suggest that HR analysts' "must-have" is knowledge of how to "sell" HR analytics in terms of communicating the findings to decision-makers. This gap points to the role of HR analysts as technology and data translators (see Brady, Forde & Chadwick, 2017; Marr, 2018; Henke, Levine, & McInerney, 2018). HR analysts should be able to explain how IT works, interpret the language of data analysis in the HR domain and communicate them in an attractive way to bridge HR analytics with business and show its relevance to stakeholders.

Further among gaps in analytical skills, we might notice two broad categories. The first important analytical skill gaps category is represented by such skills as system analysis, "*Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes*," systems evaluation "*Identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system*," and operations analysis "*Analyzing needs and product requirements to create a design.*" These skills might be seen as system thinking - identifying, determining, and analyzing organizational processes as a part of one complex system (see Levenson, 2018). This suggests that, among HRM departments, there might be a need to develop skills in seeing the "big picture" of how HR analytics might not only help HRM departments in their jobs (e.g. by automatization everyday tasks) but also how HR analytics might influence the organizational performance at a more general level. This gap in system thinking seems to repeat Levenson's (2017, 2018) suggestions that HR must implement HR analytics with the broad context of the entire organizational system in mind. For example, Levenson argued (2017) that the sole fact that something could be improved (e.g., employee engagement) does not necessarily mean that this is the most important issue that should be improved in the first place. As HR might be concentrated on the improvement of dozens of processes, thus, system thinking is needed to prioritize and conduct HR analysis in the areas that might yield the highest returns of investment from HR analytics.

The second class of gaps in analytical skills is related to problem-solving and manifests itself in such skills as complex problem-solving skills - "*Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions*" and critical thinking skills - "*Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems*." Since the use of HR analytics to solve meaningful business problems might be seen as the cornerstone of HR analytics, thus the gap in problem-solving skills might be a challenge for the successful adoption of analytics in HR departments. Moreover, it seems that the field of HRM is particularly receptive to intuitive rather than critical thinking (see: Abrahamson, 1996; Pfeffer and Sutton, 2006; Rynes, Colbert, O'Boyle, 2018). Thus, the existence of a critical thinking gap might be a barrier to insightful HR analytics and it suggests that the HRM departments should be supported in the development of critical thinking skills when engaging in HR analytics (e.g., Kahneman, 2011; Barends & Rousseau, 2018). These gaps, similarly to system thinking gaps, point to the under-appreciated fact that HR analytics is not only about mathematics and statistics. If we concentrate on more sophisticated analysis methods and bigger data sets, we might unintentionally hold back the development of HR analytics. This finding seems to repeat and support the previous voices (e.g., Boudreau & Cascio, 2017) that the impact of HR analytics lies not in the level of analysis sophistication, but in the critical understanding of the given HRM topic in a broader organizational context.

As the pioneer of data analysis John Tukey also emphasizes, "*Far better an approximate answer to the right question, which is often vague, than an exact answer to the wrong question, which can always be made precise*" (Tukey, 1962 p.13). However, to know what question is the right one, HR analysts should have the right capabilities in the system and critical thinking.

CONCLUSION

From a theoretical perspective, our analysis sheds more light on the ambiguous concept of "analytical skills" and might stimulate further research on information technology in human resource management. Particularly, a precise definition of HR "analytical skills" in terms of the O*NET content model KSA might contribute to more insightful research on the impact of HR analytics on organizational performance. If "analytical skills" might be split into detailed analytical KSA, this suggests that when investigating the effects of HR analytics on the organization's performance, it might be inevitable to account for specific aspects of analytical knowledge, skills and abilities possessed by HRM as moderators of these effects but not treating analytical skills as one unidimensional entity. For example, research by McCartney and Fu (2024) suggests that there is a need to build complementary capabilities among various people analytics capabilities. Our results on the knowledge, skills, and abilities needed in HR analytics might help provide guidance on which capabilities we should take into account (see also Thakur et al., 2024; Bahuguna et al., 2024 for the importance of moderators in understanding HR analytics capabities).

From a practical stance, our results call for standardization in HR analytics definitions and suggest the O*NET content model as a common framework for understanding HR analytical KSA. Also, our findings provide a list of the highly required analytical KSA, which might be of some help in the process of training, recruitment, and development of HRM departments willing to use HR analytics. This might be particularly important in light of previous studies that show a relationship between the analytical ability of HR specialists and their performance (Kryscynski et al., 2018). However, some gaps in analytical KSA revealed in this study might be more difficult to fill than others, and might need solutions other than simply an "HR analytics course". We propose that, to some extent, the barriers created by the KSA gaps might be compensated by 1) scientific and organizational knowledge possessed by HRM, and 2) cooperation of HRM with professional analysts as data translators. First, in everyday practice, HRM specialists do not often handle problems utterly unrelated to their prior experience and professional HRM knowledge (see Cappelli, 2017). The HRM field is well-grounded in the scientific theories of human behavior (e.g., see Miner, 2015). When conducting HR analytics on the "usual" HR topics (motivation, pay satisfaction, turnover, etc.) Instead of conducting sophisticated data mining procedures to search for patterns in data blindly, HRM specialists might draw from a body of relevant HRM knowledge to test theoretically expected patterns of relations. However, when the problems faced by HR analytics are novel and not related to the existing HRM body of knowledge, the other possible remedy for the analytical gaps might be cooperation with analytical experts external to the HRM departments (see Mondare et al., 2011; Wirges, & Neyer, 2023). This cooperation should allow not only for the outsourcing of HR analytics but for collaboration, leading to a synergy between the HRM specialists' expertise and the analyst specific analytical KSA in the process of business problem-solving (for a detailed description of this cooperation, see e.g. Barbour, Treem & Kolar, 2018). HR analytics might help to generate better insight into people's side of the organization, thus, improving HRM's positive impact on employee abilities, motivation and opportunities (Marler & Boudreau, 2017). However, to face challenges posed by HR analytics, we, as HRM specialists, should strive to learn how to fit our role into meaningful collaboration with professional analysts in the process of understanding an increasing amount of HR data. In this cooperation, HRM specialists might take the role of data translators who use critical and system thinking merged with HRM knowledge and business experience to point out the most important analytical problems and ask impactful analytical questions, leaving complex data analyses for professionals. However, all of this needs a common understanding of HR analytics skills, which will allow us to see HRM's analytical strengths and weaknesses and then compensate for weaknesses and build on strengths. If we are to avoid failing on big data challenges in HR (Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016) and want to see the realization of the promises of HR analytics (McCartney & Fu 2022) we must start with standardization in our understanding of what knowledge, skill and ability HRM need (and lack) to successfully conduct HR analytics. This might help to ensure that HR analytics will not be another management hype but has a real impact on business outcomes.

Limitations and further research

When discussing HR analytics, we often assume that the lack of "analytical skills" among HRM specialists might be fixed by proper training as soon as we build awareness of what is lacking. However, our results point to several gaps in analytical KSA across HRM, and these gaps pose a challenging question – if there are analytical KSA gaps, then to what extent is it possible to fill them? Is it possible to effectively teach HRM departments to think more critically about data or to look at organizations from a more systemic perspective that goes beyond HRM's local interests? Therefore, the important challenge for further investigation is to set out in which analytics KSA HRM might make the most progress and by what kind of training, and also in which of them providing training might be a difficult or uneconomical process, thus need action on a level of recruitment and selection of HR professionals.

Also, in this study, we have concentrated on analytical KSA, but we would like to avoid the illusion that providing HRM departments with appropriate analytical KSA will solve the problem of HR analytics. Referring to the Ability, Motivation, and Opportunity model of performance (see Blom et al., 2020), it is not only abilities (KSA in our case) but also motivation and opportunities that influence the level of performance. Thus, the HRM department needs not only analytical KSA but also motivation to use them (e.g. encouragement from stakeholders to take the risk of data analysis, pay for performance see: Aral et al., 2012) and opportunities (e.g. software, hardware, and access to cross-organization data). In other words, to make sense of HR analytics, HRM departments need not only "analytical skills" but also motivation and opportunities to use them.

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Authorship contribution statement

Konrad Kulikowski was responsible for all aspects of the study.

Conflicts of interest

The author declares no conflict of interest.

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