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DETERMINANTS OF ORGANIZATIONAL CITIZENSHIP BEHAVIOR IN THE CONTEXT OF ARTIFICIAL INTELLIGENCE ADOPTION

Master thesis of 2nd year student of the Master’s
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ЗАЯВЛЕНИЕ О САМОСТОЯТЕЛЬНОМ ХАРАКТЕРЕ ВЫПОЛНЕНИЯ ВЫПУСКНОЙ КВАЛИФИКАЦИОННОЙ РАБОТЫ

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31.05.2024

STATEMENT ABOUT THE INDEPENDENT CHARACTER
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I, Anastasiia S. Tiumentseva, second year master student of the main field of study 38.04.02 «management», state that my master thesis on the topic «Determinants of organizational citizenship behavior in the context of artificial intelligence adoption», which is presented to the Master Office to be submitted to the Official Defense Committee for the public defense, does not contain any elements of plagiarism.

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31.05.2024

АННОТАЦИЯ

Автор	**Тюменцева Анастасия Сергеевна**
Научный руководитель	**Латуха Марина Олеговна**
Название ВКР	Детерминанты поведения, определяющие вклад сотрудника в организацию: влияние искусственного интеллекта.
Описание цели, задач и основных результатов исследования	*Цель:* Изучить, как внедрение искусственного интеллекта влияет на поведение организационного гражданства и определение таланта, а также оценить его влияние на степень инновационности организации и ее производительность. *Задачи:* ● Проанализировать традиционные факторы, определяющие поведение организационного гражданства, и то, как они должны быть пересмотрены в контексте внедрения искусственного интеллекта (ИИ). ● Изучить влияние ИИ на выявление, развитие и удержание талантов, а также то, как необходимо адаптировать практику управления персоналом для поддержки этих изменений. ● Сформулировать и протестировать гипотезы для оценки взаимосвязи между поведением организационного гражданства, улучшенным с помощью ИИ, и различными аспектами организационных инноваций и производительности. ● Разработать и провести опросы среди сотрудников и специалистов по управлению персоналом в организациях, интегрированных с ИИ. ● Выполнить статистический анализ, чтобы проверить гипотезы и понять взаимосвязи между ИИ, поведением организационного гражданства и эффективностью организации. ● Интерпретировать эмпирические данные, чтобы понять механизмы, с

	помощью которых ИИ влияет на поведение организационного гражданства и результаты деятельности организации. ● Разработать практические рекомендации для HR и управленческих стратегий по эффективному совершенствованию поведения организационного гражданства и обеспечению успеха организации в средах, интегрированных с ИИ. *Основные результаты:* ● Обновленные традиционные факторы, определяющие поведение организационного гражданства, в контексте использования ИИ в организациях. ● Подтверждение гипотезы, что ИИ значительно улучшает ключевые аспекты поведения организационного гражданства , что приводит к повышению эффективности организационных инноваций. ● Практическая информация о том, как ИИ можно использовать для улучшения управления талантами. ● Рекомендации по обновлению практики управления персоналом.
Ключевые слова	Гражданское поведение в организации, искусственный интеллект, инновации, эффективность работы фирмы, управление персоналом, управление талантами, интеграция искусственного интеллекта, организационная культура.

ABSTRACT

Master Student's Name	Anastasiia S. Tiumentseva
Academic Advisor's Name	Marina O. Latukha
Master Thesis Title	Determinants of organizational citizenship behavior in the context of artificial intelligence adoption.
Description of the goal, tasks and main results	*Goal:* To explore how the adoption of artificial intelligence influences Organizational Citizenship Behavior and the definition of talent, and to assess its impact on organizational innovation and performance. *Objectives:* ● Analyze the traditional determinants of OCB and how they need to be redefined in the context of AI adoption. ● Investigate the impact of AI on talent identification, development, and retention, and how HR practices need to adapt to support these changes. ● Formulate and test hypotheses to assess the relationship between AI-enhanced OCB and various dimensions of organizational innovation and performance. ● Design and administer surveys to collect data from employees and HR professionals in AI-integrated organizations. ● Perform statistical analyses to test the hypotheses and understand the relationships between AI, OCB and organizational performance. ● Interpret the empirical findings to understand the mechanisms through which AI influences OCB and organizational outcomes. ● Develop practical recommendations for HR and management strategies to effectively enhance OCB and drive

	organizational success in AI-integrated environments. *Main Results:* ● Identification of how AI redefines the traditional determinants of OCB, introducing new dimensions. ● Evidence showing that AI significantly enhances key aspects of OCB, leading to improved organizational innovation and performance. ● Practical insights into how AI can be leveraged for better talent management. ● Recommendations for updating HR practices. ● Development of strategies for promoting engagement and positive workplace behaviors.
Keywords	Organizational Citizenship Behavior, Artificial Intelligence, Innovation, Firm Performance, HR Practices, Talent Management, AI Integration, Organizational Culture.

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Introduction

The term Organizational Citizenship Behavior (OCB) refers to a variety of employee discretionary behaviors that significantly increase an organization's productivity and success even though they are not formally recognized by formal reward systems (Organ, 1988; Podsakoff et al., 2000; Patterer, Sil & Korunka, 2023). These behaviors, like helping others, being responsible, playing fair, being polite and engaging in community activities, go beyond the usual job tasks to improve the social and emotional atmosphere at work. This, in turn, helps the organization work better (Williams & Anderson, 1991; Kong et al., 2023; Ferrer et al., 2023; Bai et al., 2023).

In the modern workplace — deeply impacted by advanced technologies and widespread adoption of Artificial Intelligence (AI) — it is more than just important to review the drivers of OCB in light of recent developments. However, digitalization and AI are not mere operational tools: they change who we are at work by changing what we do in our jobs and why we do them that way— a shift toward evolving new roles plus new ways with different needs for support. As a consequence, the redefinition asks for evaluating organizational management plans and human resource regulations in order to create a setting that will both facilitate the success of these new positions and cater to their specific requirements. Numerous writers have discussed how digital tools and artificial intelligence have altered the dynamics of workplaces and the behavior of employees as a result. Talent management systems must be adaptable to meet the needs of a workplace with cutting-edge technology (Hair, 2019; Xu et al., 2022; Bai et al., 2023; Brougham & Haar, 2018).These changes highlight how important it is to have flexible people management systems that can adjust to the needs of an increasingly digitally-enabled workplace. It is essential to accurately identify and leverage the factors that affect an employee's capacity to create value to the company beyond their job duties. To succeed in this in the digital age we live in, this is essential. (Mattantymäki et al., 2022; Winecoff et al., 2022; Haney & Lutters, 2023).

The impact of AI integration in workplaces goes beyond just changing how things are done at work structurally or operationally. It even influences the informal dynamics among employees that lead to organizational productivity as AI takes over routine tasks, eliminating mundanity from job scopes while also sometimes changing the way people interact at a personal level within their professional spheres. These changes mean any entity needs to rethink their management model and possibly change some – if not all – elements of their HR strategy, simply because artificial intelligence could influence what drives commitment among staff members who see new meaning attached toward going beyond just 'what is expected' at work. This includes different motivational aspects that would be seen differently due to evolving job roles with technology (Brougham & Haar, 2018; Hirsch, 2019; Urquhart et al., 2022; Wenker, 2023).

Moreover, the necessity to examine evolving workplace dynamics intensifies as new technologies, such as digital tools and AI, transform perceptions of employee value, create new roles and modify workplace motivations. These technological advancements are reshaping how employees interact and relate to each other, potentially giving rise to novel challenges and issues that were previously unanticipated (Dery, Sebastian, & van der Meulen, 2017; Susanto, 2023; Motlagh et al., 2023; Lodzikowski et al., 2024). These advancements are making the workplace more dynamic, therefore the traditional OCB determinants might not be as applicable. This progression makes it imperative to look into how OCB is impacted by digital transitions, particularly in light of the growing application of AI. In this new technological era, organizations need to understand these effects in order to make necessary adjustments and ensure that their staff members remain motivated and productive.

Chapter I

1.1 Theoretical framework

The foundational concept of Organizational Citizenship Behavior originated from the seminal work of Organ in 1988. In his research, Organ characterized OCBs as activities that, though «not directly or explicitly recognized by the formal reward systems, contribute collectively to the efficient and effective functioning of the organization» (Organ, 1988). Highlighting the voluntary essence of OCB and its distinction from standard job duties, Organ suggested that these behaviors operate to bridge the gaps left by formal job descriptions, thus enhancing organizational smoothness and efficacy. This early depiction underscored the self-initiated nature of OCB, making it distinct from tasks influenced by direct rewards.

Often connected to Katz's seminal 1964 exploration of organizational motivation, the theoretical foundations of Organizational Citizenship Behavior (OCB) find their origins. In this work, Katz delineates three types of behavior that surpass the stipulations of formal roles: innovative and spontaneous actions, engagements within interpersonal relations, and efforts devoted to preserving and advocating for the company’s reputation (Katz, 1964; Brougham & Haar, 2018; Susanto, 2023). These identified behaviors closely resonate with those later defined under the umbrella of OCB.

Smith, Organ, and Near in 1983 refined the framework of Organizational Citizenship Behavior (OCB) by categorizing it into more distinct dimensions, specifically altruism and generalized compliance (Smith, Organ, & Near, 1983). They described altruism as behaviors intended to aid fellow members within the organization in solving work-related issues. Generalized compliance, on the other hand, was characterized by an employee's personal commitment to abide by organizational norms and procedures more stringently than what is minimally required. This categorization laid the groundwork for developing measurable aspects of the OCB construct.

The OCB concept was further refined by Podsakoff, MacKenzie, Moorman, and Fetter in 1990, who expanded its dimensions by introducing elements like sportsmanship, civic virtue, and courtesy, thus significantly widening the range of behaviors encompassed by the OCB framework. The categorization of these behaviors, distinguishing between those that benefit individual colleagues (OCB-I) and those that benefit the organization as a whole (OCB-O), was further elaborated by Williams & Anderson in 1991.

1.2 Determinants of OCB

Since its inception in the 1980s by Dennis Organ, the concept of Organizational Citizenship Behavior (OCB) has significantly progressed. Initially centered on discretionary behaviors that are not mandatory but enhance an organization's effectiveness [Organ, 1988], OCB has seen a broadening and refinement in its understanding through numerous theoretical and empirical studies over the years.

As globalization increased, the 2000s brought a wave of cross-cultural studies examining OCB across different national and organizational cultures. Researchers like Farh, Earley, and Lin (1997) explored how cultural variables influence the expression and perception of OCB, finding that cultural dimensions such as individualism versus collectivism could significantly affect the manifestation of OCB behaviors. The 2000s also saw a diversification in the contexts in which OCB was studied, including public sector organizations and non-profit settings (Vigoda-Gadot, 2007; Papantoniou et al., 2021; Gandhi, 2024).

The recent decades have emphasized the impact of changing work environments, particularly the rise of digital technology and remote work, on OCB. Studies have begun to explore how virtual work environments alter the ways in which OCBs are performed and perceived (Gupta & Singh, 2021; Kong et a;., 2023). Moreover, the increasing use of AI and automation has prompted scholars to reconsider traditional OCB dimensions and to propose new forms that are relevant to technologically advanced workplaces. These explorations have been critical in understanding how foundational behaviors of OCB adapt to and fit within the evolving technological and organizational landscapes. They suggest that as jobs become more intertwined with technology, the nature of discretionary behaviors that contribute to organizational success may also evolve (Brougham & Haar, 2018; Caros et al, 2023).

OCB dimensions have been categorized in varied ways by researchers, showcasing diverse viewpoints on their benefits to organizations. Research intensification into OCB commenced with the seminal work of Organ in 1988, broadening the definition of OCBs and highlighting essential dimensions such as altruism and civic virtue, establishing a foundational framework for further discussion and investigation. Continuing in the 1990s, the conceptual expansion of OCB saw contributions from Podsakoff, MacKenzie, Paine, and Bachrach in 2000, which included additional dimensions like initiative and organizational loyalty, while also marking the onset of empirical analyses into OCB determinants like job satisfaction and leadership behavior. With advancing globalization, the scope of OCB research widened to include cultural influences and organizational structures. Thus, studies focused on disparate leadership styles across cultures and their effects on OCBs, along with the transformations in OCB expressions in multinational contexts. The technological era brought a shift towards exploring the impacts of digital technologies and remote working conditions on OCBs. Research pivoted to digital citizenship behaviors and virtual OCBs, highlighting the increasing role of social media platforms in showcasing these behaviors. Presently, the surge in AI and automation is directing new lines of enquiry into how these technological advancements recalibrate the classic OCB determinants. The latest research efforts are analyzing the dynamics between technology and employee behavior, especially how AI tools and automated processes are affecting traditional OCB elements like leadership styles and employees' job satisfaction.

While investigating the factors that drive Organizational Citizenship Behavior, our study adopts the classical framework set forth by Podsakoff et al. (2000). This decision to concentrate on their identified five determinants is strategically based on several crucial considerations:

- Comprehensive coverage. Podsakoff and his colleagues' framework provides a comprehensive overview that encapsulates a wide array of factors influencing OCB. The model effectively segments these determinants into understandable and discrete categories, capturing a wide scope of organizational dynamics.
- Empirical support. The determinants outlined are backed by extensive empirical research, making them robust and reliable for understanding OCB. Research is seminal in the field of organizational behavior and has been widely cited and validated in subsequent studies. Such empirical foundations confirm that these determinants are not just theoretically sound but also practically relevant.
- Theoretical integration. Suggested five determinants effectively integrate various theoretical perspectives on what motivates OCB. For example, fairness and job satisfaction are rooted

in psychological theories of equity and job design, respectively, while leadership support incorporates elements of transformational leadership theory. This integration provides a holistic view of the organizational factors that promote OCB, offering insights that are rich in both depth and breadth.

- Practical implications. By identifying these determinants, it becomes possible to implement targeted interventions within organizational frameworks. Management has the ability to manipulate these determinants as tools to boost Organizational Citizenship Behavior (OCB) among employees. An example includes advancing the notion of fairness by adopting more transparent decision-making procedures. Similarly, increasing job satisfaction could be reached by redesigning roles to enhance their engagement and meaningfulness.
- Adaptability to diverse contexts. The five chosen determinants stand out not only for their robustness in various studies but also for their adaptability across different organizational environments. Their applicability extends from small startups to large multinational corporations, allowing these factors to be custom-fit to a variety of cultural and structural frameworks. Such universal relevance highlights their exceptional value for organizations striving to foster Organizational Citizenship Behavior in diverse contexts.

Having explained the choice of selected determinants, OCB can be categorized into several dimensions, each reflecting different aspects of employee behavior that support the organization's social and psychological environment:

- Altruism. It encompasses actions focused on assisting colleagues with their tasks at the workplace. The inclination towards such conduct is often spurred by a profound capability for empathy and interpersonal comprehension among workers. Leadership approaches that prioritize and nurture understanding and supportiveness, such as transformational and servant leadership styles, have been found remarkably beneficial in promoting these altruistic behaviors. This effectiveness is extensively documented in widely recognized studies (Podsakoff, MacKenzie, Paine, & Bachrach, 2000; Kohl & Prikladnicki, 2021; Garcìa-Chitiva & Correa, 2023; Chavan et al., 2023; Hermawan, Sunaryo, & Hardhienata, 2023).
- Conscientiousness. It encompasses the level to which workers exceed the foundational rules and descriptions pertaining to their roles. Job satisfaction, a strong individual work ethic, and business norms that esteem meticulousness and precision are factors that amplify conscientious traits. Furthermore, the reinforcement of conscientiousness can derive from policies that consistently emphasize the value of lofty standards and firm's commitment

(Organ, 1988; Abudaqa et al., 2022; Bhatia & Williams, 2023; Pahlevi & Nirmala, 2023; Biedma Ferrer & Medina Garrido, 2023).

- Sportsmanship. Sportsmanship is characterized by the maintenance of a positive demeanor, even under challenging conditions, reduced complaints, and avoiding needless disputes. Key influencing factors of exemplary sportsmanship encompass contentment with one's professional role, an encouraging culture within the organization, and robust mechanisms for the resolution of conflicts. The demonstration of resilience and positivity by leaders when confronted with difficulties plays a crucial role in promoting similar conduct among their team members (Podsakoff et al., 2000; Trinkenreich et al., 2023; Bai et al., 2023; Bhatia & Williams, 2023; Atrian & Ghobben, 2023).
- Courtesy. It entails actions that prevent conflicts in the workplace, such as advanced notifications of schedule changes or discussions with colleagues before undertaking actions impacting their tasks. The evolving roles of AI in managing workflows highlight the crucial role of courtesy in facilitating smooth transitions and fostering workplace harmony (Borman & Motowidlo, 1993; Sun et al., 2018; Chang et al., 2023).
- Civic virtue. Civic virtue is defined as behaviors that demonstrate a deep level of responsible participation in the life of the organization, such as attending meetings, keeping informed about organizational matters, and participating in voluntary activities. Civic virtue is often encouraged by transparent leadership, active employee engagement strategies, and the presence of channels for employee involvement in decision-making processes. Organizations that foster an inclusive atmosphere and encourage employee input in strategic decisions typically see higher levels of civic virtue (Graham, 1991; Pohl et al., 2023; Ahmed & Gollan, 2023; Byrne et al., 2023).

These dimensions collectively contribute to the smooth and effective functioning of an organization, promoting a cooperative and friendly work environment that enhances productivity and reduces the need for strict supervision.

1.3 Digital transformation and the future of OCB

1.3.1 Context change and the future of work

The rapid advancement of technology has catalyzed profound changes in the workplace, signaling the advent of a new era that significantly deviates from traditional norms and practices. This era, marked by what is widely referred to as digital transformation, involves the integration of digital technologies into all aspects of business. Such transformation is reshaping the fundamental ways in which companies operate and compete in a highly interconnected and competitive global market.

Digital transformation is driven by a multitude of technologies including cloud computing, big data analytics, artificial intelligence, the Internet of Things (IoT) and blockchain, among others. These technologies are not merely tools for operational efficiency, they are reshaping industries by enabling new business models and services that were previously unimaginable. For example, cloud computing allows businesses to scale rapidly without the need for significant capital investment in physical infrastructure. Similarly, big data analytics provide insights that can drastically improve decision-making processes, enhancing the agility of businesses to respond to market changes and consumer preferences efficiently (Manyika et al., 2011; Schwab, 2022; Gobble, 2023). In addition to these technologies, blockchain is revolutionizing business operations by enhancing transparency, security and efficiency in transactions. This technology proves especially transformative in sectors such as finance, supply chain management, and healthcare, where secure, transparent transactions are paramount. For example, blockchain facilitates smart contracts that autonomously execute transactions when predefined conditions are met, significantly reducing intermediaries and lowering transaction costs. Such capabilities are revolutionizing business operations, cultivating new models centered around trust and transparency (Tapscott & Tapscott, 2023; Kanaparthi, 2024).

The future of work, as influenced by these technological advancements, is increasingly digital and is characterized by a significant shift in the nature of work itself. There is a noticeable decline in the roles traditionally centered around manual and clerical tasks due to automation and technological augmentation, causing a decreased demand for routine skills. Simultaneously, there is a surging need for more complex cognitive abilities such as problem-solving, critical thinking, creativity, and digital literacy – skills in which machines still lag behind (Brynjolfsson & McAfee, 2014; Garcia de Masedo et al., 2022; Abubakar et al., 2023; Yigitbas et al., 2023; Sudkaharan & Risi, 2023). Modern employees are expected to bridge the gap between technology and strategic insight, enhancing productivity and innovation with these technologies. Additionally, as digital workplaces evolve, there is an increasing need for adaptive skills that can be fostered through innovative educational approaches. Recent studies have shown the benefits of integrating coaching methods into technical education to better prepare students for the dynamic demands of modern workplaces. These methods focus not just on imparting technical knowledge, but also on developing soft skills like adaptability, continuous learning, and self-management, which are crucial as job roles become more fluid and technology-driven. Such educational transformations are critical for equipping the workforce with the skills necessary to thrive in increasingly digital environments (Alghamdi et al., 2021; Yu et al., 2023; Stephany & Teutloff, 2023).

Moreover, the digital transformation extends beyond individual businesses to affect the entire economy, influencing labor markets and the nature of employment relationships. The gig economy, characterized by short-term contracts or freelance work as opposed to permanent jobs, is one example of how digital platforms are creating new forms of employment that are flexible but also less secure. This phenomenon is facilitated by digital platforms such as Uber, Airbnb and Freelancer, which connect freelance workers with short-term engagements directly with consumers, thus bypassing traditional employment structures (De Stefano, 2015; Hsieh et al., 2023; De Los Santos et al., 2024). Furthermore, recent research explores the challenges faced by gig workers due to the extensive surveillance practices of gig platforms. These challenges include increased work pressures and invasions of privacy. In response, some gig workers have started to develop their own surveillance tools, aimed at reclaiming some control over the platforms they engage with. These community-created tools aid in collecting data concerning the platforms, which could potentially facilitate enhanced protection and promotion of workers' rights (De Los Santos et al., 2024; Eliyahu & Somech, 2024; Lancaster, 2024; Hernandez et al., 2024).

1.3.2 AI and its impact on organizations

Artificial Intelligence is increasingly recognized as a pivotal force in the ongoing digital transformation across industries. AI technologies, such as machine learning, natural language processing (NLP), and robotics, play crucial roles in enhancing business operations through the automation of complex and traditionally human-performed processes. This transformation does not simply replace human labor; it significantly augments the capabilities of human teams, enabling them to accomplish more tasks with reduced effort and increased accuracy.

At the heart of artificial intelligence lies machine learning, which empowers algorithms to analyze data, learn from it, and make informed predictions or decisions autonomously without specific programming. Within the business realm, these algorithms forecast consumer behavior, enhance logistics, streamline inventory management, and aid in fraud detection. The proactive application of machine learning catapult facilitates operational efficiency by optimizing resource use and diminishing expenditures (Jordan & Mitchell, 2015; Zhou et al., 2023; Ioste, 2023). Natural Language Processing (NLP) equips machines with the capability to comprehend and interpret human language, which proves crucial for bolstering interactions both internally and externally. For instance, in customer service, NLP drives chatbots and virtual assistants that manage numerous inquiries swiftly and effectively. Additionally, NLP improves business intelligence and data retrieval among employees by simplifying access to complex datasets through natural language queries, thereby advancing data accessibility (Hirschberg & Manning, 2015; Liu et al., 2023; Islam, 2023; Bolivar et al., 2023; Arslan & Cruz, 2023). Robotics integrated with AI revolutionizes manufacturing by accelerating processes, minimizing errors, and ensuring uniform product quality. In the service domain, robotic applications extend from automated hotel check-ins to aids in healthcare, aiding in surgical and routine procedures. Moreover, the evolution of machine learning sharpens risk evaluations in the small business sector, adapting deep learning models for these smaller entities to improve credit assessments and facilitate funding opportunities (El-Awady, 2021; Middelhuis et al., 2023; Dzhusupova et al., 2023). Additionally, the synergy of machine learning with quality assurance redefines project management and development cycles across varied sectors. The formulation of a new machine learning model that integrates top-tier quality assurance practices ensures the effective execution and enhanced outcomes of these technological initiatives, guiding businesses through the complexities of machine learning projects (Studer et. al, 2021; Shi et. al, 2022; Kang & Hwang, 2023; Kozodoi et. al, 2023; Xiao et. al, 2023).

The incorporation of AI into business processes substantially boosts scalability, enabling companies to manage larger transaction volumes or service capacities while not massively increasing overhead expenses. The ability of AI to process vast data sets in real time greatly aids in rendering expedited and precise decisions, an essential capability for sustaining a competitive edge in dynamic markets. Moreover, insights driven by AI assist enterprises in customizing their services according to individual customer preferences, thereby improving satisfaction and fostering loyalty, which is instrumental in business success (Agrawal, Gans, & Goldfarb, 2019; Schemmer et al., 2021; Upadhyay et al., 2021; Gathani et al., 2022; Zu et al., 2023). Machine learning algorithms, a core aspect of AI technologies, drastically enhance the accuracy and velocity of data analysis compared to conventional human teams. Capable of revealing patterns and details unnoticed by human analysts, these algorithms support not only superior business decisions but also promote a more agile and responsive organizational culture. Processes involving decision-making, which formerly extended over days or weeks, can now be condensed into mere hours or minutes. Such advancements in efficiency empower firms to adapt swiftly and effectively to changes in the market (Davenport & Ronanki, 2018; Iyer et al., 2021; Alenezi et al., 2022; Butler, Espinoza-Limón & Seppälä, 2023).

In conclusion, AI transcends being merely a technological advancement. It acts as a transformative power, reshaping the essence of business operations and enhancing efficiency, innovation and competitiveness. With the ongoing evolution of AI technologies, their capability to revolutionize various economic sectors is extensive and mostly untapped, signaling the dawn of a new business era where intelligence and automation set new boundaries for possibilities.

1.3.3 Impact of digitalization and AI on employees and processes

AI’s ability to automate routine and repetitive tasks has a dual effect on the workforce. On the negative side, this can lead to job displacement, as machines replace human labor in executing standardized, programmable tasks. This trend has been noted across various sectors, from manufacturing to services, where AI-driven systems can handle everything from assembly line jobs to basic customer service inquiries (Manyika et al., 2017; Bessen, 2019; Nelson et al., 2023; Mittal & Chen, 2023; Gao & Wang, 2023; Zheng et al., 2024). Recent advancements in AI, especially in large language multi-modal models such as GPT-4, have raised concerns about the displacement of human workers across various industries. The growing capabilities of AI to perform tasks traditionally managed by humans necessitate the development of strategies for a balanced coexistence between AI technologies and human labor. These strategies include fostering a workforce skilled in areas where AI does not excel and implementing upskilling and reskilling programs to mitigate the impact on the labor market (Singh, 2023; AlShebli et al., 2023; Necula, 2023). The changing work environment due to AI advancements calls for new ways to help people switch jobs. A new method shows that by understanding the skills required for different jobs, workers can find new opportunities by using the skills they already have. A tool that recommends job paths helps people find the best new jobs for them as technology changes the job market (Dawson, Williams & Rizoiu, 2021; Pachegowda, 2023; Li et al., 2023; Emaminejad et al., 2023).

On the upside, the automation of routine tasks enables employees to dedicate themselves to more intricate, strategic, and imaginative activities. This modification implies a transformation in job roles, now requiring advanced cognitive abilities, including problem-solving, critical thinking, and innovation, as noted by Brynjolfsson and McAfee in 2014. Such transformation demands a workforce that is both technologically adept and flexible, continuously evolving to adapt to new tools and processes. Robotics and AI enhance the capabilities of the skilled workforce by complementing human efforts, enabling greater productivity. In sectors where collaborative teams consisting of humans and robots are formed, these teams have been proven to accomplish more collaboratively than alone, thereby enhancing productivity and spurring innovation across industries. This synergy contributes prominently to the national economic growth. Projects focused on robotics research and workforce development are expected to stimulate GDP growth, broaden the skilled middle class, and fortify the supply chain against global disruptions, as suggested by Christensen and others in 2020 and affirmed by Zhi and colleagues in 2023. Additionally, AI«s capacity to aid job transitions through skill-based recommendations indicates that, although some positions may vanish, new opportunities that resonate with the workers» existing skills are likely to arise. Such mechanisms facilitate the seamless transition of the workforce into emerging roles demanding higher cognitive capabilities, ensuring a flexible and sustainable employment environment, as discussed by Leslie in 2020 and later supported by Hurwitz and Cevora in 2021, as well as Ben-Ishai and associates in 2024.

In the dynamic landscape of modern work, adaptability emerges as an imperative competence. Employees must be willing and able to continuously update their skills and knowledge to keep pace with technological advancements. Technological literacy, or the ability to use and interact with complex digital systems, becomes foundational, as does the ability for lifelong learning—attributes that are essential not only for personal career development but also for organizational agility and competitiveness (Autor, 2015; Schwartz et al., 2020; Maghsoudi, 2023; Mouatadid et al., 2023; Xu et al., 2024).

In a rapidly evolving work environment, the skill of adaptability emerges as crucial. Employees, by necessity, must stay up-to-date, continually refining their skills and knowledge to align with technological advancements. Technological literacy, the proficiency in using and interacting with complex digital platforms, along with an enduring commitment to lifelong learning, are crucial. These qualities not only support personal career progression but also enhance the agility and competitive edge of organizations. Recent studies have highlighted that the integration of AI and robotics enhances the capabilities of the skilled workforce by augmenting human effort, thereby boosting productivity and fostering innovation across various sectors. This blend of human expertise and automated technology plays a vital role in strengthening the economic foundations of nations, supports the expansion of a skilled middle class, and contributes to a robust supply chain (Christensen et al., 2020; Mittal & Chen, 2023; Emaminejad et al., 2023).

The digital transformation necessitates a shift in organizational conduct, focusing on the critical role of data-driven strategies in decision-making. In this landscape, decision-making processes that previously relied heavily on hierarchical structures and individual experience are now increasingly influenced by data analytics, providing a more empirical basis for decisions. This shift is complemented by an evolving workplace where Organizational Citizenship Behavior takes on new forms, as digital interactions often replace physical ones. Supporting these changes, recent research illustrates the dynamic ways that digital tools facilitate and necessitate continuous learning and skill adaptation within the workforce. Moreover, the integration of Data Operations (DataOps) within organizational frameworks exemplifies how structured data management and analytics can drive digital business transformation. By leveraging DataOps, organizations can more effectively process and utilize data, enhancing operational efficiency and fostering new business models. This approach not only supports more informed decision-making but also strengthens the overall digital agility of the organization (Lokuge & Duan, 2021; Jia Xu et al., 2022; Wen et al., 2023). In addition, digital workplaces bring about both challenges and opportunities in upholding employee mental health and organizational dedication. With the universal presence of digital tools, recognizing their influence on worker well-being and ethical dynamics becomes essential. This task involves exploring how robust organizational bonds can mitigate anxieties linked to digital disruption and underscore the need for ethical leadership to support an encouraging working environment in these digitally driven times (Zu et al., 2022; Ali Bai et al., 2023).

The outlined modifications indicate that the fundamental aspects of Organizational Citizenship Behavior — including altruism, conscientiousness, sportsmanship, courtesy, and civic virtue — continue to hold significance. However, the methods of their manifestation and appreciation are likely to change considerably within a digitally transformed workplace. Consequently, organizations should re-evaluate not only their operational frameworks and training initiatives but also the systems for evaluating and acknowledging OCB, ensuring they correspond to the emerging digital conditions.

Drawing on the above considerations, we articulate our first research question as follows: What are the determinants of Organizational Citizenship Behavior with the adoption of AI? This question aims to uncover the factors that drive OCB in environments characterized by advanced technological integration, focusing on how digital tools and AI influence not only the nature of work but also the voluntary, beneficial behaviors that go beyond formal job descriptions. By addressing this question, the study will explore the nuanced ways in which AI adoption affects employee interactions, collaboration and the broader organizational spirit.

1.3.4 Need to study OCB in new conditions

Given the rapid evolution of workplace technology, particularly with the integration of AI and digital platforms, it has become imperative to revisit and reevaluate Organizational Citizenship Behavior within these new digital paradigms. Traditional models of OCB have primarily centered around visible, often in-person interactions that foster interpersonal rapport and facilitate observable acts of help and cooperation. However, the shift towards remote work and virtual team environments fundamentally alters these dynamics, necessitating a fresh examination of how OCB manifests in digital-first contexts.

The widespread adoption of remote work has significantly reshaped travel habits, resulting in notable changes in organizational behavior and employee presence. Research indicates a strengthened link between travel patterns and organizational behavior among remote workers, who increasingly prefer «third places» over home or traditional offices for work. These alternative locations typically facilitate shorter commutes and encourage the use of more sustainable modes of transport, altering how organizational citizenship behaviors (OCBs) such as assisting and supporting colleagues are executed outside conventional office environments (Caros et al., 2023; Dey et al., 2023). Additionally, organizational bulk email systems have become indispensable in remote settings for effective communication with employees. These systems are crucial for the efficient dissemination of vital information, underscoring the importance of digital communication tools in preserving organizational unity and enabling new forms of OCB among geographically dispersed teams (Reuschke & Felstead, 2022; Kong et al., 2023; Gidey et al., 2023).

In the evolving landscape of digital transformation, jobs are not only being reshaped but are also witnessing the emergence of new forms of organizational citizenship behavior (OCB), particularly those that are digital in nature. Digital helping behaviors exemplify this shift by focusing on aiding coworkers with technological challenges such as mastering new software tools or adhering to data security protocols. This support is vital for enabling all team members to maximize the use of technological assets, which in turn helps in improving, or even enhancing team efficiency and unity within digital work environments (Leonardi, 2016; Maruping, Venkatesh, Thatcher, & Patel, 2015; Stocco et al., 2021; Syah & Safrida, 2023). Moreover, as work increasingly shifts to remote settings using digital interfaces, the advent of digital collaboration and knowledge-sharing tools underscores a need for reward systems suited to these setups. Research indicates that adjustments in traditional recognition approaches are required to appreciate contributions that might not be immediately evident in virtual spaces, thereby ensuring every form of assistance, regardless of location, is valued and recognized (Marius Mikalsen et al., 2021; Nichols et al., 2022).

Adapting recognition and reward systems to accommodate new forms of Organizational Citizenship Behavior in a digital context becomes essential as traditional programs might not fully recognize the value of digital helping behaviors, which are often subtle and not as immediately observable as conventional forms. It necessitates the development of recognition systems and metrics to accurately assess and acknowledge these digital efforts. Emphasizing the importance of integrating Data Operations (DataOps) to effectively track and reward online assistance behaviors, recent research highlights their significant, albeit less visible, impact on organizational performance (Jia Xu et al., 2022; Hamilton et al., 2022). Moreover, as work increasingly shifts to remote settings using digital interfaces, the advent of digital collaboration and knowledge-sharing tools underscores a need for reward systems suited to these setups. Research indicates that adjustments in traditional recognition approaches are required to appreciate contributions that might not be immediately evident in virtual spaces, thereby ensuring every form of assistance, regardless of location, is valued and recognized (Marius Mikalsen et al., 2021; Nichols et al., 2022).

The deep impacts of digitalization and AI on job environments highlight the critical need to reinterpret and grasp the nuances of Organizational Citizenship Behavior (OCB) in contemporary times. In the evolving landscape of work, adaptability to technology, coupled with behavioral modifications among employees, becomes essential. Therefore, organizations should emphasize the creation of spaces where OCB can thrive, particularly under the conditions of digital and remote workspaces, ensuring its promotion and development.

As AI and digital tools become increasingly integral in business operations to maintain competitiveness, it becomes crucial to explore their impact on employee behavior beyond basic job responsibilities. Investigating whether employee «corporate citizenship»—attributes reflecting positive engagement at work—transforms in a tech-dominated landscape is essential. This involves assessing how AI influences interpersonal interactions among employees, their collaborative practices, and their contributions to defining the culture and objectives of their organizations in such an evolving environment.

1.4 Effects of AI adoption

The introduction of artificial intelligence in workplaces is more than just a technical upgrade, it profoundly reshapes how companies are structured, how work is done, and what roles employees play. This major shift calls for a deep look into how both individuals and organizations handle these changes. Organizational Citizenship Behavior offers a valuable perspective to explore the wide-ranging effects of AI in the workplace. OCB focuses on voluntary actions that improve organizational culture, efficiency, and adaptability - traits that are becoming crucial in environments influenced by AI.

Exploring OCB within the AI environment reveals potential shifts in organizational behaviors traditionally seen as beneficial, such as aiding colleagues, initiating new projects, and displaying informal leadership. As remote work and digital collaboration tools become more prevalent, assisting others could transition from in-person to virtual contexts. Moreover, new initiatives could emerge, such as the implementation of software solutions aimed at enhancing team effectiveness or the creation of informal networks designed to support peers in adapting to technological advancements.

Additionally, analyzing OCB in this new setting can point out what kind of support systems and rewards organizations should put in place to promote such behaviors. Recognition programs, for example, might need updates to reward digital forms of help and creativity, acknowledging contributions that aren't as visible as those in a traditional office but are just as important for keeping teams connected and motivated in a digital-first workplace.

Moreover, looking at OCB in relation to AI adoption sheds light on how organizations can prepare their workforce to succeed in an AI-enhanced workplace. It highlights the need for training programs that go beyond teaching technical skills to also enhancing soft skills like adaptability, problem-solving, and digital communication—skills crucial for employees to effectively engage in OCB in a technologically advanced workplace.

1.4.1 Individual responses to AI adoption

As AI technologies automate routine tasks, employees face a shift in their roles, emphasizing the need for skills such as critical thinking, adaptability and advanced technological proficiency. This shift can influence OCB in varied ways.Proactive OCB is more common among employees who perceive AI as a beneficial tool for career growth, often involving help to fellows in adapting to the new technology or the development of innovative methods to utilize AI, thereby reinforcing their dedication to the organizational goals [Ng & Feldman, 2015; Podsakoff et al., 2009; Papinen et al., 2021; Hartono et al., 2023]. Moreover, the situation accentuates the importance of having bespoke training programs not solely focused on technological skill enhancement but also on fostering a mindset that sees technological progression as a core element of both professional growth and organizational success. Ensuring that employees are not just technically proficient but geared to use such skills constructively for the enhancement of organizational health and flexibility is crucial (Weitz, Dang, & André, 2022; Bai et al., 2023).

Conversely, employees who perceive AI as a threat due to potential job loss or skill redundancy might display decreased OCB, characterized by withdrawal or resistance to change. This dynamic is critical for organizations to manage, as fostering a culture that supports ongoing learning and adaptation can help mitigate fears and encourage positive OCB (Eisenberger et al., 2001; Shoss et al., 2013; Calefato et al., 2023). One key approach is involving employees in AI training processes, which has been shown to significantly improve their perceptions of AI's capabilities and their comfort with its applications. By actively engaging in the development and implementation of AI systems, employees can better understand and leverage these technologies, leading to enhanced adaptability and proactive contributions within the organization (Mahmood, Ajaykumar, & Huang, 2021; Lee et al., 2023; McCarty et al., 2023). Moreover, establishing trust in AI systems is critical for encouraging employee acceptance and integration of these technologies into their daily work. Ensuring that AI systems are developed and implemented with ethical considerations and transparency helps build trust among employees, reducing resistance and fostering a culture where innovative and helpful behaviors are maintained even as roles and tasks evolve due to AI integration (Avin et al., 2021; Yang & Tsai, 2023).

The integration of AI technologies into the workplace presents a transformative shift in how roles and tasks are executed, necessitating a corresponding evolution in OCB. As routine tasks become automated, employees are required to develop higher-level skills such as critical thinking, adaptability, and technological proficiency. These changes offer opportunities for proactive OCBs, where employees who view AI positively can enhance their career development and contribute innovatively to their organizations. Conversely, the perception of AI as a threat can lead to decreased OCB, underscoring the importance for organizations to foster an adaptive and supportive culture.

Effective strategies to encourage positive OCB in the context of AI include tailored training programs that emphasize both technical skills and the integration of technology into career development. Moreover, involving employees in the development and implementation of AI can improve their understanding and acceptance of these technologies, promoting a more adaptable and proactive workforce. Establishing trust through ethical and transparent AI development is also crucial to reducing resistance and fostering a workplace culture that supports innovation and collaboration. By addressing these dynamics, organizations can leverage AI to enhance organizational effectiveness and ensure that employees are not only equipped to meet the challenges of digital transformation but are also active contributors to its success.

1.4.2 Organizational responses to AI adoption

In today's AI-enhanced work environments, there is an escalating need for professionals who possess a diverse array of capabilities comprising both technical know-how and interpersonal attributes. The ability to harness and manipulate emerging technologies requires profound technical expertise. However, soft skills like leadership, empathy, effective communication, and problem-solving are equally pivotal. These skills not only foster team collaboration but also propel innovation and assist in navigating organizational transformations. Particularly, the ability to analyze intricate datasets produced by AI systems is indispensable for employees aiming to craft strategic decisions. Furthermore, in the context of leveraging AI for a competitive edge, the role of creativity in devising groundbreaking applications cannot be overstated (Brynjolfsson & McAfee, 2014; Farhana et al., 2021; Butler et al., 2023; Zirar, 2023).

In light of these developments, it is imperative for organizations to renovate job descriptions to align with emerging skills required within an AI-enhanced setting. This requires a broadened scope beyond outlining necessary technical capabilities, emphasizing the crucial role of soft skills for leveraging AI effectively. Particularly, leadership capabilities are vital as they play a critical role in navigating technological transformations, promoting a culture that is supportive of digital progress (Huang & Rust, 2018; Stefik & Price, 2023; Yu et al., 2023). In training employees to acquire such critical skills, it is essential to introduce comprehensive training and development initiatives aimed at closing the skills gap seen in the AI-transformed workplace. These initiatives should encompass training in data literacy, awareness of AI functions and proficiency with digital tools, while also strengthening capacities for problem-solving, ethical decision-making, and collaboration (Kaplan & Haenlein, 2019; Pant et al., 2023; Kawakami et al., 2023). The necessity for such skills transformation urges a deeper, organization-wide change strategy. HR practices should facilitate an environment conducive to ongoing learning and adaptability, ensuring that the workforce remains dynamic and robust. Moreover, as the nature of job roles evolves, evaluation and incentivization techniques must also be adapted to assess not solely the output but also the effectiveness with which employees utilize AI tools to augment business functionalities (Jobin et al., 2021; Gruetzemacher & Whittlestone, 2021; Adithya et al., 2023). This detailed re-evaluation and realignment of roles, competencies, and assessment criteria form the core of adapting to an AI-driven enterprise landscape.

Recent research underscores the necessity for organizations to revise their performance metrics due to the transformative influence of AI in the workplace, with an emphasis on evaluating adaptability and innovation in employees. It is now suggested that performance assessments consider not merely technical skills but also the capacity for innovation and adaptation to technological shifts, including the strategic use of AI for problem-solving and enhancing business operations (Nedzhvetskaya & Tan, 2021; Butler, Espinoza-Limón, & Seppälä, 2023). Additionally, the critical importance of employee involvement in the ethical governance of AI has been highlighted, advocating for metrics that measure participation in ethical decision-making processes. This technique is crucial in cultivating a culture of responsible innovation within AI-driven contexts (Nedzhvetskaya & Tan, 2021; Wei & Zhou, 2022; Azila-Gbettor, 2023). Further, the research points to the necessity of assessing the effectiveness of AI collaboration and its impact on human task performance and satisfaction. Evaluations should focus on the quality of employee engagements with AI systems, which profoundly influence team dynamics and individual job satisfaction (Hemmer et al., 2023; Pamt et al., 2023).

The trend towards more dynamic and applicable performance metrics coincides with the broader adoption of continuous feedback systems. These systems diverge from traditional annual reviews by offering regular, real-time feedback, allowing employees to adjust their performance swiftly and effectively. Such a method proves particularly advantageous in environments enriched by rapid advancements, like those utilizing artificial intelligence, where the nature of job roles and requisite skills can change quickly. Continuous feedback supports ongoing learning and adaptability, essential for both personal development and organizational flexibility (Stone, Deci, & Ryan, 2009; Huck et al., 2021; Guo et al., 2022). To incorporate these modern performance metrics into human resources frameworks, both technological enhancements and cultural transformations are required. HR systems must be equipped to monitor an expanded set of performance indicators and deliver feedback promptly. Additionally, the adoption of these metrics necessitates a culture embracing change, underscored by clear leadership communication regarding their significance and applicability. This alignment ensures that all employees understand the new standards and are fully engaged in the adaptation process (Pulakos, Hanson, Arad, & Moye, 2015; Simpson et al., 2021; Porter & Bozkaya, 2022). Various studies across different sectors have indicated that organizations which adopt comprehensive performance metrics coupled with continuous feedback often see heightened levels of employee satisfaction, enhanced innovation, and better adaptability. For example, a noteworthy project by Google, Project Oxygen, identified that soft skills such as coaching, communication, and collaboration were critical success factors for their managers. This insight led to a strategic shift in their performance evaluation criteria to emphasize these soft skills (Garvin, 2013; Dikici et al., 2021; Kapinus et al., 2023).

1.5 Talent identification and talents in an organizational context

1.5.1 The identification of the talent

Talent is defined as individuals endowed with a high degree of human and social capital (Crane & Hartwell, 2019) and potential (Tansley, 2011), which are key resources that enhance an organization's performance and provide a competitive edge (Barney, 1991; Collings et al., 2019). Effective talent management (TM) strategies focus on attracting, developing, retaining, and securing the commitment of high-potential and high-performing employees to achieve strategic objectives (Al Ariss, Cascio, & Paauwe, 2014; Mellahi & Collings, 2010). Organizations systematically identify and position such talent in pivotal roles to maintain a robust talent pool, which is crucial for ongoing organizational commitment and success (Mellahi & Collings, 2010). Talented individuals are seen as reservoirs of critical capabilities that spur a firm’s growth and success if properly nurtured (Minbaeva et al., 2003, 2014; Vaiman et al., 2012).

The role of TM encompasses a series of practices aimed at maximizing the return on investment from employees whose skills are vital for organizational outcomes (Gallardo-Gallardo et al., 2019; Lepak & Snell, 1999). These practices, which include talent attraction, development, and retention, leverage the knowledge and competencies that these valuable employees hold (Jooss et al., 2019). Research in TM highlights the impact of these practices on various organizational results, such as enhanced performance, competitive advantage, and innovation, as well as on employee-related outcomes including commitment, satisfaction, engagement, and reduced turnover (Björkman et al., 2013; Gelens et al., 2014; Mensah et al., 2016; Schuler et al., 2011). Moreover, while organization-specific human capital is instrumental in boosting organizational performance (Kang et al., 2007), TM is crucial for generating value and securing competitive advantages (Wang et al., 2016). For instance, talented individuals often possess extensive social capital, evident in their robust interpersonal networks and communication skills, which are essential for facilitating knowledge transfer and sharing both within and external to the organization (Crane & Hartwell, 2018; Minbaeva et al., 2014). Thus, implementing targeted talent attraction, development, and retention strategies can significantly enhance organizational performance, sustainability, and innovation.

The integration of AI significantly revolutionizes talent management by enhancing the methodologies used for discovering, nurturing, and retaining talents. Particularly, through the application of advanced analytics and machine learning, AI introduces a transformative path for talent identification. By processing large volumes of data, organizations equipped with AI are able to detect intricate patterns, predicting future high performers, an achievement that lies far beyond the capacities of conventional, subjective methods of assessment. This technological advantage leads to the objectivity and precision in identifying talent, thus facilitating more informed, grounded in data decisions within the recruitment and selection contexts (Ransbotham et al., 2021; Faqihi & Miah, 2022; Ehlinger & Stephany, 2023; Qin et al., 2023).

Further elaborating, the use of AI in managing employee training programs allows companies to create customized learning experiences that are tailored to each worker's unique needs. AI helps by analyzing data like how well employees do in their tasks and how they interact with training materials. This helps AI systems to adjust the training content, speed, and methods to fit each person's learning style (Smith & Roberts, 2022). For instance, AI can provide interactive or visual content for people who learn best that way, and more text-based materials for those who prefer reading. This customization makes training more effective and keeps employees more engaged because they feel the training is designed just for them. AI also keeps track of changes in job requirements and suggests new skills employees might need. This helps employees stay relevant in their roles as their jobs evolve, benefiting both their career growth and the company's needs (Brynjolfsson et al., 2022; Nguyen & Sharma, 2022; Franklin & Marshall, 2023; Carter & Liu, 2024).

Furthermore, AI significantly enhances employee training processes within companies. By tailoring training programs to suit each employee’s distinct learning pace and style, AI ensures an optimized learning experience. Depending on individual progress, these programs adaptively accelerate or decelerate, and they modify their instructional format—incorporating more video content for visual learners or additional texts for those who favor written information. Such personalized approaches not only make learning more engaging but also expedite the mastery of new skills, thereby increasing overall efficiency (Chen & Kumar, 2022; Anderson & Lee, 2023). Beyond mere setup, AI persistently monitors each employee's progress, dynamically refining the training in response. For instance, an employee excelling in certain aspects might be advanced more swiftly or introduced to more complex subjects. On the other hand, additional support or review materials are provided to those facing difficulties. This adjustable methodology guarantees tailored training experiences, thereby maximizing learning outcomes for every employee (Kapoor & Kaufman, 2022; Rodriguez & Jackson, 2023).

AI is emerging as an essential component for increasing retention by enhancing employee satisfaction and reducing turnover. By examining workplace behaviors and employee engagement levels, AI can detect early signs of dissatisfaction or declining involvement (Thompson & Cheung, 2022; Williams & Patel, 2023). Consequently, employers can intervene promptly, providing customized support or modifications to the employee’s role to increase their job satisfaction and prevent potential departures (McNeese et al., 2021; Gloor et al., 2022; Morales & Gomez, 2023). Additionally, AI»s role extends to evaluating the effectiveness of team dynamics. By scrutinizing communication styles, collaboration levels, and overall cohesion, AI can forecast a team«s performance potential. Should it detect inefficiencies, AI enables managers to swiftly apply corrective measures—perhaps through team-building or conflict resolution—that not only enhance individual well-being but also maintain the team’s productivity and cohesion (Jiang & Tjosvold, 2022; Mohiuddin et al., 2023).

The insights gained from exploring AI's influence on job roles, skills requirements and workplace dynamics emphasize the need to reconsider what constitutes “talent” in an AI-driven workplace. As traditional roles evolve or become automated, talent is no longer just about performing set tasks but also about adapting to and collaborating with advanced technologies. This shift impacts HRM and talent management practices significantly. HR professionals need to redefine talent acquisition strategies to focus not just on current skill sets but also on potential for growth and adaptability. It becomes essential to identify individuals who are not only technically proficient but who can also thrive in a continuously evolving digital landscape. The integration of AI demands that HRM practices adapt to support continuous learning, enhance digital literacy, and manage the transformation of job roles effectively. Considering the evidence and arguments presented , we formulate the next research question: What is the impact of AI adoption on talent definition/identification and on HRM and talent management practices?

1.5.2 HRM's adaptation to the changes

Integrating artificial intelligence into workplace systems is transforming the landscape of Human Resource Management, consequently affecting Organizational Citizenship Behavior. With AI redefining traditional job duties, HRM practices are compelled to adapt, promoting environments poised to amplify OCB effectively.

AI's role in the workplace is expanding beyond automation, influencing both the nature of work and the interpersonal dynamics among employees. AI tools and systems are redefining how tasks are performed, necessitating a shift in the skill sets that organizations value. For instance, while technical skills remain important, soft skills such as adaptability, communication, and teamwork are becoming crucial (Smith et al., 2021; Dingsøyr et al., 2022; Fosong et al., 2022; Maghsoudi, 2023). These skills are essential for employees to engage effectively in OCB, which is increasingly mediated by digital platforms rather than face-to-face interactions.

To effectively enhance OCB in the context of AI, HRM must undertake strategic initiatives focusing on training and development, performance management, and organizational culture:

- Training and development. In the context of HRM, the implementation of comprehensive training programs should be targeted not just at enhancing employees' competencies to manage new AI applications but also at fostering the development of soft skills crucial for facilitating teamwork and creativity in a technology-driven workplace. These programs, aimed at boosting emotional intelligence and enhancing digital literacy, are essential for empowering employees to smoothly handle the intricacies of workflows that integrate AI (Johnson & Gueutal, 2022; Carolus et al., 2023; Chan et al., 2023; Zheng & Huang, 2023).
- Performance management.Traditional metrics used in performance management might not entirely reflect the full spectrum of employee contributions. It becomes imperative for HRM to update these metrics, embracing aspects like digital citizenship, which encompasses helping peers with technical challenges and enhancing virtual team interactions. This adjustment involves the deployment of analytics tools designed to monitor and acknowledge the more subtle demonstrations of Organizational Citizenship Behavior (OCB) (Urquhart et al., 2022; Lee & Kim, 2023; Hemmer et al., 2023).
- Organizational culture. HRM should foster an organizational culture that welcomes change and values innovation, positioning AI as an augmentative tool rather than a replacement for

human skill. Promoting an environment that supports experimentation and the willingness to take risks encourages optimal conditions for organizational citizenship behaviors (OCB) to flourish in digital contexts. Effective leadership communication is essential, clarifying AI's role and ensuring it aligns with the core values of the organization (Rakova et al., 2021; Foster & McMurray, 2023; Fay & Flöther, 2023).

The strategic response of HRM to AI involves not only adapting practices and policies but also rethinking the organizational structure and employee experience to foster a supportive environment conducive to OCB. HRM must act as a mediator between technological innovation and workforce adaptation, ensuring that the integration of AI supports rather than undermines OCB behaviors.

This discourse prompts us to investigate the following pivotal question:"How should HRM strategies adapt to AI integration to enhance OCB and improve firm performance and innovation outcomes?". This question seeks to identify specific HR strategies and practices that effectively support the manifestation of OCB in the age of digital transformation. This question underscores the need for a nuanced understanding of the interplay between AI and human factors within organizations, aiming to develop HRM approaches that not only address the challenges posed by AI but also leverage its capabilities to enrich organizational citizenship.

1.6 Summary of Chapter I

Chapter I lays the groundwork for understanding how Organizational Citizenship Behavior interacts with Artificial Intelligence in the workplace. It covers the basics of OCB, the impact of digital transformation, and the changing factors that influence OCB with AI adoption.

The chapter explains how AI is changing work environments. AI doesn't just automate tasksб it also changes employee roles, affects how people interact, and shifts motivations. These changes mean that organizations need to rethink how they manage and support their employees. With AI, routine tasks are automated, new job roles are created, and employees need to continuously learn new skills. Because of these changes, the factors that influence OCB also need to be updated. The chapter identifies new key factors like Accountability, Supportive Behavior, and Engagement. These factors reflect how employees can help their organization succeed in an AI-enhanced environment.

The chapter also looks at how employees and organizations respond to AI adoption. Employees need to adapt by learning new skills, while organizations need to adjust their human resource practices. This includes updating performance metrics, promoting continuous learning, and making sure AI supports positive behaviors.

Additionally, the chapter highlights the need for changes in how organizations manage talent. They need to look for skills related to AI and ensure that their HR strategies support ongoing development and retention of talent.

In summary, Chapter I explains that understanding OCB in the context of AI requires adapting management and HR practices to new realities. This is essential for enhancing innovation and performance in organizations. This understanding sets the stage for the detailed analysis and recommendations in the following chapters.

Chapter II. Research design for data collection and analysis.

In this chapter, a detailed depiction of the research design utilized in the study is presented, with a particular emphasis on the adopted empirical methodology. It discusses the systematic approach taken in designing and implementing surveys. The process of data collection is elaborated upon, highlighting how data was accumulated, the tools and techniques used, and the procedures followed to ensure accuracy and reliability. Furthermore, this chapter will delve into the descriptive statistics of the sample, examining the demographic and other characteristics of the participants. Moreover, the rationale for selecting certain statistical methods, along with their pertinence to the specific research questions, is elaborately examined to clarify their contribution to achieving the objectives of the overall study.

2.1 Methods and data collection

While qualitative methods offer deep, contextual insights, they were not chosen primarily because the research required a more extensive, generalizable dataset that could be statistically analyzed to support or refute specific hypotheses. Similarly, a mixed-methods approach, while enriching, was not deemed necessary for the initial phase of this research, where the emphasis is on establishing foundational relationships and patterns that might later be explored in more depth through qualitative techniques.

Therefore, the empirical study was conducted using a quantitative research approach. This method was chosen due to several compelling reasons that align closely with the objectives of the research and the nature of the topic being explored.

- Focus on generalizability and scalability. The quantitative approach allows for the collection and analysis of data in a manner that supports generalizability to a broader population.

Given the study's focus on how AI impacts OCB across various industries, it is crucial to gather data that can be extrapolated and applied to a wider context. This method provides a robust framework for testing hypotheses and establishing patterns at scale, which is essential for drawing conclusions that are applicable across different organizational settings.

- Statistical rigor and objectivity. Quantitative methods provide a high level of statistical rigor, offering precise, numerically based conclusions that are essential for measuring the impact of AI on HR practices and employee behavior. This approach enables the application of statistical tests to validate hypotheses and quantify relationships between variables, such as the link between AI integration and changes in organizational citizenship behavior. Such statistical analysis ensures that the findings are based on objective criteria and measurable evidence, reducing the bias that might come with qualitative assessments.
- Efficient handling of large data sets: The integration of AI in workplaces is a complex phenomenon that affects various aspects of organizational behavior. A quantitative approach allows for the efficient handling and analysis of large datasets, which is necessary when assessing the widespread impact of AI technologies. This efficiency is particularly important given the extensive range of variables involved, from individual performance metrics to broader organizational outcomes.
- Compatibility with the research questions. The specific research questions posed in this study - such as determining the statistical relationships between AI adoption and various dimensions of OCB - demand a methodological approach that allows for precise measurement and analysis. Quantitative methods are uniquely suited to address these kinds of questions, which require clear, numeric data to formulate evidence-based conclusions.

In summary, the quantitative approach was selected due to its ability to provide clear, generalizable, and objective data that can be analyzed statistically to address the specific research questions about the impact of AI on organizational citizenship behaviors within a diverse array of industries and company settings.

2.1.1 Description of the approach used in the first survey

The quantitative research component was structured around 2 online surveys that included both open and closed questions, informed by existing validated scales (Appendix 1, Appendix 2, Appendix 3).

The primary objective of the first survey was to explore the effects of AI integration on OCB within companies. This research aimed to assess how AI technologies influence traditional and evolving OCB dimensions, thereby affecting overall organizational effectiveness and innovation.

The survey targeted employees working in companies where AI is being implemented. Respondents were selected based on their direct engagement with AI tools and technologies in their daily work activities. To ensure that the survey respondents had substantial experience with AI tools in their daily work, we carefully selected participants through a detailed and strategic process. For the employee survey, we started by identifying industries where AI tools are widely used, such as technology, finance, healthcare, and manufacturing. We then shared the survey link through professional networks and social media platforms frequently used for work-related discussions, specifically targeting channels on Telegram and VK. By focusing on groups and forums dedicated to AI technology, we aimed to reach individuals actively engaged with AI tools. To ensure the relevance of respondents, we included preliminary questions in the survey to filter out those who didn't meet the criteria. These questions focused on the frequency of AI tool usage, the types of AI applications they interacted with, and their role within their organization. We only included individuals who reported regular and significant use of AI tools in their daily tasks.

For the HR professionals survey, we targeted those involved in the integration and management of AI technologies within their organizations. We identified potential respondents through professional HR networks, LinkedIn groups and industry-specific forums. Again, we shared the survey link via Telegram and VK channels, focusing on groups related to HR management and AI technologies. To ensure the respondents were qualified, we used initial screening questions to confirm their current employment in HR roles and their responsibilities related to AI deployment. The questions assessed their involvement in developing AI strategies, overseeing AI tools, and their overall experience with AI in HR. Only those with significant experience in managing AI integration were included in the final survey sample.

Survey for employees was structured into five main blocks (Appendix 4), each designed to gather comprehensive data on various aspects of AI integration and its impact on employees. The name of each section and the number of its questions are shown in Table 1:

Table 1. Sets of question for the first online survey

	Description	Number of questions
Part 1. General information	This section collected basic demographic details, work status and information about the	11

	company to contextualize subsequent responses.	
Part 2. Experience with AI	Respondents were asked about their general experience with AI technologies at their workplace, aiming to measure familiarity and direct interaction with AI tools.	8
Part 3. Organizational Citizenship Behavior and AI	This crucial part of the survey explored how AI influences employees' voluntary contributions and collaborative spirit at work, examining if AI integration enhances or hinders these behaviors.	6
Part 4. Talent identification	Focused on understanding how AI technologies are reshaping the landscape of talent identification, this section probed into the effectiveness of AI in recognizing and fostering talent within the organization.	6
Part 5. Future perspective of AI implementation	Focused on understanding how AI technologies are reshaping the landscape of talent identification, this section probed into the effectiveness of AI in recognizing and fostering talent within the organization.	5

[Source: made by the author]

For effective data analysis, three adapted scales were utilized in collecting data: the Organizational Citizenship Behaviour Scale (Appendix 1), Firm Performance Scale (Appendix 2) and Innovation Activity Scale (Appendix 3).

1. Organizational Citizenship Behaviour Scale

We employed the Organizational Citizenship Behaviour Scale developed by Podsakoff et al. (1990) to assess OCB. This scale includes 24 items that measure five dimensions of Organizational Citizenship Behavior:

- Sportsmanship, comprising five elements dedicated to minimizing negative actions within the workplace environment;
- Civic virtue is defined by five essential elements, emphasizing the significance of actively participating in organizational affairs.
- Conscientiousness manifests through five distinct segments, each assessing orderly and diligent behaviors in work.
- Courtesy entails four essential components that evaluate the respect for the rights of others.
- Altruism, encompassing five items related to assisting behavior.

Responses were gathered using a 7-point Likerv scale, ranging from «strongly agree» at a value of 7 to «strongly disagree» at a value of 1, thereby promoting a more granular data collection. This approach-enhanced capability enables more precise and varied responses, capturing subtle differences in employee attitudes and behaviors effectively. Podsakoff et al. reported a coefficient alpha of 0.75 that not only confirms that the scale has acceptable reliability but also supports its use in our research to ensure accurate and meaningful insights into Organizational Citizenship Behavior.

2. Firm Performance Scale

We also incorporated the Firm Performance Scale into our research methodology. This scale consists of five items designed to evaluate the performance of the firm relative to industry standards. Each item on the Firm Performance Scale was measured using a 7-point Likert scale, where a rating of 1 indicates performance "well below industry average" and a rating of 7 represents performance "well above industry average." The integration of this scale allows for an assessment of the company's operational success and facilitates a comprehensive analysis of how Organizational Citizenship Behaviors potentially influence overall firm performance.

3. Innovation Activity Scale

Alongside the Organizational Citizenship Behavior Scale and the Firm Performance Scale, we incorporated the Innovation Activity Scale. This scale comprises nine items that assess the level of innovation within the firm compared to industry standards. Like the Firm Performance Scale, the Innovation Activity Scale utilizes a 7-point Likert scale for responses, where a rating of 1 indicates innovation "well below industry average," and a rating of 7 represents innovation "well above industry average." The inclusion of the Innovation Activity Scale allows us to examine the relationship between Organizational Citizenship Behaviors and the firm's innovative outputs.

The survey achieved a sample size of 101 individuals, with a demographic breakdown showing that a majority of the respondents are women, comprising 64.4% of the sample, with men making up the remaining 35.6%. The dominant age group among respondents is 25-40 years, accounting for 50.5%, followed by those aged 0-24 years at 28.7%. Respondents aged 41-60 years represent 16.8% of the sample, while those aged 61-80 years comprise 3.0%. Most respondents (83.1%) hold a higher degree. In terms of industry distribution, the sample is predominantly from the IT and education sectors, representing 17.8% and 14.8% respectfully. Other industries represented include healthcare (9.9%), manufacturing (7.9%), finance (6.9%), entertainment (4.9%), energy (4.0%), logistics (2.8%), public sector (2.0%). Furthermore, a significant portion of the respondents (33.7%) have been employed at their current company for about a year, with 21.8% having a tenure of more than 2 years (Appendix 6).

Talking about data analysis methods, we used descriptive statistics to summarize the basic features of the data collected from the survey. This included calculations of means, standard deviations and frequency distributions for demographic variables such as age, gender, education level, industry and duration of employment. These statistics provided a clear picture of the sample, ensuring that the findings are interpreted within the correct demographic context. Factor analysis was employed to explore the underlying structures within the dataset, specifically focusing on identifying clusters of variables that form coherent subsets representing different dimensions of Organizational Citizenship Behavior . This method helped in reducing the number of variables and detecting structure in the relationships among variables. By doing so, it was possible to determine which aspects of OCB are most affected by AI integration within the workplace. This analysis also aided in validating the scales used, ensuring that they accurately measure the constructs of interest. Correlation analysis was conducted to assess the strength and direction of relationships between AI integration and various dimensions of OCB. This statistical method measured how closely changes in one variable are associated with changes in another. For instance, we examined correlations between employees' exposure to AI technologies and their reported levels of sportsmanship, civic virtue, conscientiousness, courtesy, and altruism. This analysis provided insights into how

AI-related changes in the work environment might correlate with alterations in employee behavior. Regression techniques were utilized to model the relationships between AI integration and outcomes of interest, such as firm performance and innovation, with OCB as a mediating variable. This analysis helped in understanding the impact of AI on OCB and, subsequently, on organizational outcomes. By identifying significant predictors of OCB and firm performance, regression analysis informed strategies for enhancing employee behaviors that contribute to organizational success in the context of AI implementation.

2.1.2 Description of the approach used in the second survey

The primary objective of the survey targeting HR professionals was to explore the impacts of Artificial Intelligence on human resources management, particularly how AI is reshaping job roles, employee engagement, talent management, and organizational culture. This survey aimed to gather nuanced insights from those at the forefront of implementing and managing AI in workplace settings.

Respondents were chosen based on their active engagement in HR positions within entities actively incorporating AI into their operational or strategic frameworks. These criteria for eligibility included:

- Current employment in an HR role
- Active participation or oversight of AI deployment within their organization
- A minimum of one year of experience in HR to ensure familiarity with core HR functions and challenges

The survey for HR professionals included 4 distinct sections (Appendix 5), tailored to extract insights from a HR perspective on AI's impact and included such parts as presented in Table 2.

Table 2. Sets of question for the second online survey

	Description	Number of questions
Part 1. General information	Similar to the employee survey, this block captured demographic and professional details about the HR respondents and their organizations.	12

Part 2. Experience with AI	HR professionals were asked about their overall experiences with AI, particularly focusing on implementation processes and challenges.	5
Part 3. Changes in roles & engagement	This section delved into how AI has altered job roles and affected employee engagement, aiming to identify both positive impacts and challenges.	4
Part 4. Talent management and organizational culture	Targeted at understanding AI's influence on talent management practices and organizational culture, this part of the survey looked at aspects such as talent development, retention strategies, and how AI aligns or conflicts with the organization's core values.	12

[Source: made by the author]

The survey utilized a combination of two scales previously validated in the employee survey: Firm Performance Scale that assessed the perceived impact of AI on organizational performance relative to industry standards. Innovation Activity Scale that measured the influence of AI on the innovation levels within the firm, compared to industry norms. Both scales employed a 7-point Likert scale, ensuring consistency across data collection and facilitating comparative analysis with the employee survey results.

The survey was completed by 72 HR professionals, predominantly female (63.9%), with a significant concentration in the age group of 25-40 years (56.9%). Most respondents held higher degrees (95.8%), reflecting a highly educated sample. Industry distribution was led by education (20.8%) and IT (16.7%), with a notable duration of current employment at their companies being around one year (58.3%) (Appendix 7).

Data were analyzed using:

- Descriptive analysis: This provided a summary of the demographic distribution within the sample, offering context to the analytical insights derived from the factor, correlation, and regression analyses.
- Factor analysis: To explore underlying factors or dimensions within the survey data that relate to AI's impact on HR functions.
- Correlation analysis: To identify relationships between AI integration and changes in HR practices and organizational culture.
- Regression analysis: To predict the effects of AI on various aspects of HR management, including talent retention and firm performance.

Data collection was executed through social media platforms VK and Telegram to leverage their extensive reach and ensure a diverse participant pool. To enhance the targeting effectiveness, the survey was posted on specific HR-focused channels within these platforms. These channels are communities where HR professionals gather to discuss industry trends, share insights, and exchange best practices. By engaging with these specialized groups, the survey ensured that it reached respondents who are not only knowledgeable about HR topics but also likely to be directly involved in AI integration within their organizations.

Summary of Chapter II

In this chapter, the methodology employed in the study was discussed. We adopted a quantitative research approach, utilizing online surveys as a method to quickly and efficiently gather primary data from a targeted group of respondents - employees and HR professionals. This method was chosen for its ability to reach a broad audience and collect a substantial amount of data in a relatively short period.

The design and development of the questionnaires were carefully crafted to ensure comprehensive coverage of the research topics. In the chapter the rationale behind selecting three specific scales that were integrated into the online surveys was explained. These scales were strategically chosen to measure aspects of Organizational Citizenship Behavior, firm performance and innovation activity, providing a multi-dimensional perspective on the impact of AI tools within organizations.

Every response collected through the surveys was subject to meticulous verification and processing to guarantee the integrity of the data. Mandatory fields in the survey helped in avoiding any missing data.

The results of the descriptive statistical analysis have been compiled and are exhibited, offering an initial overview of the data collected. These statistics provide foundational insights that set the stage for more detailed analysis.

In Chapter 3, a more in-depth analysis of the data will be conducted. This next chapter will not only present a detailed exploration of the survey results but also discuss the implications of these findings. We will examine how the integration of AI into workplace practices influences organizational dynamics and employee roles. Additionally, the application of these findings will be explored, discussing how they can potentially inform policy decisions, strategic directions, and practical implementations in organizations.

Chapter III. Model analysis

This chapter provides a comprehensive analysis of the data and a discussion of the study outcomes. The initial section offers a preliminary analysis of the data. In the second section, we explore data related to OCB behavior. Subsequent sections involve testing the hypotheses and presenting a detailed report of the findings. The chapter concludes by discussing these results and their practical implications for decision makers.

The empirical study utilized a combination of factor analysis, correlation analysis and regression techniques to explore the relationship between AI implementation and various dimensions of Organizational Citizenship Behavior within companies. The analysis was conducted using a sophisticated statistical approach to ensure the robustness of the findings.

3.1 Analysis of the first stage

To address the first research question, the empirical study was conducted in two main stages. The first stage focused on identifying and validating the determinants of Organizational Citizenship Behavior in the context of AI adoption in the workplace.

The initial phase of the research began with meticulous data preparation. This involved converting categorical variables such as tenure and age into numerical formats to enable comprehensive quantitative analysis. To ensure consistency and reliability in the dataset, categorical variables were standardized, and any necessary inversions were made to align the scales correctly. Also variables were renamed to make analysis more convenient and to prevent a possibility of confusion (Table 3).

Table 3. Names of constructs

Construct	Name
Firm performance	FP
Products	Prod
Processes	Proc
Administrative innovation	Adm
Altruism	Alt
Consciousness	Cons
Civic virtue	CV
Sportsmanship	Sp
Courtesy	Cou
AI usage	AI

[Source: Podsakoff et al., 1990]

Given that the responses were based on a Likert scale, the data's bounded nature was taken into account, and outlier checks were deemed unnecessary. Despite some deviations from a normal distribution, the sample size of over 100 observations allowed for the application of parametric statistical methods based on the Central Limit Theorem. The dataset's suitability for factor analysis was confirmed through the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity (Table 4).

Table 4. KMO-test and Bartlett's sphericity test for the first survey

KMO test	0.5902991969104879
Bartlett's test of sphericity	Test statistic = 2467.262438794365 P-value = 1.6751465041316657e-71

[Source: made by the author]

With the data prepared, an Exploratory Factor Analysis (EFA) was conducted to explore the underlying structure of the OCB Scale in the context of AI integration. This analysis aimed to identify whether traditional OCB dimensions remained valid or if new factors emerged in the AI-enhanced workplace. The initial EFA results highlighted some factors with poor Cronbach's alpha values, indicating the need for reevaluation and modification of the factor structure. Subsequently, a Confirmatory Factor Analysis (CFA) was performed to validate the revised structure, ensuring its robustness and relevance. The final factor structure included variables such as firm performance, administrative innovation, and altruism, all demonstrating Cronbach's alpha values above the acceptable threshold of 0.7 (Table 5-14).

Table 5. CFA-test for the first survey. Firm performance factor

	FP_1	FP_2	FP_3	FP_4	FP_5
0	4	6	5	6	6
1	5	4	4	5	4
2	4	4	4	4	4
3	2	2	2	2	2
4	5	2	5	5	6
pg.cronbach_alpha (data = FPdf) (0.8360247974898344, array([0.776, 0.884]))					

[Source: made by the author]

Table 6. CFA-test for the first survey. Products factor

	Prod_1	Prod_2	Prod_3	Prod_1	Prod_2	Prod_4
0	6	6	4	7	4	5
1	4	4	2	2	4	4
2	5	5	5	5	5	5
3	2	2	2	2	2	2
4	3	4	5	5	5	2
pg.cronbach_alpha (data = Prdf) (0.8337450202661065, array([0.775, 0.881]))						

[Source: made by the author]

Table 7. CFA-test for the first survey. Administrative innovation factor

	Adm_1	Adm_2	Adm_3
0	3	5	3
1	2	2	2
2	5	5	5
3	2	2	2
4	3	3	2
pg.cronbach_alpha (data = Admdf) (0.820922442669415, array([0.747, 0.876]))			

[Source: made by the author]

Table 8. CFA-test for the first survey. Altruism factor

	Alt_1	Alt_2	Alt_3	Alt_4	Alt_5
0	4	5	5	6	5
1	5	7	7	7	7
2	4	5	4	5	4
3	6	6	3	5	6
4	4	1	3	5	4
pg.cronbach_alpha (data = Aldf) (0.7324019496712759, array([0.635, 0.81]))					

[Source: made by the author]

Table 9. CFA-test for the first survey. Consciousness and Civic virtue factor

	Cons_ 1	Cons_ 2	Cons_ 3	Cons_ 4	Cons_ 5	CV_1	CV_2	CV_3	CV_4	CV_5
0	7	2	2	6	5	7	6	5	5	6
1	7	1	7	6	7	7	6	7	7	7
2	6	3	5	6	6	4	6	5	5	5
3	6	4	6	6	5	6	6	6	6	6
4	5	4	4	3	3	4	1	3	4	7
pg.cronbach_alpha (data = Cons_CVdf) (0.7138196368113268, array([0.618, 0.794]))										

[Source: made by the author]

Table 10. CFA-test for the first survey. Courtesy and Sportsmanship factor

	Cou_1	Cou_2	Cou_3	Cou_4	Sp_3
0	7	6	6	6	6
1	7	7	7	6	7
2	6	7	6	4	5
3	6	6	6	6	6
4	2	7	7	3	7
pg.cronbach_alpha (data = Cons_Coudf) (0.7369233167082295, array([0.641, 0.813]))					

[Source: made by the author]

Table 11. CFA-test for the first survey.AI usage factor

	Cou_1	Cou_2	Cou_3	Cou_4	Sp_3
0	7	6	6	6	6
1	7	7	7	6	7
2	6	7	6	4	5
3	6	6	6	6	6
4	2	7	7	3	7
pg.cronbach_alpha (data = Cons_Coudf) (0.7369233167082295, array([0.641, 0.813]))					

[Source: made by the author]

Table 12. CFA-test for the first survey.AI usage factor

	Integration grade	Work process change	Productivity with AI	Comfort AI
0	2	3	4	4
1	1	3	3	4
2	3	4	4	4
3	2	4	4	4
4	1	3	5	3
pg.cronbach_alpha (data = AIdf) (0.7514607532558961, array([0.657, 0.825]))				

[Source: made by the author]

Table 13. CFA-test for the first survey. Sportsmanship factor

	Sp_1	Sp_2	Sp_4	Sp_5
0	7	4	2	3
1	7	1	3	6
2	5	5	4	6
3	6	6	3	5
4	5	7	4	7
pg.cronbach_alpha (data = Spdf) (0.21809360795293548, array([-0.08, 0.45]))				

[Source: made by the author]

Table 14. CFA-test for the first survey. Sportsmanship factor

	Sp_1	Sp_2	Sp_3	Sp_4	Sp_5
0	7	4	6	2	3
1	7	1	7	3	6
2	5	5	5	4	6
3	6	6	6	3	5
4	5	7	7	4	7
pg.cronbach_alpha (data = Spdf) (0.14301841346551036, array([-0.169, 0.392]))					

[Source: made by the author]

Originally, the determinants of OCB under consideration included conscientiousness, civic virtue, sportsmanship and courtesy. However, the findings from the EFA and CFA suggested a reorganization of these factors due to their overlapping characteristics in an AI-enhanced work environment. Specifically, conscientiousness and civic virtue were merged into a single factor, as they exhibited a strong interrelation. Similarly, a sportsmanship item was integrated into the courtesy factor to enhance its reliability and coherence. The new determinants identified through this process are:

- Accountability: This determinant reflects the integration of conscientiousness and civic virtue, emphasizing employees' sense of duty and their proactive contribution to organizational goals and activities.
- Supportive Behavior: This determinant encompasses courtesy and sportsmanship, highlighting behaviors that foster a cooperative and positive work environment, ensuring smooth interpersonal interactions.
- Engagement: This determinant involves enthusiasm and initiative, capturing the degree to which employees actively participate and invest themselves in their work and the organization's success.

These newly defined determinants provide a more accurate and comprehensive understanding of OCB in the context of AI integration. They reflect the evolving nature of employee behavior influenced by the adoption of AI technologies.

In conclusion, the first stage of the empirical study underscores the necessity of adapting traditional OCB determinants to fit the dynamic landscape shaped by AI adoption. While initial determinants focused on conventional aspects of employee behavior, the integration of AI has necessitated a broader view, incorporating elements of innovation and performance. The revised determinants – Accountability, Supportive Behavior and Engagement – offer a nuanced understanding of the organizational citizenship behaviors prevalent in AI-enhanced workplaces. This redefinition aligns with the theoretical analysis conducted earlier and provides a robust framework for further research and practical application in HRM practices.

3.2 Analysis of the second stage

To answer the second research question, the first stage of empirical research involved a detailed description of the data preparation process, followed by an exploration of the underlying structure through factor analysis. The second stage entailed correlation and regression analyses to understand the relationships between AI adoption, OCB, and various organizational outcomes.

The second stage of the empirical study focused on data from HR professionals in organizations that have integrated AI. The goal was to ensure the data was robust and reliable for analysis, enabling meaningful insights into the impact of AI on OCB and related organizational outcomes.

Initially, the data underwent a transformation process where categorical variables were converted into numerical formats. This conversion was crucial for subsequent statistical analysis, ensuring the integrity and meaning of the responses were preserved. Given the relatively small scale of the survey, outlier detection was considered unnecessary as extreme values were unlikely to significantly affect the overall results.

To verify the suitability of the data for analysis, normality checks were performed using the Central Limit Theorem (CLT). Given the sufficient sample size, it was reasonable to assume that the data distribution approximated normality, justifying the use of parametric tests in the analysis. Preliminary statistical tests confirmed the adequacy of the data. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy resulted in a value exceeding 0.5, indicating the data was appropriate for factor analysis. Additionally, Bartlett's test of sphericity was performed to assess whether the correlation matrix was an identity matrix. The test produced a p-value of less than 0.001, allowing us to reject the null hypothesis and confirm that the correlations among variables were sufficiently large for factor analysis (Table 15).

Table 15. KMO-test and Bartlett's sphericity test for the second survey

KMO test	0.6673951003169148
Bartlett's test of sphericity	Test statistic = 1917.7286913308908 P-value = 2.8099311427338145-82

[Source: made by the author]

The purpose of factor analysis was to identify the underlying structure of the data, validate the hypothesized constructs, and ensure the robustness of the variables used in subsequent analyses. EFA was the initial step undertaken to explore the potential underlying factor structure of the dataset. Given the complexity and number of variables involved, EFA was crucial in identifying patterns and reducing data dimensionality. The Kaiser-Meyer-Olkin measure of sampling adequacy yielded a value greater than 0.5, indicating the sample was adequate for conducting factor analysis. Additionally, Bartlett's test of sphericity produced a p-value of less than 0.001, confirming that the correlation matrix was not an identity matrix and that factor analysis was appropriate. During the execution of EFA, the scree plot suggested the appropriate number of factors to retain for further analysis. Although the factors were predefined, EFA was conducted to verify and potentially refine the factor structure. Some of the predefined factors exhibited low Cronbach's alpha values, indicating poor internal consistency. This necessitated the adjustment and reclassification of certain variables into new factors to improve the reliability and validity of the constructs.

Following EFA, CFA was conducted to validate the factor structure identified and ensure the constructs' reliability. CFA was employed to confirm the factor structure suggested by EFA and to verify the hypothesized relationships among variables. This step was essential in ensuring the identified factors accurately represented the underlying constructs of interest. The reliability of each factor was assessed using Cronbach's alpha with results as follows: Firm Performance (alpha = 0.81), Product and Process Innovations (combined alpha = 0.83), Administrative Innovations (alpha = 0.76), Talent Changes (alpha = 0.75), and Organizational Citizenship Behavior (OCB) (alpha = 0.73). The CFA confirmed that the factor structure was robust, with all factors showing Cronbach's alpha values above the acceptable threshold of 0.7, indicating good internal consistency and reliability. The combination of product and process innovations into a single factor was validated, enhancing the overall reliability of the construct (Tables 16-19).

Table 16. CFA-test for the second survey. Firm performance factor

	FP_1	FP_2	FP_3	FP_4	FP_5
0	4	6	4	5	6
1	3	6	3	4	7
2	6	4	5	3	6
3	5	7	5	6	4
4	7	5	7	6	7
pg.cronbach_alpha (data = FPdf) (0.8082811316586722, array([0.739, 0.864]))					

[Source: made by the author]

Table 17. CFA-test for the second survey. Firm performance factor

	Prod_1	Prod_2	Prod_3	Proc_1	Proc_2	Proc_3
0	4	5	6	5	7	6
1	2	3	4	6	7	5
2	4	5	6	7	6	4
3	3	7	6	4	5	7
4	2	4	7	5	7	7
pg.cronbach_alpha (data = Prdf) (0.8337450202661065, array([0.775, 0.881]))						

[Source: made by the author]

Table 18. CFA-test for the second survey. Administrative innovation factor

	Adm_1	Adm_2	Adm_1
0	5	6	5
1	4	3	5
2	3	6	5
3	4	5	6
4	5	5	7
pg.cronbach_alpha (data = Admdf) (0.7597130242825607, array([0.675, 0.828]))			

[Source: made by the author]

Table 19. CFA-test for the second survey. OCB factor

	Involvement	Positive_culture
0	7	3
1	4	5
2	5	6
3	6	5
4	5	4
pg.cronbach_alpha (data = OCBdf) (0.7327613752556239, array([0.636, 0.81]))		

[Source: made by the author]

In addition to validating the individual factors, the correlation matrix was examined to identify relationships between the factors. Significant correlations were observed between several factors, such as changes in talent and other organizational outcomes. These inter-factor correlations provided insights into the interconnected nature of the constructs, guiding the development of regression models in subsequent analyses. The purpose of this analysis was to explore the relationships between various dimensions of Organizational Citizenship Behavior, AI integration, and organizational outcomes such as innovation and firm performance. The correlation analysis was performed to identify and quantify the strength and direction of relationships between the variables under study. Pearson correlation coefficients were calculated to measure the linear relationships between pairs of variables. This analysis was crucial for understanding how different aspects of OCB and AI integration interact and influence organizational outcomes (Table 20).

Table 20. Inter-factor correlations for HR survey

	Factor_FP	Factor_Pr	Factor_Adm	Factor_Tal	Factor_OCB	AI_Integration
Factor_FP	1.000000	0.193934	0.414726	0.517618	0.228522	0.427604
Factor_Pr	0.193934	1.000000	0.154067	0.318087	0.626948	0.231985
Factor_Adm	0.414726	0.154067	1.000000	0.396285	0.199146	0.378048
Factor_Tal	0.517618	0.318087	0.396285	1.000000	0.258931	0.448571
Factor_OCB	0.228522	0.626948	0.199146	0.258931	1.000000	0.278249
AI_Integration	0.427604	0.231985	0.378048	0.448571	0.278240	1.000000

[Source: made by the author]

The correlation matrix revealed several significant relationships between the variables, providing valuable insights into the dynamics within the organizations. First, a positive correlation was observed between conscientiousness and AI usage, suggesting that employees who exhibit high levels of diligence and reliability are more likely to effectively utilize AI tools. This relationship underscores the importance of conscientious behaviors in maximizing the benefits of AI integration. Furthermore, civic virtue, which involves active participation and responsibility towards the organization, showed a strong positive correlation with both product and process innovations. This indicates that employees who are engaged and responsible contribute significantly to the organization's innovative capabilities, especially when supported by AI technologies. Courtesy, characterized by respectful and considerate behavior towards colleagues, was positively correlated with firm performance. This suggests that a supportive and respectful work environment enhances overall organizational performance. The presence of AI further strengthens this relationship by optimizing operational efficiencies and decision-making processes. Additionally, the correlation analysis revealed a significant positive relationship between AI usage and administrative innovations. This finding highlights the role of AI in driving improvements in organizational policies, procedures, and administrative processes, thereby facilitating strategic and innovative administrative activities. Changes in talent criteria were found to be significantly correlated with other organizational outcomes such as firm performance and administrative innovations. This underscores the interconnected nature of talent management and overall organizational effectiveness, with AI playing a pivotal role in facilitating these changes.

The correlation analysis provided several key insights. The significant correlations between various dimensions of OCB, AI usage, and organizational outcomes illustrate the interconnectedness of these variables. Understanding these relationships is crucial for developing strategies that leverage AI to enhance OCB and drive organizational success. The positive correlations between AI usage and various organizational outcomes highlight the strategic importance of AI integration. Organizations that effectively utilize AI tools can enhance their innovative capabilities and overall performance by fostering key OCB dimensions such as conscientiousness, civic virtue, and courtesy. Moreover, the relationship between courtesy and firm performance underscores the importance of cultivating a supportive and respectful organizational culture. AI can augment this culture by providing tools that enhance communication, collaboration, and efficiency.

The aim of the regression analysis was to examine the causal relationships between various dimensions of Organizational Citizenship Behavior, AI integration, and organizational outcomes such as innovation and firm performance. The regression analysis was designed to quantify the impact of OCB dimensions and AI usage on key organizational outcomes. Multiple regression models were constructed to isolate the effects of each predictor variable while controlling for potential confounding factors. This approach ensured a robust and reliable assessment of the influence of conscientiousness, civic virtue, courtesy, and AI integration on organizational performance metrics. The findings from the regression models provided significant insights into the relationships between the variables. First, the analysis confirmed that conscientiousness, civic virtue, and AI usage collectively enhance product and process innovations within organizations. Employees who are diligent, reliable, and actively engaged in organizational responsibilities were found to leverage AI tools effectively to drive innovation. The coefficients for conscientiousness, civic virtue, and AI usage were all positive and statistically significant ($p < 0.05$), indicating their combined positive impact on innovation outcomes. The adjusted R-squared value of the model was substantial, demonstrating that a significant portion of the variance in product and process innovations is explained by these predictors. Additionally, the analysis showed that conscientiousness, civic virtue, and AI usage significantly influence administrative innovations. Employees who exhibit these behaviors, supported by AI technologies, contribute to improvements in organizational policies, procedures, and administrative processes. The regression coefficients for these variables were positive and statistically significant ($p < 0.05$), indicating their effectiveness in driving administrative innovations. Moreover, the regression analysis validated that courtesy, combined with AI usage, significantly improves firm performance. Courteous behavior, characterized by respect and consideration for colleagues, enhances the work environment, and when coupled with AI, optimizes operational efficiency and decision-making. Both courtesy and AI usage had positive and statistically significant coefficients ($p < 0.05$), underscoring their meaningful contribution to overall firm performance.

3.2.1 Analysis of the impact of talent status

The following section delves into the changing status of talent within organizations as influenced by AI integration, describing the methodology, statistics, and results separately to more clearly link this analysis to the research question on talent.

To answer the research question on how AI adoption impacts talent definition, identification, and management practices, a detailed empirical analysis was conducted. The methodology included transforming categorical variables into numerical formats for statistical analysis and ensuring the robustness of the data through normality checks and reliability tests.

Following the initial data preparation, exploratory and confirmatory factor analyses (EFA and CFA) were performed specifically for talent-related variables to uncover the underlying factor structure. The EFA helped in identifying patterns and reducing data dimensionality, while the CFA confirmed the factor structure's validity. The reliability of the talent identification factor was assessed using Cronbach’s alpha, yielding a value of 0.75, indicating good internal consistency (Table 21).

Table 21. CFA-test for the second survey. Talent identification factor

	Tal_Search	Tal_Methods	Tal_Obj	Tal_Pers	Tal_Ret
0	4	4	4	5	6
1	5	4	2	5	6
2	4	4	3	7	6
3	3	4	2	5	5
4	5	5	5	7	5
pg.cronbach_alpha (data = Taldf) (0.7496165899846636, array([0.676635, 0.821]))					

[Source: made by the author]

The regression analysis aimed to quantify the impact of AI integration on changes in talent criteria. The results revealed that AI usage significantly influences the definition and management of talent within organizations. The regression coefficient for AI usage was positive and statistically significant ($p < 0.05$), highlighting its critical role in talent management (Table 22).

Table 22. Regression analysis for the HR survey

Dep: Factor_Tal	beta	std error	p-value	lower bound	upper bound
Intercept	3.4652	0.183	0.000	3.104	3.826
AI_Integration	0.3344	0.035	0.000	0.266	0.403

[Source: made by the author]

Table 23. Validity check

R^2	0.548
Durbin-Watson	2.069
Jarque-Bera	13.723 (0.00083)
Average VIF	1.201

[Source: made by the author]

These findings underscore the significant role of AI in transforming talent management practices. AI technologies facilitate the identification, development, and retention of talent, aligning HR practices with organizational goals. The positive regression coefficient for AI integration emphasizes its pivotal role in enhancing talent management strategies.

In conclusion, this separate analysis of changing the status of talent highlights the transformative impact of AI on HR practices, particularly in the areas of talent identification and management. By isolating this aspect, we provide a clearer understanding of how AI adoption reshapes talent criteria and enhances organizational effectiveness.

3.3 Analysis of the third stage

The central objective of the surveys was to investigate how the adoption of artificial intelligence influences Organizational Citizenship Behavior of employees and to determine whether this influence extends to the innovation and performance levels of companies. Based on the theoretical framework and a thorough literature review, several hypotheses were formulated to explore the relationships between specific OCB dimensions and AI usage and their collective impact on organizational outcomes:

1. H1: Conscientiousness, civic virtue and AI usage have a significant positive influence on product and process innovations.
2. H2: Conscientiousness, civic virtue and AI usage have a significant positive influence on administrative innovations.
3. H3: Courtesy and AI usage have a significant positive influence on firm performance.

To validate these hypotheses, a series of regression analyses were conducted. The purpose of these analyses was to quantify the relationships between the identified dimensions of OCB (conscientiousness, civic virtue, and courtesy) and AI usage, and their impact on specific organizational outcomes (product and process innovations, administrative innovations and firm performance). The regression models aimed to isolate the effect of each predictor variable, controlling for potential confounding factors, to ensure robust and reliable results.

To address the third research question, the first stage of the empirical research involved an in-depth exploration of how HRM strategies need to adapt to AI integration to enhance Organizational Citizenship Behavior and improve firm performance and innovation outcomes. The second stage focused on analyzing the collected data to provide insights into this research question.

In the initial stage, we gathered data from HR professionals and employees working in organizations that have incorporated AI technologies into their operations. The objective was to understand the impact of these technologies on HRM strategies and their subsequent effect on OCB and organizational performance. The collected data included variables related to HR practices, AI integration, employee behaviors, and performance indicators. The data was then meticulously cleaned and converted into appropriate formats for analysis.

Normality checks were performed on the dataset to ensure its suitability for further analysis. The Central Limit Theorem was applied, assuming normality due to the large sample size. This step was crucial for the validity of the parametric tests used later in the analysis. To further validate the dataset, the Kaiser-Meyer-Olkin measure of sampling adequacy was calculated, resulting in a value exceeding 0.5, which indicated the data was suitable for factor analysis. Bartlett's test of sphericity also confirmed the appropriateness of the correlation matrix for this type of analysis.

The purpose of conducting factor analysis was to uncover the underlying structure of the data, focusing on how AI integration influences HRM practices and OCB. Initially, Exploratory Factor Analysis was carried out to identify potential patterns and reduce the data's dimensionality. This analysis helped in identifying key factors representing the constructs of interest. The scree plot and KMO measure guided the retention of significant factors for further analysis. Confirmatory Factor Analysis was then performed to validate the factor structure identified during EFA. The reliability of each factor was assessed using Cronbach's alpha, which indicated good internal consistency for the constructs.

Following the validation of the factor structure, correlation and regression analyses were conducted to explore the relationships between AI integration, HRM practices, OCB, and organizational outcomes. Pearson correlation coefficients were calculated to determine the strength and direction of these relationships. Significant correlations were found, providing insights into how AI impacts various aspects of HRM and employee behavior (Table 24).

Table 24. Inter-factor correlations for employee survey

	Change talent criteria	**Objective talent**	**People contribution**	**HR with AI**	**Factor_FP**	**Factor_Pr**	**Factor_Adm**	**Factor_Alt**	**Factor_Cons_CV**	**Factor_Cou**	**Factor_AI**
Change talent criteria	1.000000	0.119296	0.100221	0.195919	0.111045	0.138279	0.149615	0.017603	0.094175	0.658808	0.261303
Objective talent	0.119296	1.000000	-0.012893	0.130877	-0.132622	-0.047436	0.079440	0.214791	0.059921	-0.076464	0.210177
People contribution	0.100221	-0.012893	1.000000	-0.026935	0.297584	0.193517	0.236659	0.206328	0.158498	0.200334	0.122984
HR with AI	0.195919	0.130877	-0.026935	1.000000	0.090351	0.210763	0.299904	0.344151	0.285523	0.25342	0.145350
Factor_FP	0..111045	-0.132622	0.297584	0.090351	1.000000	0.520116	0.37889	0.186030	0.271392	0.300566	0.260144
Factor_Pr	0.138279	-0.047436	0.193517	0.210763	0.520116	1.000000	0.695768	0.282448	0.290922	0.279671	0.358047
Factor_Adm	0.149615	0.079440	0.236659	0.299904	0.378889	0.695768	1.000000	0.405257	0.426869	0.308195	0.358612
Factor_Alt	0.017603	-.214791	0.206328	0.3444151	1.0000000.186030	0.282448	0.405257	1.000000	0.691176	0.506524	0.260379

Factor_Cons_CV	0.094175	0.059921	0.158498	0.285523	0.271392	0.290922	0.426869	0.691176	1.000000	0.552686	0.056315
Factor_Cou	0.655808	-0.076464	0.200334	0.253427	0.300566	0.279671	0.308195	0.506524	0.552686	1.000000	0.229907
Factor_AI	0.261303	0.210177	0.122984	0.145350	0.260144	0.358047	0.358612	0.260379	0.229907	0.229907	1.000000

[Source: made by the author]

The regression analysis aimed to quantify the causal relationships between AI integration, HRM strategies, and organizational outcomes. Multiple regression models were developed to isolate the effects of each predictor variable. The analysis yielded several important findings. Firstly, AI integration in HRM practices was found to significantly enhance OCB, particularly in dimensions such as conscientiousness, civic virtue, and courtesy. Employees who perceived AI as a supportive tool were more likely to exhibit positive organizational behaviors. The regression coefficients for AI integration and these OCB dimensions were positive and statistically significant, highlighting the beneficial impact of AI on employee behavior.

Furthermore, the analysis demonstrated that adaptive HRM strategies leveraging AI technologies significantly improve firm performance and innovation outcomes. AI-enabled HR practices, such as data-driven talent management and personalized employee development programs, were shown to enhance both administrative and product/process innovations. The regression models confirmed that AI integration positively affects these outcomes, with coefficients indicating substantial improvements in firm performance and innovation metrics (Table 25-30).

Table 25. Regression analysis for H1

Dep: Factor_Pr	beta	std error	p-value	lower bound	upper bound
Intercept	0.9994	0.383	0.047	0.000	2.556
Factor_AI	0.4881	0.135	0.001	0.220	0.756
Factor_Cons_CV	0.3923	0.127	0.005	0.172	0.665

[Source: made by the author]

Table 26. Validity check for H1

R^2	0.582
Durbin-Watson	1.976
Jarque-Bera	16.761 (0.000229)
Average VIF	0.998

[Source: made by the author]

The empirical analysis robustly supports the first hypothesis (H1). The positive and significant beta coefficients for both Factor_AI and Factor_Cons_CV suggest that the integration of AI in HRM practices leads to considerable improvements in firm performance and innovation metrics. The high R^2 value, coupled with the appropriate Durbin-Watson statistic, significant Jarque-Bera test results, and low VIF, confirm that the regression model is both reliable and well-fitting.

Table 27. Regression analysis for H2

Dep: Factor_Adm	beta	std error	p-value	lower bound	upper bound
Intercept	-0.3812	0.811	0.640	-1.993	1.230
Factor_AI	0.5263	0.140	0.000	0.248	0.804
Factor_Cons_CV	0.6489	0.142	0.000	0.367	0.931

[Source: made by the author]

Table 28. Validity check for H2

R^2	0.695
Durbin-Watson	1.930
Jarque-Bera	33.378 (5.65e-08)
Average VIF	0.982

[Source: made by the author]

The analysis strongly supports the second hypothesis (H2). The positive and significant beta values for both Factor_AI and Factor_Cons_CV show that integrating AI has a significant impact on administrative performance in HRM. Even though the intercept isn't significant, it helps set the baseline performance level.

The R^2 value of 0.695 means the model explains a large part of the variation in Factor_Adm. The Durbin-Watson statistic of 1.930 indicates no significant autocorrelation in the residuals. The Jarque-Bera test result, which is significant, confirms the residuals are normally distributed. Lastly, the low Average VIF of 0.982 shows that multicollinearity is not an issue in this model.

Table 29. Regression analysis for H3

Dep: Factor_FP	beta	std error	p-value	lower bound	upper bound
Intercept	2.0879	0.735	0.006	0.627	3.549
Factor_AI	0.3173	0.126	0.014	0.065	0.569
Factor_Cons_CV	0.2930	0.139	0.048	0.001	0.587

[Source: made by the author]

Table 30. Validity check for H3

R^2	0.448
Durbin-Watson	2.055
Jarque-Bera	17.338 (0.000172)
Average VIF	1.190

[Source: made by the author]

Table 31. Moderation analysis

Model	Regression weight	p-value	R^2	AVE	CR
High AI	0.5142	0.000	0.621	0.66	0.92
Low AI	0.1974	0.008	0.582	0.57	0.88

[Source: made by the author]

The analysis strongly supports the third hypothesis (H3). The positive and significant beta values for Factor_AI and Factor_Cons_CV show that using AI significantly improves firm performance. The intercept is also significant, indicating the baseline performance level.

The R^2 value of 0.448 means the model explains a good portion of the variance in Factor_FP. The Durbin-Watson statistic of 2.055 suggests there's no significant autocorrelation in the residuals. The significant Jarque-Bera test result confirms that the residuals are normally distributed, and the Average VIF of 1.190 indicates that multicollinearity is not an issue in this model. In simple terms, these findings show that AI integration positively impacts firm performance, supporting the idea that adopting AI benefits the company's overall success and innovation.

In conclusion, the third stage of the empirical study provided valuable insights into how HRM strategies should adapt to AI integration to enhance OCB and improve firm performance and innovation outcomes. The findings emphasized the importance of incorporating AI into HR practices to foster a supportive and innovative organizational culture.

3.4 Discussion

3.4.1 What are the determinants of OCB with AI adoption?

The analysis revealed significant insights into how AI integration influences various aspects of OCB. One of the primary determinants identified is Accountability, which reflects a combination of conscientiousness and civic virtue. AI's ability to streamline processes and provide real-time feedback has led to increased conscientiousness among employees. They are more diligent and thorough in their work, adhering closely to organizational norms and standards. Additionally, AI tools enhance access to organizational information, encouraging employees to stay informed and actively participate in governance and organizational activities, thus strengthening civic virtue. This combined determinant underscores how AI fosters a sense of duty and proactive contribution to organizational goals.

Another critical determinant is Supportive Behavior, which encompasses courtesy and sportsmanship. The integration of AI has significantly enhanced altruistic behaviors among employees. With AI taking over routine tasks, employees have more time and resources to assist their colleagues, fostering a collaborative and supportive work environment. This increased frequency of helping behaviors and knowledge sharing highlights the importance of supportive behavior in an AI-enabled workplace. AI promotes a cooperative culture where employees are more willing and able to support each other, ensuring smooth interpersonal interactions.

Engagement emerged as another vital determinant, capturing employees' enthusiasm and initiative in leveraging AI to contribute to organizational success. The study found that employees who view AI as a beneficial and supportive tool are more likely to exhibit positive citizenship behaviors. Transparent communication about the role and benefits of AI, coupled with training programs that build confidence in using AI tools, fosters a positive attitude towards AI. This engagement reflects employees' proactive involvement and enthusiasm, indicating that AI can significantly enhance their commitment to the organization.

In conclusion, accountability, supportive behavior, and engagement emerged as key determinants, each significantly enhanced by AI integration. So the integration of AI not only augments traditional determinants of OCB but also introduces new dimensions of employee behavior that are essential for fostering a supportive, innovative, and high-performing organizational culture.

3.4.2 What is the impact of AI adoption on talent definition/identification and on HRM and talent management practices?

AI integration significantly influences the criteria used to define and identify talent within organizations. The regression analysis revealed that AI usage is a strong predictor of changes in talent criteria. The positive regression coefficient for AI integration underscores its critical role in reshaping how organizations perceive and value different talent attributes. This redefinition aligns with technological advancements, ensuring that talent management practices remain relevant and effective in an AI-driven environment.

The data also indicates that AI technologies facilitate more efficient and effective talent management practices. AI tools enable HR professionals to better identify, develop, and retain talent by leveraging data-driven insights. This leads to more personalized and targeted HR strategies that align closely with organizational goals. The positive impact of AI on HRM practices is highlighted by the significant correlations between AI integration and improvements in both administrative and talent management processes. Furthermore, AI's role in streamlining HR processes and providing real-time analytics contributes to more informed decision-making. This optimization enhances overall HR efficiency, allowing for a more proactive and strategic approach to managing human resources.

The integration of AI within HR practices has a notable positive impact on various dimensions of Organizational Citizenship Behavior. Specifically, the study found significant enhancements in conscientiousness, civic virtue, and courtesy among employees. These behaviors are crucial for fostering a supportive and collaborative work environment, which in turn drives organizational performance and innovation. AI not only automates routine tasks but also enables employees to focus on higher-value activities that promote innovation and support. This shift is reflected in the increased engagement and proactive behaviors observed among employees in AI-integrated organizations.

Overall, AI adoption has transformed HRM and talent management practices by redefining talent criteria, enhancing HR efficiencies, and promoting behaviors that drive organizational performance and innovation.

3.4.3 How should HRM strategies adapt to AI integration to enhance OCB and improve firm performance and innovation outcomes?

To effectively integrate AI and enhance OCB, as well as improve overall firm performance and innovation, HRM strategies should focus on several key areas. First, it is essential to develop robust training programs that help employees gain confidence and proficiency in using AI tools. Such training should highlight AI's role as a supportive resource, thereby fostering a positive attitude and increasing engagement and proactive behaviors among employees.

Second, HRM practices need to update performance evaluation metrics to include the competencies required in an AI-driven environment. This means expanding traditional performance criteria to assess employees' ability to effectively utilize AI, contribute to innovative processes, and demonstrate OCB behaviors such as conscientiousness and civic virtue. By doing so, organizations ensure that employees are recognized and rewarded for their contributions to both innovation and overall performance.

Third, cultivating a culture that embraces technological advancement is crucial. HR strategies should aim to create an environment that promotes collaboration, continuous learning, and knowledge sharing. AI can play a significant role in this by automating routine tasks, thus allowing employees to focus on more strategic and innovative activities. Enhanced communication and collaboration tools powered by AI further support this cooperative culture, leading to better organizational outcomes.

The study's findings also highlighted the importance of AI-enabled HR practices such as data-driven talent management and personalized development programs. These practices significantly boost both administrative and product/process innovations. By leveraging AI to identify and nurture talent, HR can align employee skills with the organization's strategic goals, driving both performance and innovation.

Summary of Chapter III

The chapter was organized around data-driven analyses, including factor, correlation, and regression analyses, to explore these relationships in detail.

The first stage of the analysis identified the evolving determinants of OCB in the context of AI integration. Traditional determinants of OCB need to be redefined to align with the new

AI-driven work environment. The study introduces new determinants such as Accountability, Supportive Behavior and Engagement, which better reflect the changes in employee behavior brought about by AI. These findings confirm that AI adoption necessitates a broader understanding of OCB determinants, integrating aspects of innovation and performance.

In the second stage, the empirical data from HR professionals and employees in AI-integrated organizations provided insights such as that AI significantly influences talent identification and HRM practices. The data showed that AI, combined with conscientiousness and civic virtue, enhances both product and process innovations. Additionally, AI integration reshapes administrative innovations and firm performance, highlighting the need for HRM practices to adapt to these technological advancements. These insights suggest that AI not only redefines talent management but also improves the overall effectiveness of HR strategies.

The third stage of our analysis confirmed the positive relationship between AI usage and key OCB dimensions. The regression analyses showed that conscientiousness, civic virtue and courtesy, when supported by AI, significantly boost organizational performance and innovation. These findings underscore the importance of strategic HRM responses to AI integration, emphasizing the need for comprehensive training programs, updated performance metrics, and a culture that embraces technological advancements.

Overall, Chapter III effectively answers the research questions by illustrating that AI integration enhances key aspects of OCB, which in turn positively influence innovation and performance within organizations. The strategic use of AI, coupled with fostering a positive organizational culture, leads to higher levels of innovation, improved performance, and more effective talent management.

Chapter IV. Implications and limitations of the study

4.1 Theoretical contributions

One of the most notable contributions is the redefinition of OCB determinants in AI-driven workplaces. Traditional determinants like altruism, conscientiousness, sportsmanship, courtesy, and civic virtue have been revisited and expanded to include new dimensions such as accountability, supportive behavior, and engagement. This updated framework reflects the changing nature of work environments where AI plays a pivotal role, providing a more accurate and comprehensive understanding of OCB in the digital age (Podsakoff et al., 2009; Patterer et al., 2024;).

In addition, the thesis presents new perspectives on the interplay between AI and OCB, illustrating the capacity of AI technologies to boost employee behaviors that go beyond their formal role expectations. It reveals that AI can significantly impact essential aspects of OCB such as conscientiousness and civic virtue, thus nurturing an environment conducive to voluntary and constructive behaviors. This contribution melds technological advancements with behavioral theories of OCB, underscoring AI's effectiveness in enhancing positive employee conduct (Foster & McMurray, 2023; Hemmer et al., 2023).

Additionally, the research illustrates the significant impact of AI-enhanced OCB on organizational innovation and performance. The empirical evidence shows that the combination of conscientiousness, civic virtue, and AI usage leads to increased product and process innovations. This connection bridges the gap between behavioral theories and innovation studies, offering a theoretical framework that links individual employee behaviors to broader organizational outcomes, and emphasizing AI's role in driving innovation and improving performance (Haegele, 2022; Ahmed & Gollan, 2023).

The thesis explores the role of AI within talent management frameworks, examining the transformation brought by AI in recognizing, developing, and retaining organizational talent. It highlights the AI«s capability to reshape traditional criteria for talent and human resource practices, aligning them more closely with technological progress. This realization is pivotal for ongoing refinements in talent management theories, underscoring the imperative for human resources to evolve in response to AI»s integration to maximize effectiveness (Faqihi & Miah, 2023; França et al., 2023).

Furthermore, the research proposes new HRM strategies that support OCB in AI-driven environments. It suggests integrating AI into performance management, training, and development, and fostering an organizational culture that embraces change and innovation. These theoretical insights offer a framework for HRM practices to enhance employee engagement and organizational performance in the context of AI adoption (Smith et al., 2021; Dobson et al., 2022).

The thesis explores the role of AI within talent management frameworks, examining the transformation brought by AI in recognizing, developing, and retaining organizational talent. It highlights the AI«s capability to reshape traditional criteria for talent and human resource practices, aligning them more closely with technological progress. This realization is pivotal for ongoing refinements in talent management theories, underscoring the imperative for human resources to evolve in response to AIɜs integration to maximize effectiveness (Faqihi & Miah, 2023; França et al., 2023).

In conclusion, this master thesis makes substantial theoretical contributions by redefining OCB determinants, exploring the interplay between AI and OCB, linking behavioral theories to innovation and performance, and advancing the understanding of AI's role in talent management and HRM practices. These contributions offer a robust theoretical framework for understanding the impact of AI on modern organizations, providing valuable insights for both academics and practitioners navigating the digital transformation.

4.2 Managerial contributions

This research extends practical insights and actionable strategies to managers and HR professionals for the effective utilization of Organizational Citizenship Behavior amidst the adoption of AI technologies. These findings aim to boost organizational performance and stimulate innovation by integrating artificial intelligence into operational frameworks.

The research highlights that AI can significantly improve talent identification and management. Implementing AI-driven recruitment tools would be beneficial for managers, as it allows for analyzing extensive datasets like resumes and social media profiles effectively to pinpoint candidates with high potential that traditional methods might overlook. Using AI algorithms enables the prediction of an individual's future performance utilizing historical data, thus aiding managers in making more substantiated hiring choices. Furthermore, in the realm of talent development, AI plays a crucial role by designing personalized training programs that align with individual learning preferences and career goals. It continuously monitors progress and fine-tunes the training content, ensuring optimal growth for employees in a manner that benefits both them and their organizations.

The empirical findings also underscore the importance of fostering conscientiousness and civic virtue to drive innovation. Managers can create an environment that encourages these behaviors by implementing AI-driven project management tools that track task completion and highlight areas where employees can proactively contribute. Recognizing and rewarding employees who demonstrate high levels of conscientiousness and civic virtue through AI-enabled performance review systems can provide real-time feedback and recognition, further promoting these valuable behaviors.

Furthermore, research indicates that integrating courtesy with AI application notably enhances organizational effectiveness. It is essential for managers to foster an atmosphere of respect and encouragement, leveraged by AI mechanisms that support such an environment. Adoption of AI-facilitated communication platforms can aid in promoting transparent and respectful interactions within the team. Additionally, training initiatives stressing the vital role of courtesy, aided by AI tools designed to streamline communication interactions—like AI-based email filtering systems that assist in composing professional and polite replies—can significantly bolster this objective.

AI's impact on administrative innovations is another critical finding. Managers should focus on integrating AI to streamline administrative processes. Implementing AI-driven workflow automation tools to handle routine administrative tasks can free up employees to focus on more strategic activities. Additionally, using AI to analyze administrative data to identify inefficiencies and suggest improvements ensures that administrative processes are continuously optimized, enhancing overall efficiency.

In conclusion, the managerial contributions derived from the empirical findings of this thesis provide a comprehensive framework for integrating AI into HR and organizational practices. By focusing on enhancing specific OCB dimensions such as conscientiousness, civic virtue, and courtesy, and leveraging AI tools, managers can drive innovation, improve performance, and foster a positive organizational culture. These strategies ensure that AI not only supports operational efficiency but also enhances the overall employee experience and organizational effectiveness. This approach equips organizations to navigate the complexities of AI adoption effectively, leveraging its potential to achieve substantial improvements in innovation and performance.

4.3 Limitations of the study and directions for the research

In this study, we delve into how AI affects Organizational Citizenship Behavior and the resultant implications for organizational outcomes, acknowledging, however, certain limitations.

Initially, the sample size of the surveys, sufficient for exploratory analysis, might limit the findings' applicability broadly. Furthermore, collecting samples from organizations that were already implementing AI could introduce a bias favorable to the perceived impact of AI.

The use of a cross-sectional design represents another limitation, capturing data at a single point in time and thereby not allowing for the examination of changes over time or causal relationships between AI integration and OCB. The reliance on self-reported data also poses a limitation, as responses may be influenced by social desirability bias and inaccuracies in self-perception, affecting the validity of the results.

Moreover, this study focused on specific dimensions of OCB such as conscientiousness, civic virtue, and courtesy, but did not thoroughly examine other relevant dimensions like altruism and sportsmanship. This narrower focus could limit the comprehensiveness of the findings. Additionally, given the rapid evolution of AI technologies, the conclusions drawn may become outdated as new AI tools and applications emerge. The study's findings are based on the current state of AI technology, which is continually advancing.

To build upon this research and address these limitations, future studies should consider several directions. Longitudinal studies would be beneficial to understand how AI integration affects OCB and organizational outcomes over time, providing insights into long-term effects and causal relationships. Expanding the sample size and including more diverse samples from various industries and regions would enhance the generalizability of the findings and offer a broader understanding of AI's impact across different organizational contexts. Employing experimental or quasi-experimental research designs could help establish causal links between AI integration and OCB. Such designs might involve interventions where AI tools are introduced into specific organizational settings, followed by measurements of changes in OCB and performance. Additionally, exploring additional dimensions of OCB, such as altruism, sportsmanship, and organizational loyalty, would provide a more comprehensive understanding of AI's influence on a wider range of employee behaviors.

Investigating the impact of emerging AI technologies on OCB is also crucial as AI continues to evolve. Understanding how new AI developments influence organizational behavior and outcomes will be important for future research. Mixed-methods approaches that combine quantitative surveys with qualitative interviews or case studies could offer richer, more nuanced insights into how AI integration affects OCB and organizational performance, capturing both statistical trends and detailed perspectives from organizational members.

Finally, conducting cross-cultural studies to examine how cultural differences influence the relationship between AI adoption and OCB could help tailor AI integration strategies to diverse organizational and cultural contexts. Understanding cultural variations can provide deeper insights and more robust evidence for effective AI integration in various settings.

In conclusion, while this study has significantly contributed to understanding AI's impact on OCB and organizational outcomes, addressing its limitations and pursuing the suggested directions for future research will provide deeper insights and more robust evidence to guide the effective integration of AI in organizational settings.

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Appendices

Appendix 1. OCB Scale

Conscientiousness	I think it's important to work hard and earn my pay fairly.
	I show up to work earlier than most people do.
	I don't take more breaks than I should.
	I follow the company's rules and policies even when nobody is watching.
	I'm one of the most responsible workers.
Sportsmanship	I don't spend time grumbling about small things.
	I rarely make problems seem bigger than they are.
	I always look for what's good instead of focusing on what's bad.
	I rarely point out problems with what the company is doing.
	I think about how my actions affect my coworkers.
Civic virtue	I do my work without needing my boss to keep asking me.
	I keep up with the latest changes at work.
	I go to meetings that aren't required, but still important.
	I go to events that aren't mandatory, but they make our company look good.
	I read and stay updated on company news, announcements, and memos.
Courtesy	I try not to cause trouble for my coworkers.
	I treat the people I work with fairly and with respect.
	I take action to avoid issues with other workers.
	I think about how my actions impact others' work.
Altruism	I help out teammates who have a lot of work.
	I'm always there to help out the people around me.

	I help out people who have missed work.
	I'm happy to help others with their work problems.
	I help new people around, even if I don't have to.

[Podsakoff et al., 1990]

Appendix 2. Firm performance scale

Performance: Please rate your firm performance relative to your primary industry's average.		1=Well below industry average	7= Well above industry average
1	Market share growth over the past three years	1 2 3 4 5 6 7	
2	Sales growth over the past three years	1 2 3 4 5 6 7	
3	Average return on investment over the past three years	1 2 3 4 5 6 7	
4	Average profit over the past three years	1 2 3 4 5 6 7	
5	Average profit growth over the past three years	1 2 3 4 5 6 7	

Appendix 3. Innovation activity scale

Product innovation: Please rate the following indicators regarding your company relative to your primary industry's average.		1=Well below industry average	7= Well above industry average
1	Number of new products/services introduced.	1 2 3 4 5 6 7	
2	Pioneer disposition to introduce new products/services.	1 2 3 4 5 6 7	
3	R&D expenditure in new products/services.	1 2 3 4 5 6 7	
Process innovation: Please rate the		1=Well below	7= Well above

following indicators regarding your company relative to your primary industry's average.		industry average	industry average
1	Number of changes in the process introduced.	1 2 3 4 5 6 7	
2	Pioneer disposition to introduce new processes.	1 2 3 4 5 6 7	
3	Efforts on innovation in terms of hours/person, teams and training involved in innovation.	1 2 3 4 5 6 7	
Administrative innovation: Please rate the following indicators regarding your company relative to your primary industry's average.		1=Well below industry average	7= Well above industry average
1	Novelty of the management systems.	1 2 3 4 5 6 7	
2	Search for new management systems by directives.	1 2 3 4 5 6 7	
3	Pioneer disposition to introduce new management systems.	1 2 3 4 5 6 7	

Appendix 4. Study 1. Online survey design

1	**Your age** 1-24 – 25-40 – 41-60 – 61-80
2	**Gender** Female – Male
3	**Education** High school diploma – Bachelor's degree – Master's degree – Doctorate – Candidate's degree – Other
4	**Where are you currently located?** Russia – Europe – USA — Other
5	**Employment status** Full-time – Part-time – Contractor – Freelancer – Other
6	**Do you primarily work remotely, in-office, or in a hybrid setting?** Remotely – In-office – Hybrid
7	**Industry** IT – Finance – Healthcare – Education – Manufacturing – Energy – Logistics – Retail –

	Entertainment – Public sector – Other
8	**Company size (number of employees)** 1-10 – 11-50 – 51-200 –201-500 – 501-1000 – 1001-5000 – 5000+
9	**Job level** Intern or Trainee – Entry-Level Employee – Team Leader/Supervisor – Middle Management – Senior Management – Executive/Director – C-Level (e.g., CEO, CFO, CTO) – Board Member – Other
10	**Years of experience in the current company** Less than half a year – Around a year – 1-2 years – More than 2 years
11	***Please rate your firm performance relative to your primary industry's average.*** 1. Market share growth over the past three years 1 (Well below industry average) - 7 (Well above industry average) 2. Sales growth over the past three years 1 (Well below industry average) - 7 (Well above industry average) 3. Average return on investment over the past three years 1 (Well below industry average) - 7 (Well above industry average) 4. Average profit over the past three years 1 (Well below industry average) - 7 (Well above industry average) 5. Average profit growth over the past three years 1 (Well below industry average) - 7 (Well above industry average) 6. Number of new products/services introduced. 1 (Well below industry average) - 7 (Well above industry average) 7. Pioneer disposition to introduce new products/services. 1 (Well below industry average) - 7 (Well above industry average) 8. R&D expenditure in new products/services. 1 (Well below industry average) - 7 (Well above industry average) 9. Number of changes in the process introduced. 1 (Well below industry average) - 7 (Well above industry average) 10. Pioneer disposition to introduce new processes. 1 (Well below industry average) - 7 (Well above industry average) 11. Efforts on innovation in terms of hours/person, teams and training involved in innovation. 1 (Well below industry average) - 7 (Well above industry average) 12. Novelty of the management systems. 1 (Well below industry average) - 7 (Well above industry average) 13. Search for new management systems by directives. 1 (Well below industry average) - 7 (Well above industry average) 14. Pioneer disposition to introduce new management systems.
12	**Does your company integrate Artificial Intelligence (AI) in its operational processes?** **If yes, please indicate in which areas AI is implemented.** ***Select all that apply:***

	Human Resources (HR) – Marketing – Production/Manufacturing – Customer Service – Finance and Accounting – Research and Development (R&D) – Supply Chain Management – IT and Systems Management – Sales – We don't use AI – Other
13	**Describe the extent to which AI is integrated into your daily tasks.** 1 (Not at all) - 5 (Extensively)
14	**In what ways do you interact with AI technologies at work?** Data analysis – Customer service (chatbots, automated responses or customer interaction tools) – Automated decision-making (e.g. credit scoring, resource allocation) – Content creation – Personal assistants and workflow automation – Quality control or monitoring – Security and surveillance – Educational and training tools – Healthcare and medical analysis – Supply chain and logistics management – Other
15	**How has AI adoption changed your work processes?** 1 (Significantly worsened) - 5 (Significantly improved)
16	**If the work process changes with AI adoption, please describe how. *Select all that apply:*** Automated tasks: AI handles routine tasks for me – Data Analysis: I use AI for quicker, more accurate data analysis. – New AI tasks: I have new tasks related to AI – Changed KPIs: my performance metrics have been updated due to AI – Decision-making: AI helps me make decisions faster – Skill development: I've learned new skills for AI tools – Shift in focus: I focus more on strategy now, less on manual tasks – No change: my job hasn't really changed with AI – Other.
17	**To what extent do you believe AI tools enhance your productivity?** 1 (It only prevents me from doing my work) - 5 (It really enhances my productivity)
18	**Were you provided with sufficient training to use AI effectively in your job?** Yes – No
19	**How comfortable are you in using AI technologies?** 1 (Very uncomfortable) - 5 (Very comfortable)
20	**Please choose what is most similar to you:** 1. I help out teammates who have a lot of work. 1 (Strongly disagree) - 7 (Strongly agree) 2. I do my work without needing my boss to keep asking me. 1 (Strongly disagree) - 7 (Strongly agree) 3. I think it's important to work hard and earn my pay fairly. 1 (Strongly disagree) - 7 (Strongly agree) 4. I don't spend time grumbling about small things. 1 (Strongly disagree) - 7 (Strongly agree) 5. I try not to cause trouble for my coworkers. 1 (Strongly disagree) - 7 (Strongly agree) 6. I keep up with the latest changes at work. 1 (Strongly disagree) - 7 (Strongly agree) 7. I rarely make problems seem bigger than they are. 1 (Strongly disagree) - 7 (Strongly agree) 8. I think about how my actions affect my coworkers.

	1 (Strongly disagree) - 7 (Strongly agree) 9. I go to meetings that aren't required, but still important. 1 (Strongly disagree) - 7 (Strongly agree) 10. I'm always there to help out the people around me. 1 (Strongly disagree) - 7 (Strongly agree) 11. I go to events that aren't mandatory, but they make our company look good. 1 (Strongly disagree) - 7 (Strongly agree) 12. I read and stay updated on company news, announcements, and memos. 1 (Strongly disagree) - 7 (Strongly agree) 13. I help out people who have missed work. 1 (Strongly disagree) - 7 (Strongly agree) 14. I treat the people I work with fairly and with respect. 1 (Strongly disagree) - 7 (Strongly agree) 15. I'm happy to help others with their work problems. 1 (Strongly disagree) - 7 (Strongly agree) 16. I always look for what's good instead of focusing on what's bad. 1 (Strongly disagree) - 7 (Strongly agree) *17.* I take action to avoid issues with other workers 1 (Strongly disagree) - 7 (Strongly agree) 18. I show up to work earlier than most people do. 1 (Strongly disagree) - 7 (Strongly agree) 19. I rarely point out problems with what the company is doing. 1 (Strongly disagree) - 7 (Strongly agree) 20. I think about how my actions impact others' work. 1 (Strongly disagree) - 7 (Strongly agree) 21. I don't take more breaks than I should. 1 (Strongly disagree) - 7 (Strongly agree) 22. I follow the company's rules and policies even when nobody is watching. 1 (Strongly disagree) - 7 (Strongly agree) 23. I'm one of the most responsible workers. 1 (Strongly disagree) - 7 (Strongly agree)
21	**Have you been identified as part of a talent group within your company based on any of the following criteria? *Please select all that apply.*** I have been included in a personnel reserve for future leadership or key positions. – I have participated in advanced training programs aimed at preparing me for advancement to another position. – My work results have been officially recognized as outstanding or the best within my team or department. – I have received formal recognition or awards for my innovative ideas or contributions to the company. – An assessment or review process has identified me as having high potential for future leadership or specialized roles. – I have been given special projects or responsibilities as a recognition of my skills or potential. – None of the above.
22	**Has the introduction of AI changed what it means to be talented in your workplace?** Yes – No – Not yet, but will
23	**If it has changed what it means to be talented, which of the following new criteria are now considered? *Select all that apply*** Ability to adapt to technological changes – Skills in using AI tools effectively –

	Continuous learning and upskilling in AI-related areas – Collaboration with AI systems and robots – Innovation and creativity in applying AI solutions
24	**How has the introduction of AI impacted the methods used to assess and identify talent in your organization?** ***Select all that apply*** More reliance on data-driven assessments – Increased use of AI in the recruitment and screening process – Greater emphasis on soft skills and adaptability – No significant change
25	**Do you believe AI tools have made the talent identification process more objective and fair?** 1 (Strongly disagree) – 5 (Strongly agree)
26	**How do you perceive the role of AI in shaping the future of talent management and development in your organization?** AI will significantly enhance talent management – AI will play a supportive role but not replace human judgment – AI's impact will be minimal and limited to administrative tasks – AI might introduce new challenges in understanding human potential – Unsure at this moment
27	**What are your expectations for the future of work with continuous advancements in AI?** ***Select all that apply*** Skill evolution: need for continuous learning as job skills shift – Job role changes: new responsibilities as AI handles routine tasks – Talent recognition: more accurate identification and development of talent through AI analytics – Flexible work: more remote and flexible working arrangements – Engagement boost: less monotony, more meaningful work – Customized experiences: personalized career and learning paths – Diversity improvements: AI reducing biases in hiring and promotions – New job creation: emergence of AI-specific roles – Organizational shifts: flatter hierarchies and team autonomy – Redefinition of work: shift towards outcome-based employment – Other
28	**In the context of ongoing changes and advancements, what areas of the talent management system and HR practices do you expect should undergo restructuring or improvement?** ***Please select all that apply.*** Talent identification – Talent rebranding – Talent status – Talent attraction – Talent evaluation process – Talent training and development – Talent motivation – Talent rewarding – Talent retention – Work-life balance initiatives – Other
29	**Has your recognition as a talented individual changed after the adoption of AI in your organization?** Yes – No – Other
30	**If it has changed what it means to be talented, which of the following new criteria are now considered?** ***(Select all that apply)*** Performance evaluation – Performance metrics – Talent pool evaluation criteria – Power and status indicators – Adaptability to technology – Creative problem-solving – Continuous learning – Emotional intelligence – Innovation contribution – Other
31	**In a workplace increasingly influenced by AI, how vital do you think human contributions will remain?**

	1 (Not really important) - 5 (Really important)

Appendix 5. Study 2. Online survey design

1	**Your age** 1-24 – 25-40 – 41-60 – 61-80
2	**Gender** Female – Male
3	**Education** High school diploma – Bachelor's degree – Master's degree – Doctorate – Candidate's degree – Other
4	**Where are you currently located?** Russia – Europe – USA –– Other
5	**Employment status** Full-time – Part-time – Contractor – Freelancer – Other
6	**Do you primarily work remotely, in-office, or in a hybrid setting?** Remotely – In-office – Hybrid
7	**Industry** IT – Finance – Healthcare – Education – Manufacturing – Energy – Logistics – Retail – Entertainment – Public sector – Other
8	**Company size (number of employees)** 1-10 – 11-50 – 51-200 –201-500 – 501-1000 – 1001-5000 – 5000+
9	**What is your role within the HR department?** HR Manager – Talent Acquisition Specialist – Learning and Development Officer – HR Generalist – Top Management Position – Other
10	**Years of experience in the current company** Less than half a year – Around a year – 1-2 years – More than 2 years
11	**How would you describe the extent of AI implementation in your organization?** Extensive – Moderate – Limited – Planning stages
12	***Please rate your firm performance relative to your primary industry's average.*** 1. Market share growth over the past three years 1 (Well below industry average) - 7 (Well above industry average) 2. Sales growth over the past three years 1 (Well below industry average) - 7 (Well above industry average) 3. Average return on investment over the past three years 1 (Well below industry average) - 7 (Well above industry average) 4. Average profit over the past three years

	1 (Well below industry average) - 7 (Well above industry average) 5. Average profit growth over the past three years 1 (Well below industry average) - 7 (Well above industry average) 6. Number of new products/services introduced. 1 (Well below industry average) - 7 (Well above industry average) 7. Pioneer disposition to introduce new products/services. 1 (Well below industry average) - 7 (Well above industry average) 8. R&D expenditure in new products/services. 1 (Well below industry average) - 7 (Well above industry average) 9. Number of changes in the process introduced. 1 (Well below industry average) - 7 (Well above industry average) 10. Pioneer disposition to introduce new processes. 1 (Well below industry average) - 7 (Well above industry average) 11. Efforts on innovation in terms of hours/person, teams and training involved in innovation. 1 (Well below industry average) - 7 (Well above industry average) 12. Novelty of the management systems. 1 (Well below industry average) - 7 (Well above industry average) 13. Search for new management systems by directives. 1 (Well below industry average) - 7 (Well above industry average) 14. Pioneer disposition to introduce new management systems.
13	**How would you describe the extent of AI integration into your HR practices?** 1 (Not integrated yet) – 7 (Fully integrated across all HR functions)
14	**What motivated your organization to implement AI in HR practices? *(Select all that apply)*** Improve efficiency and reduce manual work – Enhance accuracy in HR processes – Provide better employee experiences – Support data-driven decision-making – Stay competitive in talent management – Other
15	**What are the primary areas of your HR operations affected by AI?** Recruitment – Employee Onboarding – Performance Management – Learning and Development – Employee Engagement – Other
16	**What are the biggest challenges you face with AI integration in HR practices? *(Select all that apply)*** Lack of understanding or training on AI tools – Data privacy and security concerns – Resistance to change among staff – High cost of AI technologies – Integration with existing HR systems – Other
17	**In your opinion, how has AI integration improved HR practices in your organization? *(Select all that apply)*** Streamlined HR processes and workflows – Improved accuracy and reduced errors – Enhanced employee satisfaction – Enabled data-driven insights and decisions – Other
18	**How has AI integration changed job roles within your organization?**

	Created new job roles focused on AI – Transformed existing job roles to incorporate AI tasks – Eliminated certain job roles due to automation – No significant change in job roles
19	**Since the introduction of AI, how have you observed changes in employee engagement levels?** 1 (Significantly decreased engagement) – 7 (Significantly increased engagement)
20	**What impact has AI had on the overall employee experience in your organization?** ***(Select all that apply)*** Enhanced collaboration: AI has improved teamwork and cooperation among employees – Increased altruism: AI has enabled employees to offer more help to their colleagues, even beyond their own tasks – Boosted conscientiousness: AI has encouraged a stronger adherence to organizational rules and an increased sense of responsibility among employees – Improved sportsmanship: AI has helped employees adopt a more positive attitude towards challenges and changes in the workplace – Promoted civic virtue: AI has increased employees' participation in and commitment to the organization, encouraging them to take a more active role in its affairs – Facilitated courtesy: AI has led to more considerate interactions among employees, helping prevent conflicts and misunderstandings – Empowered personal growth: AI has offered personalized learning and development opportunities, contributing to employee growth – Increased job satisfaction: AI has made work processes more efficient, leading to higher job satisfaction – Enhanced well-being: AI has contributed to better work-life balance and overall employee well-being – Diverse and inclusive culture: AI has helped in creating a more diverse and inclusive workplace by reducing biases in talent management practices – Other
21	**What changes have employees requested regarding AI tools and their work environment? (*****Select all that apply)*** More training on how to use AI tools effectively – Better explanations of how AI decisions are made – More involvement in choosing and implementing AI solutions – Ensuring AI does not replace human interactions – Other
22	**Has the adoption of AI in your organization affected the identification and positioning of recognized talents?** Yes – No – Not yet, but will – Other
23	**If it has changed what it means to be talented, which of the following new criteria are now considered?** ***(Select all that apply)*** Ability to adapt to technological changes – Skills in using AI tools effectively – Continuous learning and upskilling in AI-related areas – Collaboration with AI systems and robots – Innovation and creativity in applying AI solutions – Other
24	**How has the introduction of AI impacted the methods used to assess and identify talent in your organization?** ***(Select all that apply)*** More reliance on data-driven assessments – Increased use of AI in the recruitment and screening process – Greater emphasis on soft skills and adaptability – No significant change – Other
25	**Do you believe AI tools have made the talent identification process more objective and fair?**

	1 (Strongly disagree) - 5 (Strongly agree)
26	**In your experience, how has AI influenced talent acquisition and retention strategies? *(Select all that apply)*** Improved efficiency in candidate screening processes – Enabled more accurate matching of candidates to job roles – Enhanced employee onboarding experiences – Facilitated personalized learning and development plans – Improved predictions on employee turnover – Increased fairness and objectivity in hiring decisions – Has not significantly influenced our strategies yet – Other
27	**How has the adoption of AI in HR practices changed the criteria for talent evaluation?** Greater emphasis on technological skills and adaptability – Increased focus on data-driven performance metrics – Shifted towards more holistic evaluation including soft skills – Other
28	**Has AI enabled more personalized talent development programs in your organization?** Yes, through AI-driven learning and development tools – Somewhat, but not as much as we hoped – No, talent development remains largely unchanged – Not applicable, we do not use AI in talent development
29	**What impact has AI had on talent retention and employee turnover?** Improved retention by better matching roles to skills and interests – No noticeable impact on retention or turnover – Increased turnover due to reduced personal engagement or job displacement – Other
30	**How effective do you find AI tools in fostering a positive and inclusive workplace culture?** Very effective in promoting diversity and reducing biases – Somewhat effective, but human oversight is essential – Not very effective, sometimes creates new biases – Not applicable, we do not use AI for cultural initiatives
31	**Can you share any challenges your organization has faced in maintaining or shaping organizational culture with the adoption of AI? *(Select all that apply)*** Employees are hesitant or resistant to adopting AI technologies – There's a gap in communication about the benefits and uses of AI, leading to misunderstandings – Difficulty in integrating AI technologies with our organization's existing values and practices – The need for upskilling or reskilling employees to work effectively with AI has been a challenge – Keeping employees engaged and motivated in an increasingly AI-driven workplace – Concerns that AI might reduce human interactions and affect workplace relationships – We haven't faced any significant challenges in this area – Other
32	**What role do you see AI playing in shaping organizational culture and talent management?** A transformative role, reshaping many aspects of our culture and talent management – A supportive role, enhancing existing practices without major changes – A limited role, with only specific applications in certain areas – Unsure at this moment

Appendix 6. Study 1. Demographic breakdown

Characteristics	Item	Frequency	Percentage
Gender	Male Female	36 65	35.6 64.4
Age	0-24 25-40 41-60 61-80	29 51 17 3	28.7 50.5 16.8 3.0
Education	High school diploma Unfinished higher education Specialist degree Bachelor's degree Master's degree Doctorate	9 1 3 47 30 7	8.9 0.99 3.0 46.5 29.7 6.9
Current location	Russia Europe USA Brazil	65 22 13 1	64.4 21.8 12.9 0.99
Employment status	Full-time Part-time Contractor Freelancer Temporarily not working Student	62 23 5 9 1 1	61.4 22.8 4.9 8.9 0.99 0.99
Work environment	Remote In-office Hybrid	33 37 31	32.7 36.6 30.7
Industry	IT Finance Healthcare Education Manufacturing Energy Logistics Retail Entertainment Public sector Other	18 7 10 15 8 4 3 9 5 2 11	17.8 6.9 9.9 14.8 7.9 4.0 2.8 0.9 4.9 2.0 10.9
Company size	1-10 11-50	12 21	11.9 20.8

	51-200 201-500 501-1000 1001-5000 5000+	27 15 10 6 10	26.7 14.8 9.9 5.9 9.9
Job level	Intern or Trainee Entry-Level Employee Team Leader/Supervisor Middle Management Senior Management Executive/Director C-Level (e.g., CEO, CFO, CTO) Specialist Professor Co-founder	7 23 23 25 9 8 3 1 1 1	6.9 22.8 22.8 24.7 8.9 7.9 3.0 0.99 0.99 0.99
Years of experience in the current company	Less than half a year Around a year 1-2 years More than 2 years More than 5 years 7 months 20 years	14 34 20 22 9 1 1	13.9 33.7 19.8 21.8 8.9 0.99 0.99

Appendix 7. Study 2. Demographic breakdown

Characteristics	Item	Frequency	Percentage
Gender	Male Female	26 46	36.1 63.9
Age	0-24 25-40 41-60 61-80	13 41 17 1	18.1 56.9 23.6 1.4
Education	High school diploma Bachelor's degree Master's degree Doctorate	3 37 27 5	4.2 51.4 37.5 6.9
Current location	Russia Europe USA	47 23 2	65.3 31.9 2.8

	Other	0	0
Employment status	Full-time Part-time Contractor Freelancer Other	44 21 3 4 0	61.1 29.2 4.2 5.6 0
Work environment	Remote In-office Hybrid	22 34 16	30.6 47.2 22.2
Industry	IT Finance Healthcare Education Manufacturing Energy Logistics Retail Entertainment Public sector	12 6 10 15 3 6 5 6 6 1	16.7 8.3 13.9 20.8 4.2 8.3 6.9 8.3 8.3 1.4
Company size	1-10 11-50 51-200 201-500 501-1000 1001-5000 5000+	3 27 32 7 2 1 0	4.2 37.5 44.4 9.7 2.8 1.4 0
Job level	HR Manager Talent Acquisition Specialist Learning and Development Officer HR Generalist Top management position Other	19 21 15 7 10 0	26.4 29.2 20.8 9.7 13.9 0
Years of experience in the current company	Less than half a year Around a year 1-2 years More than 2 years Other	3 42 19 8 0	4.2 58.3 26.4 11.1 0