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PEOPLE ANALYTICS AND ARTIFICIAL INTELLIGENCE IN THE ANALYSIS OF ORGANIZATIONAL BEHAVIOR

Radosław WOLNIAK[1*], Izabela JONEK-KOWALSKA[2]

[1] Silesian University of Technology, Organization and Management Department, Economics and Informatics Institute; rwolniak@polsl.pl, ORCID: 0000-0003-0317-9811
[2] Silesian University of Technology, Organization and Management Department, Economics and Informatics Institute; Izabela.Jonek-Kowalska@polsl.pl, ORCID: 0000-0002-4006-4362
[*] correspondence author

Purpose: The purpose of this publication is to analyse the potential of AI implementation in people analytics.
Design/methodology/approach: Critical literature analysis. Analysis of international literature from main databases connecting with researched topic.
Findings: The main findings of the study indicate that the integration of artificial intelligence into People Analytics significantly extends the analytical capacity of organizational behavior research by enabling dynamic, multi-level, and behaviorally grounded analysis of employee activity, interaction, and decision-making. The paper demonstrates that AI-driven People Analytics shifts the focus from static, descriptive HR indicators toward predictive and pattern-oriented explanations rooted in real-time, multi-source data, allowing classical organizational behavior theories to be operationalized at unprecedented scale and temporal resolution. Empirical applications reviewed in the study show that AI supports more accurate identification of engagement dynamics, turnover risk configurations, team interaction structures, leadership behaviors, well-being trajectories, and skill development processes, while also revealing latent patterns that remain invisible to traditional methods. At the same time, the findings emphasize that the scientific and practical value of AI-based analytics depends on strong theoretical framing, contextual interpretation, and ethical governance, without which algorithmic insights risk reductionism and loss of explanatory depth in organizational research.
Originality/Value: Detailed analysis of all subjects related to the problems connected with the usage analysed scientific problem.
Keywords: People Analytics; Artificial Intelligence; organizational behavior; human resource analytics; machine learning; employee engagement; workforce decision-making; predictive analytics; data-driven management.
Category of the paper: literature review.

1. Conceptual Foundations of People Analytics and Artificial Intelligence in Organizational Research

People Analytics has emerged as a distinctive analytical paradigm within organizational research, positioned at the intersection of human resource management, organizational behavior, data science, and decision theory. Its conceptual core lies in the systematic use of data related to employees, work processes, and organizational contexts to explain, predict, and influence individual and collective behavior in organizations. Unlike traditional HR analytics, which has largely focused on descriptive indicators and retrospective reporting, People Analytics emphasizes explanatory and predictive reasoning, often supported by advanced statistical modeling and artificial intelligence techniques. This shift reflects a broader transformation in management sciences toward evidence-based decision-making under conditions of complexity and uncertainty.

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From a theoretical perspective, People Analytics can be understood as an extension of organizational behavior research grounded in empirical positivism, but augmented by computational approaches. Classical theories of organizational behavior—such as motivation theories, social exchange theory, job design models, and leadership frameworks—provide the conceptual scaffolding for interpreting behavioral data. AI-driven analytics does not replace these theories; rather, it operationalizes them in new ways. Behavioral constructs that were previously measured through limited survey instruments are now increasingly inferred from multi-source, high-frequency data, including digital traces of work activities, communication patterns, and performance dynamics. This transformation alters not only the scale of analysis, but also the epistemological assumptions about how organizational knowledge is generated (Antczak et al., Bottesch et al., 2025; Lim, Jang, 2025; Kaur et al., 2025; Zheng, Sikora, 2025).

Artificial intelligence plays an important role in this evolution by enabling the processing and interpretation of complex, high-dimensional datasets that exceed the capacity of conventional analytical methods. In organizational research, AI is primarily associated with machine learning, natural language processing, and network analysis. These approaches are designed to identify latent patterns, non-linear relationships, and interaction effects within behavioral data. Conceptually, this introduces a shift from variable-centered explanations toward pattern-centered reasoning. Rather than testing isolated hypotheses about single predictors, AI-based People Analytics often explores configurations of factors that jointly shape organizational behavior (Zhu et al., 2025; Parter et al., 2025; Rafi et al., 2025).

At the same time, this computational orientation raises important conceptual distinctions. Traditional organizational research typically prioritizes theory-driven model specification, where variables and relationships are defined ex ante based on established frameworks. In contrast, AI-driven analytics often relies on data-driven discovery, where patterns emerge inductively from the data. This does not imply a rejection of theory, but it does require

a rethinking of the role of theory in the research process. Theory increasingly functions as an interpretative lens used to make sense of algorithmic outputs, rather than as a strict blueprint for model construction. This creates a hybrid epistemology, combining inductive learning with deductive interpretation (Gokhale et al., 2025; Mahar, 2025; Pareek, 2025; Jonek-Kowalska, Wolniak, 2021, 2023).

People Analytics also draws conceptually on decision science and management control theory. The fundamental promise of the approach is not merely improved description of organizational phenomena, but enhanced decision quality. AI-supported People Analytics aims to reduce cognitive biases, information asymmetries, and bounded rationality in managerial decision-making. From this perspective, organizational behavior is treated as a dynamic system in which individual actions, social interactions, and structural constraints co-evolve over time. AI models, particularly predictive and simulation-based ones, allow researchers and practitioners to explore counterfactual scenarios, assess intervention effects, and anticipate unintended consequences of managerial actions (Han et al., 2024; Handa et al., 2025; Aggarwal, Kaur, 2024).

An important conceptual foundation of People Analytics lies in its treatment of employees as both agents and data subjects. Organizational behavior research has long emphasized human agency, meaning-making, and contextual embeddedness. AI-driven analytics, however, risks reducing behavior to measurable signals if not theoretically grounded. Conceptually robust People Analytics frameworks therefore stress the need to contextualize data within organizational culture, institutional norms, and power relations. Behavioral patterns identified by algorithms acquire meaning only when interpreted in relation to these broader social structures. This interpretive layer is essential to avoid technological determinism and to preserve the explanatory richness of organizational research (Atakan, 2024; Frumento et al., 2025; Di Lauro et al., 2025; Rosak-Szyrocka, Wolniak, 2025a, 2025b).

Another issue concerns the level of analysis. Organizational behavior traditionally distinguishes between individual, group, and organizational levels. People Analytics, supported by AI, enables simultaneous multi-level analysis, linking micro-level behavioral data with meso-level team dynamics and macro-level organizational outcomes. Conceptually, this supports more integrated models of organizational behavior, where cross-level interactions can be examined empirically rather than assumed theoretically. However, it also requires careful attention to aggregation logic, temporal alignment, and causal inference, as correlations across levels do not automatically imply meaningful behavioral mechanisms (Sasitekha et al., 2024; Skotnicka-Zasadzień, Wolniak, 2026; Bandyopadhyay, Banerjee, 2025; Freeda et al., 2024).

Ethical and normative considerations form an integral part of the conceptual foundations of People Analytics. The use of AI in analyzing organizational behavior raises questions about privacy, autonomy, transparency, and fairness. From a theoretical standpoint, these issues intersect with stakeholder theory and theories of organizational justice. Conceptually sound People Analytics frameworks recognize that data-driven insights are not value-neutral. Choices

regarding what data are collected, how models are trained, and how results are used reflect implicit assumptions about control, trust, and the role of employees in the organization. Embedding ethical reasoning into the conceptual design of People Analytics is therefore not an external constraint, but a core theoretical requirement (Banerjee et al., 205; Davanzo, 2025; Kaur et al., 2025; Kapil, Rawat, 2025).

The conceptual foundations of People Analytics and artificial intelligence in organizational research rest on a synthesis of classical organizational behavior theory, computational analytics, and decision science (table 1). AI extends the analytical reach of organizational research by enabling the exploration of complex behavioral patterns, yet it simultaneously challenges established epistemological and ethical assumptions. A theoretically informed approach to People Analytics treats AI not as a substitute for organizational theory, but as an analytical instrument whose value depends on rigorous conceptual framing. Such an approach allows organizational research to remain analytically robust while adapting to the data-rich realities of contemporary work environments (Md et al., 2025; Bhati, 2024; Corrigan et al., 2025).

Table 1.
Conceptual foundations of People Analytics and AI in organizational research

Conceptual dimension	Core assumptions	Implications for organizational behavior research
People Analytics as an analytical paradigm	Organizational behavior can be systematically explained and predicted using multi-source employee and process data rather than isolated HR indicators	Shifts research focus from descriptive HR metrics toward explanatory and predictive models of individual and collective behavior
Role of artificial intelligence	AI enables identification of non-linear, latent, and high-dimensional behavioral patterns beyond the limits of classical statistical methods	Encourages pattern-centered and configuration-based explanations instead of single-variable causal testing
Theory–data relationship	Theory provides interpretative and contextual grounding, while AI supports inductive pattern discovery	Requires hybrid epistemology combining data-driven learning with theory-based interpretation
Decision-oriented perspective	Behavioral insights should improve managerial decision quality under complexity and bounded rationality	Positions organizational behavior research closer to decision science and management control
Level of analysis integration	Individual, team, and organizational behaviors are interdependent and dynamically linked	Enables empirical investigation of cross-level interactions rather than purely conceptual models
Contextual embeddedness of behavior	Behavioral data acquire meaning only within organizational culture, norms, and power structures	Prevents reduction of human behavior to purely technical or algorithmic representations
Ethical and normative foundations	Data-driven analysis of employees is not value-neutral and affects trust, fairness, and autonomy	Integrates organizational justice and stakeholder theory into People Analytics design
Temporal and dynamic perspective	Organizational behavior evolves over time rather than remaining static	Supports longitudinal, predictive, and scenario-based behavioral modeling

Source: Author's own work.

2. Applications of AI-Driven People Analytics in Understanding Organizational Behavior

AI-driven People Analytics has become an increasingly important instrument for empirical research on organizational behavior, primarily because it enables the observation and analysis of behavioral phenomena at a scale, granularity, and temporal resolution that were previously inaccessible. Its applications extend well beyond operational HR reporting, contributing to theory-informed explanations of how individuals and groups behave in complex organizational systems. From an analytical standpoint, artificial intelligence allows behavioral constructs to be examined as dynamic, multi-dimensional processes rather than static attributes measured at single points in time (table 2).

AI-driven People Analytics concerns the analysis of employee engagement and motivation. Traditional engagement research relies heavily on self-reported survey data, often collected annually or biannually. AI methods make it possible to complement these measures with behavioral proxies derived from digital work traces, communication frequency, task completion rhythms, and collaboration patterns. Machine learning models can identify combinations of behavioral signals that correspond to sustained engagement, disengagement, or transitional states between them. Conceptually, this enables engagement to be treated as a fluctuating behavioral condition rather than a stable psychological trait, offering a more realistic representation of everyday organizational life (Das, Samal, 2025; Takascova, Petrinec, 2025).

Another important area of application is the analysis of employee turnover and retention. Predictive models based on AI are increasingly used to identify early warning signals of voluntary exit, drawing on heterogeneous data such as career trajectories, internal mobility, performance evaluations, workload indicators, and social network position. From the perspective of organizational behavior, the value of these applications lies not in prediction alone, but in the ability to uncover structural patterns associated with withdrawal behaviors. AI-driven clustering and classification techniques can reveal distinct profiles of turnover risk, indicating that exit decisions are often embedded in broader configurations of work conditions, social relations, and developmental opportunities.

AI-supported People Analytics also contributes significantly to the understanding of team dynamics and collaboration. Organizational behavior research has long emphasized the importance of informal interaction patterns, trust, and coordination for team effectiveness. Advances in network analysis and natural language processing allow researchers to reconstruct interaction networks from communication data and to examine how information flows, influence structures, and collaboration intensity evolve over time. These applications enable the empirical study of emergent team behaviors, such as the formation of informal leadership, sub-grouping, or coordination breakdowns, which are difficult to capture through conventional research designs.

Leadership analysis represents another domain where AI-driven People Analytics offers new insights. Rather than conceptualizing leadership solely through formal roles or self-assessments, AI models can analyze behavioral manifestations of leadership, including communication style, responsiveness, decision patterns, and relational positioning within networks. Natural language processing techniques applied to written or spoken communication can identify linguistic markers associated with supportive, directive, or participative leadership behaviors. This approach aligns leadership research more closely with observed behavior, reducing reliance on perceptual measures and enabling longitudinal analysis of leadership development and effectiveness (Jones et al., 2025; Mahar, 2025; Rafi et al., 2025; Zhen, Sikora, 2025).

Well-being and workload management constitute a further application area with strong implications for organizational behavior theory. AI-based People Analytics can detect patterns indicative of cognitive overload, work intensification, or work–life boundary erosion by analyzing temporal work patterns, task switching frequency, and communication outside standard working hours. These insights support a behavioral understanding of stress and burnout as cumulative processes shaped by organizational design and digital work practices. Importantly, such analyses shift attention from individual resilience toward structural conditions that systematically influence employee well-being (Wolniak, Stecuła, 2024; Wolniak et al., 2025).

Diversity, inclusion, and equity analyses have also been increasingly supported by AI-driven People Analytics. Machine learning techniques can be used to identify disparities in career progression, performance evaluation, or access to developmental opportunities across demographic and organizational groups. From an organizational behavior perspective, these applications help uncover subtle, systemic patterns of bias that may not be visible through aggregate statistics. When theoretically grounded, AI-supported analyses contribute to a more nuanced understanding of how organizational practices reproduce or mitigate inequality through everyday behavioral processes.

AI-driven People Analytics further enables the study of learning and skill development within organizations. By analyzing patterns of task performance, training participation, and knowledge sharing, AI models can identify learning trajectories and skill acquisition pathways. This supports a behavioral view of learning as an ongoing, socially embedded process rather than a discrete outcome of formal training interventions. Such applications are particularly relevant in knowledge-intensive and digitally mediated work environments, where informal learning plays a central role in organizational adaptation (Aggarwal, Kaur, 2024; Corrigan et al., 2025; Frumento et al., 2025; Lim, Jang, 2025; Pareek, 2025).

Table 2.
Implementation of artificial intelligence in People Analytics for organizational behavior analysis

Application area	AI-based analytical approaches	Contribution to understanding organizational behavior
Employee engagement and motivation	Machine learning models using behavioral proxies from digital work traces and communication patterns	Conceptualizes engagement as a dynamic behavioral state rather than a static attitudinal construct
Employee turnover and retention	Predictive modeling, classification, and clustering based on career, performance, and social network data	Reveals structural configurations of withdrawal behavior embedded in work conditions and social relations
Team dynamics and collaboration	Social network analysis, temporal interaction modeling, and communication analytics	Enables empirical analysis of emergent team behaviors, coordination patterns, and informal structures
Leadership behavior	Natural language processing and network-based role analysis	Shifts leadership research toward observed behavioral manifestations rather than perceptual measures
Employee well-being and workload	Temporal pattern analysis, anomaly detection, and workload modeling	Frames stress and burnout as cumulative, system-level behavioral processes
Diversity, equity, and inclusion	Bias detection models and comparative outcome analysis across groups	Identifies systemic and often invisible behavioral mechanisms reproducing inequality
Learning and skill development	Pattern recognition in task performance and training participation data	Supports a behavioral view of learning as a continuous, socially embedded process
Organizational change and adaptation	Predictive and scenario-based AI models	Improves understanding of behavioral responses to structural and technological change

Source: Author's own work.

The table 3 presenting existing AI-driven People Analytics applications illustrates both the functional diversity of contemporary analytical tools and their shared epistemological assumption that organizational behavior can be empirically reconstructed from multi-source digital data. Platforms such as Visier People Analytics, SAP SuccessFactors People Analytics, and Workday People Analytics represent an integrated workforce analytics approach in which transactional HR data are combined with predictive and scenario-based models. From the perspective of organizational behavior research, their primary contribution lies in shifting attention away from static workforce descriptions toward the analysis of behavioral processes, including turnover dynamics, internal mobility, and performance trajectories.

A distinct category is formed by applications embedded directly in digital work infrastructures, exemplified by Microsoft Viva Insights. By relying on collaboration metadata rather than self-reported information, these tools enable continuous observation of communication intensity, coordination patterns, and temporal work structures. This allows organizational behavior to be analyzed as an observable, ongoing process situated in everyday work practices, rather than as a set of attitudes captured at discrete moments. As a result, phenomena such as collaboration overload, fragmentation of attention, and boundary management become empirically accessible.

Another important group of applications focuses on social interaction and informal relational structures, as illustrated by Humanyze. By combining sensor-based data with communication analytics, such tools make it possible to empirically map social networks and interaction frequencies within organizations. This has substantial implications for organizational behavior theory, as constructs such as social capital, cohesion, and informal leadership can be operationalized using behavioral data rather than inferred indirectly through surveys or managerial assessments.

Applications such as Peakon and Culture Amp represent a hybrid approach that integrates traditional attitudinal measurement with AI-supported sentiment analysis and trend detection. Their analytical value lies in treating engagement, organizational climate, and employee voice as dynamic phenomena that evolve over time. For organizational behavior research, this supports a process-oriented understanding of collective attitudes, emphasizing short-term fluctuations and feedback loops rather than stable, long-term states.

The table also highlights platforms oriented toward skills, learning, and internal labor markets, including Eightfold AI and Gloat. By inferring competencies from work histories, project participation, and learning activities, these tools enable a behavioral analysis of career development, job crafting, and self-directed mobility. This perspective reframes learning and development as adaptive behavioral processes embedded in organizational contexts, rather than as outcomes of formal training interventions alone.

Taken together, the applications summarized in the table demonstrate that AI-driven People Analytics does not constitute a single technological solution but rather an ecosystem of tools addressing different dimensions of organizational behavior. Their common contribution is the ability to move organizational behavior research toward more processual, multi-level, and behaviorally grounded analyses. At the same time, the table implicitly underscores the need for strong theoretical framing, as the interpretive value of algorithmic outputs depends on their integration with established organizational behavior theories and contextual understanding.

Table 3.
Existing AI-driven People Analytics applications used in organizational behavior analysis

Application name	Core functionality	Relevance for understanding organizational behavior
Visier People Analytics	Advanced workforce analytics platform integrating HRIS data, predictive models, and scenario simulations	Enables analysis of behavioral drivers of turnover, engagement, and internal mobility at individual and group levels
Workday People Analytics	Embedded AI analytics using machine learning on performance, skills, and career data	Supports behavioral interpretation of career trajectories, performance dynamics, and skill development patterns
Microsoft Viva Insights	Behavioral analytics based on Microsoft 365 collaboration metadata	Reveals patterns of collaboration, workload distribution, boundary management, and team interaction rhythms
Humanyze	Wearable- and sensor-based analytics combined with communication data	Empirically captures face-to-face interaction, social connectivity, and informal collaboration behaviors

Cont. table 3.

Peakon (Workday Peakon Employee Voice)	AI-supported continuous listening platform integrating surveys and sentiment analysis	Models engagement and voice behavior as dynamic organizational processes
Eightfold AI	Talent intelligence platform using deep learning for skill inference and career matching	Supports behavioral understanding of learning, capability development, and talent mobility
Culture Amp	Engagement and performance platform using predictive analytics and NLP	Links organizational culture indicators with observable behavioral responses and performance outcomes
SAP Success Factors People Analytics	Workforce analytics combining HR data with predictive and comparative benchmarks	Enables behavioral analysis of workforce stability, performance variation, and succession risks
Gloat	AI-based internal talent marketplace	Provides insight into self-directed career behavior, project-based collaboration, and motivation patterns
IBM Watson Talent Insights	AI-driven labor market and workforce analytics platform	Contextualizes organizational behavior within external skill demand and workforce dynamics

Source: Author's own work.

3. Conclusion

This paper concludes that Artificial Intelligence–driven People Analytics constitutes a substantive methodological and conceptual advancement in organizational behavior research rather than a purely technological enhancement. By integrating computational analytics with established organizational behavior theories, AI enables the systematic analysis of employee behavior as a dynamic, multi-level, and context-dependent process, extending beyond the limitations of traditional, survey-based and descriptive HR approaches. The reviewed evidence demonstrates that AI-supported People Analytics allows for more precise identification of behavioral patterns related to engagement, turnover, collaboration, leadership, well-being, learning, and inclusion, while simultaneously improving the explanatory and predictive power of organizational research.

At the same time, the analysis clearly indicates that the effectiveness of AI in People Analytics is contingent upon rigorous theoretical grounding and careful epistemological positioning. AI methods do not replace organizational theory; rather, they transform its role from ex ante model specification toward interpretative sense-making of algorithmically detected patterns. This hybrid logic—combining inductive data-driven discovery with deductive theoretical interpretation—emerges as a defining characteristic of contemporary People Analytics. Without such integration, there is a risk of reducing complex human behavior to technical signals devoid of organizational meaning.

The paper also highlights that ethical and normative considerations are inseparable from the analytical design of AI-driven People Analytics. Issues of privacy, transparency, fairness, and employee autonomy are not peripheral constraints but central theoretical dimensions that shape trust and legitimacy within organizations. Consequently, future development of People Analytics should embed ethical reasoning directly into analytical frameworks, governance structures, and managerial decision processes.

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