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AI-Driven Talent Management and Sustainable Competitive Advantage in the FMCG Sector: The Role of Organizational Resilience and AI-Tech Trust

By Bassant Adel Mostafa[1]

ABSTRACT:
This study examines the role of AI-driven talent management in attaining a sustainable competitive advantage for fast-moving consumer goods companies in Egypt. Specifically, it explores the mediating role of organizational resilience and the moderating effect of AI-tech trust in a highly volatile and dynamic business environment. Data were collected through an online self-administered questionnaire from 290 HR professionals from the FMCG sector in Egypt. The results reveal that AI-driven talent management enhances organizational resilience, thereby contributing to sustainable competitive advantage.

Moreover, AI-tech trust positively moderates the relationship between AI-driven talent management and sustainable competitive advantage through organizational resilience. The results extend the resource-based view and dynamic capability view by demonstrating how AI-driven talent management and organizational resilience operate as dynamic capabilities that sustain competitiveness. The findings offer practical insights for FMCG leaders on leveraging AI-driven talent management to enhance organizational resilience and long-term competitiveness. As one of the earliest empirical investigations in a developing economy context, this study highlights the strategic importance of AI-driven talent management for sustaining competitiveness through organizational resilience and AI-tech trust in the FMCG sector.

Keywords: Talent management, Artificial Intelligence, Sustainable Competitive Advantage, Organizational Resilience Capacity, AI-tech trust

1. Introduction

In today's volatile, highly competitive global landscape, organizations face unprecedented challenges that threaten their ability to achieve sustainable performance and maintain competitive advantage (CA) (Odugbesan et al., 2023). The need to sustain CA is increasingly pressing due to economic downturns, rising inflation, rapid technological advancements, and the intensifying "war for talent" (Bouaziz & Smaoui Hachicha, 2018). To navigate such complexities, organizations must leverage their capabilities to ensure survival and sustain performance by adapting to evolving market demands (Ferreira et al., 2020; Musa & Enggarsyah, 2025; Teece, 2014). Fast-moving consumer goods (FMCGs) are everyday consumer products characterized by high turnover and short shelf life (Bocken et al., 2022). In Egypt, the FMCG sector is one of the largest in Africa and the Middle East, with a market size valued at billions of dollars (Statista Research Department, 2024). Egypt's food industry contributed approximately

| [1] The British University in Egypt "BUE", Faculty of Business Administration, Economics and Political Science, Cairo, Egypt. Address: El Sherouk City, Suez Desert Road, Cairo 11837 - P.O. Box 43

24.5% of GDP and 23.3% of employment. The sector is expected to grow due to a rising population (over 110 million people) and increasing consumer demand (Business Today Egypt, 2022).

The fast-paced nature of FMCG products requires companies to continually innovate and adapt to evolving consumer preferences and market dynamics. This competition pushes companies to seek sustainable competitive advantage (SCA) (Kang et al., 2023). However, traditional management approaches seem insufficient to address an unpredictable and turbulent environment (YahiaMarzouk & Jin, 2022). From this perspective, as the competition intensifies, organizations increasingly rely on talent management (TM) to attract, develop, and retain skilled employees as a core resource (Abiwu & Martins, 2022) that enhances organizational competitiveness (Jibril & Yeşiltaş, 2022; Latukha, 2018). Organizations that manage their human capital effectively are more likely to achieve high performance and long-term competitiveness (França et al., 2023; Pagan-Castaño et al., 2022).

While prior research links TM to organizational performance, its contribution to sustainable competitiveness remains unclear (Abiwu & Martins, 2024). In parallel, the rapid adoption of Artificial Intelligence (AI) is transforming traditional HR practices, offering organizations new tools to enhance TM efficiency and strategic alignment (Arora & Damarla, 2025). AI-powered systems leverage virtual/augmented reality, predictive analytics, and process automation to customize employee learning and optimize acquisition, development, and retention processes by enabling more precise, data-driven decision-making. However, despite its promising potential, AI applications in TM remain in their infancy (França et al., 2023), with the full spectrum of its impact yet to be realized (Di Prima et al., 2024; França et al., 2023). This raises an important question: how do AI-driven TM practices contribute to building SCA, and what mechanisms strengthen or weaken this relationship?

The FMCG industry's vulnerability to economic uncertainty, fierce competition, supply chain disruptions, economic fluctuations, and shifting customer preferences (Kudakwashe & Pooe, 2024) underscores the importance of organizational resilience (OR), which is a critical factor for maintaining operational stability and achieving long-term success (Musa & Enggarsyah, 2025). OR enables organizations to build/acquire capabilities and utilize resources to adapt and sustain operations effectively before a crisis, facilitates adaptation during a crisis, and enables learning and continuous operations post-crisis (Browder et al., 2024). Organizations should cultivate OR to remain competitive (Bouaziz & Smaoui Hachicha, 2018; Bouteraa & Bouaziz, 2023; Musa & Enggarsyah, 2025). This aligns with resource-based view (RBV), which asserts that CA depends on organizational capability of acquiring valuable, scarce, and inimitable resources (Wang et al., 2022), and the dynamic capability view (DCV) which highlights the need to integrate, reconfigure, and adapt internal and external organizational resources and capabilities such as OR to continuously adjust their practices for sustaining its CA in changing environments (Musa & Enggarsyah, 2025; YahiaMarzouk & Jin, 2022).

HRM practices are acknowledged as central to building resilience by ensuring the availability of skilled and adaptable talent capable of responding to challenges and facilitating recovery (Al-Ayed, 2019; Bouaziz & Smaoui Hachicha, 2018) however, the specific role of AI-driven TM in fostering OR and sustaining CA remains underexplored

(Bouteraa & Bouaziz, 2023; Browder et al., 2024; Lee et al., 2022). Moreover, employees' willingness to adopt AI technologies depends heavily on trust (Arora & Mittal, 2025), and distrust may hinder their effective use (Kambur & Akar, 2022; Pillai et al.,2024). This positions AI trust (AIT) as a critical moderating factor in shaping the relationship between AI-driven TM, OR, and SCA.

This study makes several contributions to both theory and practice. Theoretically, it extends the RBV and DCV by situating AI-driven TM as a strategic capability that fosters OR and, in turn, SCA. Although AI-driven TM serves as a dynamic capability, but in volatile context marked with rapid changes, and talent scarcity, AI effectiveness depends on several factors like organizational digital preparedness, inadequate data infrastructure may limit the strategic advantage of AI-driven TM (Al Jabri, et al. 2024). Trust in AI technology also serves as a boundary condition, that can restrict employee acceptance and diminish the resilience-boosting effects of AI-enabled TM practices (Arora & Mittal, 2025; Lukyanenko et al., 2022).

While prior research has examined TM in relation to competitiveness (Abiwu & Martins, 2022; Jibril & Yeşiltaş, 2022; Latukha, 2018), little attention has been given to the role of AI-driven TM practices in developing resilience, which is essential for sustaining performance in turbulent environments. By positioning OR as a mediating mechanism, the study offers new insights into how AI can enhance the adaptability and long-term viability of organizations. Furthermore, it introduces AI trust (AIT) as a novel moderating variable, emphasizing its pivotal role in determining whether AI adoption in TM yields positive or adverse outcomes (Arora & Mittal, 2025). By doing this, it emphasizes that trust in AI tools may either increase or decrease the favorable outcomes of AI-driven TM for resilience and competitiveness. Practically, the research provides evidence-based guidance for FMCG firms operating in highly volatile markets, demonstrating how AI-enabled TM systems can be leveraged not only to streamline HR processes but also to strengthen resilience and secure long-term competitiveness.

2. Literature Review and hypotheses development

2.1 Talent Management and the Role of Talent in Organizations

TM is grounded in the DCV (Collings et al., 2019) and RBV theory of the organization, which defines VRIN (valuable, rare, inimitable, and non-substitutable) resources as the primary basis for SCA (Kogut & Zander, 1992). RBV is commonly used in TM research to highlight talent as a key organizational resource (Harsch & Festing, 2020) that contributes to achieving CA in a dynamic context (Gallardo-Gallardo et al., 2015). TM is crucial for improving an organization's competitive position; regardless of the technology and infrastructure in place, the human element remains the distinguishing factor (Abu-Darwish et al., 2022). Sparrow & Makram (2015) define TM as a value-creating process through which organizations attract, acquire, and retain unique talent by leveraging their capabilities to generate the value necessary for organizational sustainability (Abiwu & Martins, 2024). This involves "value capture" (integrating skills into the organization context), "value leverage" (pertaining to talent development), and "value protection" (emphasizing talent retention). Viewing TM as a value-driven process reinforces its role in strengthening dynamic capabilities (Harsch & Festing, 2020). Although researchers have offered varying classifications of TM functions (Abiwu & Martins, 2024; Abu-Darwish et al., 2022; Al-Haraisa et al., 2021; Jibril & Yeşiltaş, 2022; Latukha, 2018), but there is strong consensus around three widely accepted dimensions: talent recruitment, development, and retention.

2.2 Applications of AI in Talent Management

AI refers to non-human intelligence designed to perform specific tasks and activities such as analyzing information, adapting, retrieving knowledge, and making decisions (Arora & Mittal, 2025; Dawson & Agbozo, 2024). Its adoption is driven by the need to solve problems, reduce workload, lower operational costs, and automate repetitive tasks (Rožman et al., 2022), thereby AI enables employees to redirect efforts toward higher-value and creative activities (Mikalef & Gupta, 2021). Its applications in HR remain at a developmental stage, with significant potential for further enhancement and innovation (Rožman et al., 2022; Tusquellas et al., 2024).

AI-driven technologies can enhance HR professionals' capabilities, enabling them to gain a competitive edge through the technologies and expertise they employ (Dawson & Agbozo, 2024). By enabling a data-driven and personalized approach to HR, AI enhances strategic decision-making, predicts employee behavior, and reduces administrative burdens, which in turn improves efficiency and enriches the employee experience (Arora & Mittal, 2025; Faqihi & Miah, 2023). Within the realm of TM, AI should not be considered as an independent decision-making tool. Most of the AI tools in HR practices serve an augmentative role, enhancing human judgment through data-driven insights in TM practices related decisions (Raisch & Krakowski, 2021). Although some operations, such as resume screening, can be automated, talent selection remains under human oversight, with AI augmenting data and process accuracy, efficiency, and speed rather than substituting managerial judgment.

Talent acquisition (TA) requires significant investment in attracting and selecting new hires who meet technical and functional job requirements and align with organizational values (Pillai & Sivathanu, 2020; Singh, 2018). AI is transforming the TA functions in organizations, it helps automate routine tasks, including advertising job openings and resume screening. Chatbots significantly diminish the time recruiters allocate to screening candidates and conducting preliminary interviews with job seekers (Dawson & Agbozo, 2024; Roppelt et al., 2025). Some robotic systems utilize speech recognition and natural language processing (NLP) technology to automate recruitment processes. These systems can administer interviews with numerous applicants and shortlist the most suitable candidates who perfectly fit the position (Pillai & Sivathanu, 2020). Thus, AI analyzes applicant profiles to determine whether they possess the required competencies much more quickly (Rožman et al., 2022).

The role of AI in employee learning and development is a vital component of TM (Tusquellas et al., 2024). AI personalizes employee development by analyzing employees' historical performance, feedback, and learning preferences (Chen, 2023; Kambur & Akar, 2022). It then suggests targeted training aligned with both employees' career and organizational goals (França et al., 2023; Levenson, 2018). AI tools provide continuous performance assessment and real-time feedback (Dawson & Agbozo, 2024; Rožman et al., 2022), helping employees identify current skill levels and explore career paths (Faqihi & Miah, 2023). Predictive analytics enables HR to anticipate future skill requirements based on market trends, technological advancements, or industry changes, enabling HR to proactively equip staff through tailored upskilling programs, ensuring workforce readiness, and enabling the organizations to remain competitive (Tusquellas et al., 2024). Overall, AI-driven personalization is reshaping talent development by aligning individual growth with organizational agility (Chen, 2023; Kambur & Akar, 2022).

Retaining high-performing talent is a significant challenge for HR, as engagement and motivation are crucial for sustainable business operations (Faqihi & Miah, 2023). AI plays a vital role in employee retention through using predictive analytics (Faqihi & Miah, 2023). AI-driven tools analyze employee performance data to identify patterns that signal an employee's propensity to depart, offering insights into potential turnover risks, such as declines in engagement scores, performance changes, or a lack of career progression (Arora & Damarla, 2025; Bastida et al., 2025). This enables HR teams to execute targeted engagement strategies to mitigate employee attrition before a resignation occurs (Levenson, 2018). AI-powered pulse surveys enhance retention by providing insights into employees' attitudes and motivations (Faqihi & Miah, 2023). These tools utilize NLP to assess employees' performance reviews, and email communication, providing HR with real-time insights into employee morale and satisfaction. By utilizing data-driven insights, AI may assist organizations in executing proactive, customized, and effective retention strategies with a high degree of accuracy (Arora & Damarla, 2025; Bastida et al., 2025; Tusquellas et al., 2024).

Together, AI-enabled acquisition, development, and retention form an integrated talent management cycle. By automating candidate sourcing and selection to better attract individuals with the right skills and cultural fit. Once hired, AI-driven learning and predictive analytics personalize development pathways, aligning employee growth with evolving organizational needs. Finally, retention tools powered by AI provide early warnings of disengagement and support proactive strategies to sustain commitment. This continuum demonstrates how AI not only optimizes individual HR practices but also connects them into a unified, data-driven system that strengthens organizational resilience and long-term competitiveness. Therefore, this study builds on Rožman et al. (2022), who developed a scale for integrating AI into TM and suggested its validation through quantitative analysis.

2.3 Organizational Resilience

Resilience refers to an ecosystem's capacity to adapt in the face of uncertainties and crises, including economic, political, and technological threats and instabilities (Bouaziz & Smaoui Hachicha, 2018; Bouteraa & Bouaziz, 2023). In a business context, OR underpins organizations' continuity, sustainability, and competitiveness (Bouteraa & Bouaziz, 2023). Hillmann & Guenther (2021) analyzed the resilience concept, demonstrating its characteristics in multiple ways, including a capability, capacity, process, strategy, behavior, outcome, or a mix of these. It applies to various events, from unexpected ecological surprises to disruptive events such as data loss, climate change, and environmental change (YahiaMarzouk & Jin, 2022). OR is a dynamic capability that supports an organization to utilize its resources and capabilities not only to recognize unforeseen events and respond correctly but to manage risks and seize on emerging opportunities (Bouteraa & Bouaziz, 2023; Eichholz et al., 2024).

Resilience is an organization's ability to dynamically reinvent business models and strategies in response to changing conditions while proactively managing change before it becomes a significant issue (Bouaziz & Smaoui Hachicha, 2018). This study adopts the OR scale developed by YahiaMarzouk & Jin (2022), which evaluates OR levels rather than their underlying factors. Their framework includes robustness, the ability to withstand and recover from adversity, including measures to assess an organization's resistance capacity (Bouaziz & Smaoui Hachicha, 2018). Agility reflects an organization's capability to quickly recognize and respond to opportunities and threats in an unstable environment, while integrity encompasses employee cohesion under unfavorable circumstances (YahiaMarzouk & Jin, 2022).

2.4 Sustainable Competitive Advantage

Competitive advantage (CA) is a strategic goal for business organizations (Al-Haraisa et al., 2021). Porter (1985) defines it through cost, differentiation, and focus strategies, helping organizations stand out from competitors lacking a CA. This definition indicates that an organization's ability to produce a product at a lower cost can create CA. At the same time, customers perceive unique attributes in the offering (differentiation) or believe that all their requirements are satisfied by that competitor's offerings (focus) (Abiwu & Martins, 2022). Similarly, CA is a strategy that generates value and is not concurrently employed by existing or potential competitors that they cannot replicate (Musa & Enggarsyah, 2025). This concept encompasses selecting tangible or intangible organizational resources, including processes, information, knowledge, capabilities, and skills to formulate a "value-creating strategy" that allows an organization to achieve greater economic profits than its competitors (Kryscynski et al., 2021; YahiaMarzouk & Jin, 2022).

This study asserts that CA is not solely achieved by outperforming rivals through lower prices and superior quality but can also be attained through an organization's capacity to attract, develop, and retain high-performing employees (Abiwu & Martins, 2024). This idea aligns with the RBV's stance, which suggests that organizations can achieve a CA by acquiring and maintaining intellectual capital, thereby attracting the right people (Kogut & Zander, 1992). According to Abiwu & Martins (2022), talent is the most valuable resource for an organization in achieving its strategic objectives and CA. From the discussion above, it can be suggested that there is no standard measurement of SCA. However, this study employs the RBV theory to assess SCA.

2.5 AI-driven Talent Management and Sustainable Competitive Advantage

Organizational efforts to attain sustainable performance focus on developing a CA in the market in which it operates (Odugbesan et al., 2023). According to RBV theory, human capital is a critical driver of organizational development (Siegling et al., 2014), attracting, developing, and retaining high-potential employees is crucial for achieving SCA

(Latukha, 2018). Similarly, the DCV highlights that organization's talents are unique capabilities that competitors are unable to replicate, positioning talents as a more sustained resource than any physical or financial assets (Latukha, 2018). Thus, effective TM contributes directly to an organization's ability to achieve SCA (Di Prima et al., 2024; Latukha, 2018).

With the rise of AI, organizational success is increasingly shaped by technology that augments human intelligence and reshapes HR practices (Singh et al., 2023). AI revolutionizes talent acquisition, employee development, and retention strategies (Stone et al., 2024). By streamlining recruitment processes (Nawaz et al., 2024), enabling personalized learning to improve learning quality (Chen, 2023), in addition to improving workforce analytics, AI enhances efficiency, employee experience, and decision-making (Garg et al., 2022), thereby strengthening organizational competitive positioning (Singh et al., 2023).

Although scholars have examined the relationship between AI and CA conceptually from the lens of capability (Hossain, 2022; Ma et al., 2024), but empirical research on how AI-driven TM fosters SCA through the RBV perspective is limited. It is important to note that human capital cannot be equated with financial capital. Therefore, organizations must comprehend that surviving the war for talent is increasingly crucial for preserving and cultivating the intangible resources that foster CA (Black & van Esch, 2021; França et al., 2023), through positioning AI-enabled TM practices as a strategic source of differentiation (Conte & Siano, 2023; Pagan-Castaño et al., 2022). Consequently, the subsequent hypothesis is posited:

H1. AI-driven TM has a positive impact on SCA

2.6 AI-driven Talent Management and Organizational Resilience

Research highlights HRM's significant role in developing resilient organizations (Al-Ayed, 2019; Bouaziz & Smaoui Hachicha, 2018; Bouteraa & Bouaziz, 2023). From the RBV perspective, HRM practices help cultivate employees' skills, knowledge, and abilities, thereby directly enhancing OR by strengthening organizational capabilities. Collings et al. (2019) & Lee et al. (2022) asserted that TM practices are key to fostering OR, particularly in adapting to crises, as organizations depend on top talent to help them operate in unpredictable environments (Bouteraa & Bouaziz, 2023). In line with DCV, resilience reflects an organization's ability to reconfigure and adapt these human resources to meet emerging challenges, which is supported by empirical studies stating that talent identification, attraction, training, and development impact an organization's resilience capacity to adapt and respond to crises through agility and adaptive capacity (Battour et al., 2021; Bouaziz & Smaoui Hachicha, 2018). Similarly, Bouaziz & Smaoui Hachicha (2018); Bouteraa & Bouaziz (2023); argue that continuous upskilling builds preparedness, enabling employees to anticipate and recover from disruptions, key features of resilience.

Talent retention significantly influences organizational performance and resilience, as organizations that retain skilled employees build robustness and ensure continuity (Bouteraa & Bouaziz, 2023). Retention protects critical knowledge and human capital, safeguarding rare resources (RBV) while sustaining adaptive capacity (DCV).

Organizations that retain talent are robust, forward-thinking, and strategically equipped to endure external threats (McKinsey, 2025). Building on the critical role of TM in fostering OR, it can be seen that AI integration further strengthens resilience. AI is transforming talent attraction and recruitment, workforce development, and retention (Shady, 2023; Upadhyay & Khandelwal, 2018). In which AI-powered workforce analytics improves OR by automating candidate screening, anticipating job fit, minimizing recruitment biases, predicting future skill gaps, anticipating changing workforce needs, and supporting continuous upskilling, these capabilities ensure that organizations remain resilient and equipped for industry shifts (Deloitte, 2021; IBM, 2023; Shady, 2023; Upadhyay & Khandelwal, 2018). Given that AI-driven TM practices serve as key enablers for building a dynamic capability (resilience) and maintaining competitiveness (Di Prima et al., 2024; Gallardo-Gallardo et al., 2020). Thus, the following hypothesis is developed:

H2. AI-driven TM has a positive impact on OR

2.7 Organizational Resilience and Sustainable Competitive Advantage

When operating in an uncertain and dynamic environment, organizations should strengthen their capabilities to survive and sustain their CA (Ferreira et al., 2020; Musa & Enggarsyah, 2025). Building resilience enables firms to adapt to changing market demands and thrive despite disruptions (Duchek, 2020; Eichholz et al., 2024). This capacity allows organizations to better anticipate, cope with, and adjust to unforeseen circumstances, thereby fostering and maintaining CA (Eichholz et al., 2024; Hillmann & Guenther, 2021). OR plays a critical role in fostering CA by enhancing an organization's capacity to sustain operations while recovering swiftly from challenges through efficient resource mobilization and acquisition (Musa & Enggarsyah, 2025; YahiaMarzouk & Jin, 2022). It incorporates proactive initiatives to strengthen its competitive position (YahiaMarzouk & Jin, 2022). In this regard, Organizations can utilize their dynamic capabilities, such as OR, to reconfigure internal and external resources, thereby creating a resource advantage (Liu & Yang, 2020; Wang et al., 2022).

This process involves developing and renewing their capabilities, which means reinventing their core competencies to effectively navigate a competitive environment (Wang et al., 2022; YahiaMarzouk & Jin, 2022). Therefore, OR dimensions (robustness, agility, and integrity) serve as complementary components that help organizations identify emerging opportunities and efficiently align resources to establish and sustain CA even during stable business operations (Eichholz et al., 2024; Liu & Zhang, 2024; Wang et al., 2022). This foresight possessed by OR can continuously track and monitor industry innovations (Teixeira & Werther, 2013), to enhance understanding of market trends and align products better with market demands, thus contributing to the organizational SCA (Chen et al., 2021; Wang et al., 2022). Accordingly, the following hypothesis is suggested:

H3. OR has a positive impact on SCA

2.8 Mediation Effect of Organization Resilience

Drawing on DCV and RBV theories, SCA is achieved by possessing tangible and intangible organizational resources, specifically human resources (YahiaMarzouk & Jin, 2022). AI-driven TM strengthens these resources by enhancing OR (Bouaziz & Smaoui Hachicha, 2018; Bouteraa & Bouaziz, 2023; Deloitte, 2021; Harsch & Festing, 2020; Upadhyay & Khandelwal, 2018). As a dynamic capability, OR coordinates, integrates, and reconfigures resources, enabling organizations to adjust their practices, adapt, and create new resource configurations, ultimately sustaining long-term advantage (YahiaMarzouk & Jin, 2022). Accordingly, this study suggests that OR mediates the relationship between AI-driven TM and SCA. Specifically, AI-driven TM enhances resilience by equipping employees with adaptive skills and embedding agility into organizational processes, thereby driving sustainable competitive advantage (Mushtaq & Akhtar, 2024). These TM practices improve day-to-day operations and strengthen the organization's ability to withstand unexpected crises by establishing a robust framework and support system for employees and the organization (Ngoc Su et al., 2021).

Moreover, the mediation effect of OR can be illustrated by aligning AI-driven TM practices with each resilience capability. AI-driven recruitment enhances organizational robustness by optimizing person–job and organization alignment, mitigating poor talent selection risk (Shady, 2023; Upadhyay & Khandelwal, 2018). Furthermore, AI-driven talent development improves organizational agility by equipping employees with adaptive capabilities, promoting continuous learning, and allowing better responses to environmental challenges (Chen, 2023; Kambur & Akar, 2022). AI-driven retention strategies, leveraged by predictive analytics and tailored engagement strategies, enhance organizational integrity by cultivating employees' dedication, trust, and continuity (Bouteraa & Bouaziz, 2023; Faqihi & Miah, 2023). These resilience capabilities collectively empower firms to withstand challenges, adapt to disruptions, and sustain operations, so transforming AI-driven TM into SCA rather than short-term performance improvements.

While many studies have established the significant role of TM in creating SCA (Abiwu & Martins, 2024; Abu-Darwish et al., 2022; Al-Haraisa et al., 2021; Jibril & Yeşiltaş, 2022; Latukha, 2018), few have examined whether AI-driven TM enhances SCA through OR. Addressing this gap, the current study aims to demonstrate the role of AI-driven TM in generating organizational capability that ensures the organization has skilled, engaged, committed, developed, and motivated employees, thereby leveraging organizational ability to be resilient (Arora & Mittal, 2025; Dawson & Agbozo, 2024; Faqihi & Miah, 2023; Rožman et al., 2022). This talent foundation, which drives the organization's resilience, enhances its capacity to achieve sustained CA. Therefore, it is hypothesized that OR mediates the relationship between AI-driven TM and SCA.

H4. OR mediates the relationship between AI-driven TM and SCA.

2.9. Moderation Effect of AI-Technology Trust

Despite considerable attention to the benefits of AI adoption, organizations encounter several challenges that hinder their ability to attain greater performance (Bag et al., 2021; Dawson & Agbozo, 2024), including system bias, distrust towards data gathering and algorithms, and concerns regarding decision-making frameworks and the governance of workplace decisions (Okunlaya et al., 2022). These challenges are amplified by employees' fears that AI may replace human roles, reduce motivation, and diminish interpersonal interaction (Glikson & Woolley, 2020; Mahmoud et al., 2020; Malik et al., 2023). Concerns over data privacy, technological anxiety, and limited human interaction further intensify resistance among HR practitioners (Mahmoud et al., 2020; Pillai et al., 2024; Tusquellas et al., 2024). Trust is a pivotal enabler of AI-driven transformation; trust in AI reflects users' expectations that technology will fulfill its responsibilities in meeting the requirements of a specific context (Lukyanenko et al., 2022). From an RBV, AI-Tech Trust represents a valuable intangible resource that amplifies the effectiveness of AI investments. From a DCV, it enables firms to reconfigure and integrate AI-driven practices more effectively, ensuring that technological adoption aligns with evolving market demands.

HR professionals' trust in AI influences their readiness to use it (Glikson & Woolley, 2020; Montag et al., 2023). Therefore, technology adoption is influenced mainly by the degree of trust (Arora & Mittal, 2025). When trust is high, organizations are better positioned to leverage AI-driven TM to develop resilience, enhance adaptability, and sustain CA. When trust is low, AI adoption becomes partial, limiting its contribution to building resilience and diminishing its strategic impact. Accordingly, this study uses the term "AI-Tech Trust" to signify HR practitioners' confidence in the use of AI-powered tools in TM practices (Arora & Mittal, 2025). It is proposed that OR mediates the relationship between AI-driven TM and SCA, and that the strength of this relationship could be strengthened or weakened by AI-Tech Trust. Thus, the following hypotheses were proposed:

H5. AI-Tech Trust serves as a moderated mediator in the link between AI-driven TM and SCA through OR, where the mediation effect is significant when AI-Tech Trust is high and insignificant when AI-Tech Trust is low.

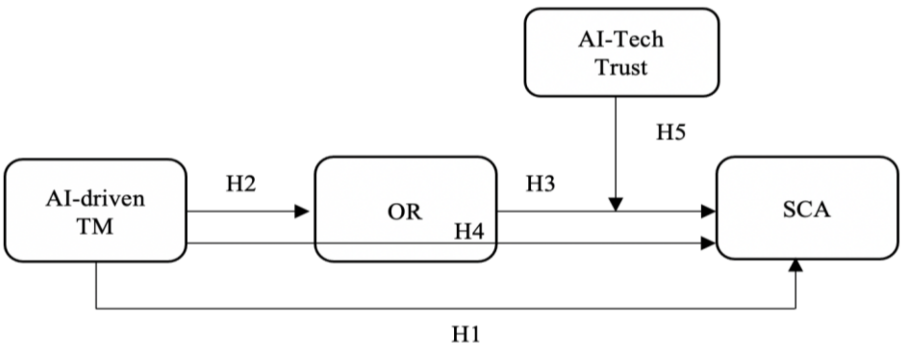

Figure 1. Hypothesized Model
Source(s): Authors' own work

3. Methods

3.1 Data collection and sampling

This research was a cross-sectional study to explore the perceptions of HR practitioners in FMCG organizations operating in Cairo regarding the effect of AI-driven TM on fostering organizational SCA. Data was collected over two months, from April 2025 to May 2025, through an online self-administered questionnaire. The study employed a non-probability snowball sampling technique to expand sample coverage, thereby improving the breadth and representativeness of the research (Liu & Zhang, 2024). Initially, the researcher initiated with purposive selection of HR professionals working in FMCG organizations known to the researcher, through professional networks and social media platforms. These individuals were then asked to share the survey link with other eligible HR professionals in their networks working in the FMCG sector.

This chain-referral approach facilitated the recruitment of a broader sample from the target population, leveraging the professional connections of the initial respondents. The participants were restricted to HR professionals who incorporate AI tools into the talent cycle, including detection, attraction, recruitment, and retention. The sample size was determined based on the Sekaran & Bougie (2010) criteria, which recommended a sample of 384 participants. A total of 300 completed questionnaires were returned. After careful review, responses with missing or incomplete data were excluded, leaving a final sample of 290 valid observations. This represents a response rate of 76%.

3.2 Instrument Development

To ensure that only relevant respondents participated in the study, the questionnaire started with a filtering question: "Have you used any of the Artificial Intelligence tools in performing talent management practices?" Respondents who answered "No" were directed to the end of the survey and were not allowed to complete it. This filtering process ensured that the survey data reflected the experiences and opinions of HR professionals with AI expertise in talent management. The second section concerns the respondents' demographic profile, including age, gender, Job title, and years of experience in their current organizations. The third section focuses on the study variables, incorporating a mix of positively and reverse-coded items to mitigate monotonic response patterns and reduce common-method bias (Malhotra et al., 2006). The questionnaire was pre-tested with a panel of 15 HR academic experts to ensure clarity and comprehensiveness. Since they encountered no difficulties understanding the items, no modifications were made based on their feedback. This validation process enhanced the content and face validity of the instrument. All respondents provided informed consent before completing the questionnaire.

The study emphasized the confidentiality and anonymity of the data to mitigate ethical issues and diminish common method biases. Participants were informed that their responses would be used exclusively for research purposes and that their identities would be kept confidential throughout the study. In this study, 119 individuals (41%) were males, whereas 171 participants (59%) were females. 32 (11%) human resources directors, 146 (50%) hiring managers, and 112 (39%) training managers. 55 (19%) individuals had a tenure of 3 years or less, 61 (21%) participants had a tenure of 3 to 6 years, 99 (34%)

respondents had a tenure of 6 to 9 years, and 75 (26%) participants had a tenure of 9 years or more with their current employers. Finally, 38 (13%) of the participants are between the ages of 21 and 30, followed by 140 (48%) between the ages of 31 and 40, and 112 (39%) are 41 and above.

3.3 Construct Operationalization

The AI-driven TM fifteen-item scale developed by Rožman et al. (2022) was used to measure AI-driven TM. The Cronbach's alpha for the scale was 0.883 in the current study. The OR nine-item scale developed by YahiaMarzouk & Jin (2022) was utilized; its Cronbach's alpha value was 0.813. The SCA scale developed by Liu and Zhang (2024) was used. It comprised six items, and its Cronbach's alpha value was 0.762. Finally, the AIT scale developed by Arora & Mittal (2025) was used to measure respondents' perceptions of trust in AI technology. It comprises four items, with a Cronbach's alpha of 0.917; all items are measured on a 5-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree).

4. Results

Descriptive statistics, correlation analysis, and exploratory factor analysis were conducted using SPSS 24, whilst confirmatory factor analysis was conducted using AMOS 24. The PROCESS macro version 3.4, developed by Hayes et al. (2017), was used to test the research hypotheses. Demographic information, such as gender, age, tenure, and Job title, was incorporated into the questionnaire as control variables to mitigate their potential impact on TM and SCA (Cai et al., 2023).

Common Method Bias: The study employed various statistical methods to test for common method variance (CMV). Harman's single-factor test was utilized. This involved performing an exploratory factor analysis, which revealed that all items could be categorized into four distinct groups. The test identified four components with an eigenvalue exceeding 1. The highest total variance accounted for by a single factor was 39.597% of the variance, which is below the recommended threshold of 50%. Also, reverse-coded items were incorporated into the questionnaire to mitigate monotonic replies and reduce CMV (Malhotra et al., 2006). Finally, the VIF values were examined and determined to range from 1.412 to 2.478. Consequently, these findings indicate the absence of significant common-method bias and potential multicollinearity problems (Hair et al., 2010)

Table 1. Descriptive statistics and correlation results

Variable	1	2	3	4	5	6	7
1. Age	1						
2.Job title	0.464**	1					
3. Tenure	0.578**	0.150*	1				
4. AI-TM	0.133*	0.273*	-0.065	1(0.795)			
5. OR	0.045	0.147*	-0.137	0.554**	1(0.858)		
6. SCA	0.022	0.083	-0.018	0.555**	0.518**	1(0.849)	
7. AIT	0.013	-0.095	0.032	0.403**	0.474**	0.336**	1(0.860)

Note(s): **p < 0.05, Square root of AVE (in italics)
Source(s): Author's own work

Table 1 indicates that AI-driven TM shows a significant positive correlation with SCA ($r = 0.555$, $p < 0.05$), OR ($r = 0.554$, $p < 0.05$), and AIT ($r = 0.403$, $p < 0.05$). Additionally, OR is positively associated with SCA ($r= 0.518$, $p < 0.05$). Among the individual variables, age and Job title show a weak association with AI-TM, and job title weakly correlates with OR.

Table 2. Construct reliability and validity

Items	Principal axis factor loadings (>0.5)	AVE (>0.5)	CR (>0.5)	Cronbach's alpha
AI-driven TM		0.633	0.962	0.883
(AI-TM2)	0.961			
(AI-TM1)	0.945			
(AI-TM 3)	0.918			
(AI-TM 4)	0.845			
(AI-TM 6)	0.833			
(AI-TM 7)	0.818			
(AI-TM 5)	0.804			
(AI-TM 8)	0.793			
(AI-TM 10)	0.772			
(AI-TM 11)	0.767			
(AI-TM I9)	0.734			
(AI-TM 12)	0.705			
(AI-TM 13)	0.667			
(AI-TM 15)	0.645			
(AI-TM 14)	0.632			
Organizational Resilience		0.736	0.957	0.813
(OR6)	0.984			
(OR2)	0.978			
(OR3)	0.930			
(OR5)	0.822			
(OR4)	0.814			
(OR1)	0.789			
(OR7)	0.776			
(OR8)	0.730			

Sustainable Competitive Advantage		0.721	0.939	0.762
(SCA1)	0.987			
(SCA2)	0.929			
(SCA3)	0.874			
(SCA5)	0.846			
(SCA6)	0.714			
(SCA4)	0.708			
AI-Tech Trust		0.739	0.918	0.917
(AIT3)	0.942			
(AIT2)	0.922			
(AIT4)	0.845			
(AIT1)	0.713			

Note(s): CR is Composite reliability; AVE is Average variance extracted; factor loadings are significant at ρ<0.001 Source(s): Author's own work

Exploratory factor analysis (EFA) was performed to confirm high loadings on main constructs and low loadings on cross-loadings within the data. Prior to analysis, the few items for OR were reversed. Table 2 illustrates that the EFA results indicated that all factor loadings exceeding 0.60 were loaded on separate constructs (Hu & Bentler, 1999). Confirmatory factor analyses (CFA) were conducted to assess construct validity, and the research model demonstrated an acceptable fit. CMIN/df = 1.491, TLI = 0.912, CFI = 0.933, RMSEA = 0.061, RMR =0.067, GFI = 0.924, NFI = 0.901, following the suggested parameters: χ^2/df< 2; TLI> .90; CFI> .90; and RMSEA< .07, RMR< .08, GFI> .80, NFI> .90 (Segars & Grover, 1993).

Table 2 demonstrates that the CR and α values range from 0.762 to 0.917. These values above 0.70 indicate that the relevant constructs demonstrate adequate internal consistency and acceptable reliability (Fornell & Larcker, 1981). The study employed the Heterotrait-monotrait ratio of correlations (HTMT) to evaluate discriminant validity, which is confirmed when the HTMT ratio is below 0.9 (Henseler et al., 2015). The results indicated that the AVEs for all the latent constructs exceeded 0.50 and were lower than their corresponding constructs' CRs (Hair et al., 2014). Table 1 demonstrates that all constructs possess an HTMT value below 0.9, and the square roots of AVE exceed the correlation coefficients among the inter-constructs, affirming adequate discriminant and convergent validity.

Table 3. Mediating effect of OR

Model	β	**SE**	**LLCI**	**ULCI**
AI-TM → SCA	.3986***	.0574	.2856	.5115
AI-TM → OR	.5779***	.0489	.4766	.6730
OR → SCA	.2836***	.0551	.1751	.3920
AI-TM→OR→ SCA	.1630***	.0367	.0969	.2399

*Note(s): *p < 0.05, **p < 0.01, ***p < 0.001, N = 290; Bootstrap resamples = 5,000, unstandardized coefficients. Source(s): Author's own work*

The research hypotheses were evaluated utilizing the PROCESS macro for SPSS, designed by Hayes et al. (2017). This method has been extensively used in prior studies because of its ability to yield reliable outcomes. Particularly when examining complex models such as moderated mediation, the PROCESS macro is frequently recommended for this type of analysis. The analysis was conducted with a 95% confidence interval and 5,000 resamples. The findings in Table 3 indicate that AI-TM positively influences SCA (β = .3986, 95% CI = [.2856, .5115], $p < 0.001$). Thus, Hypothesis 1 is supported. In addition, AI-TM has a positive effect on OR (β = .5779, 95% CI = [.4766, .6730], $p < 0.001$). Thus, Hypothesis 2 is also supported. Moreover, OR has a positive effect on SCA (β = .2836, 95% CI = [.1751, .3920], $p < 0.001$). Thus, Hypothesis 3 is confirmed. To assess the mediation effect of OR on the relationship between AI-TM and SCA, the confidence intervals for the direct effect were examined. Since the lower (LLCI) and upper (ULCI) bounds of the confidence interval do not include zero, this confirms that the indirect effect is statistically significant (β=.1630, 95% CI = [.0969, .2399]). In this case, Hypothesis 4 is supported.

Table 4. Moderated mediation analysis (AIT)

Model	**β**	**SE**	**LLCI**	**ULCI**
AI-TMI	.4210***	.0601	.3028	.5393
OR	.2357**	.2159	.1893	.6607
AIT	.4605*	.2114	.0445	.8765
Int_1(OR* AIT)	.1268**	.0529	.0227	.2309
Moderated Mediation Model (Mediator, OR; Moderator, AIT)				
Conditional indirect effects	β	SE	LLCI	ULCI
Low AIT	.1407	.0768	-.0104	.2919
Middle AIT	.2491***	.0575	.1360	.3623
High AIT	.3576***	.0693	.2212	.4939
Index of moderated mediation	.0729***	.0307	.0108	.1311

Source(s): Author's own work

AIT is proposed as a moderated mediator in the relationship between AI-TM and SCA through OR (Hypothesis 5). A moderated mediation analysis was conducted using Model 14 in the PROCESS Macro, as represented in Table 4. The results indicate that the strength of this relationship varies based on the level of AIT (β=.0729, 95% CI=.0108, .1311). Specifically, when AIT is high, the effect is significant (β=.3576, 95% CI=.2212, .4939); however, when AIT is low, the effect is insignificant (β=.1407, 95% CI=-.0104, .2919). This result supports Hypothesis 5.

To illustrate the moderated mediation role of AIT and to visually show the effect, a simple slope graph was generated using the approach recommended by Aiken & West (1991), as shown in Figure 2. The simple slope regression plot reveals that AI-TM's impact on SCA through OR is significant when AIT levels are high, but this effect diminishes when AIT levels are low. The figure highlights that as employees' perception of AIT rises, the influence of AI-TM on SCA through OR also increases.

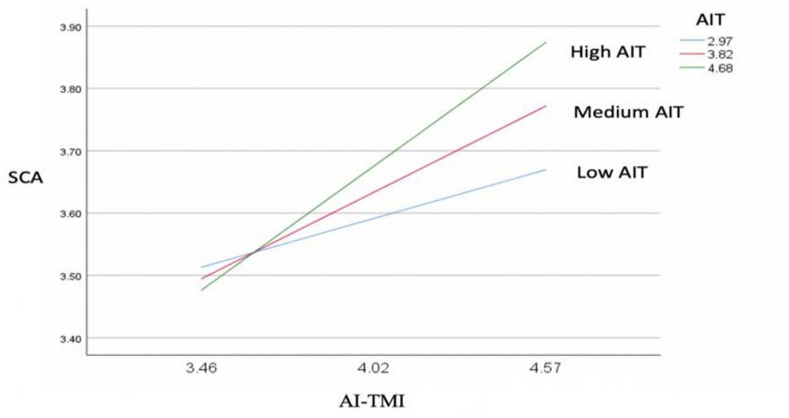

Figure 2. Conditional indirect effects of AIT
Source(s): Author's own work

5. Discussion

The ability to attract, develop, retain, engage, and manage talent remains a significant strategic challenge for organizations in the 21st-century knowledge-driven economies. The results of the main hypothesis demonstrated a significant relationship between AI-driven TM with its combined dimensions and organizational SCA in the FMCG sector in Egypt, which supports H1. Existing studies have emphasized the critical role of TM as a primary source of CA for organizations with talent attraction, retention, and development identified as a direct contributor to sustainable competitiveness (Abiwu & Martins, 2022; Abu-Darwish et al., 2022; Al-Haraisa et al., 2021; Jibril & Yeşiltaş, 2022; Latukha, 2018). However, while these studies highlight the importance of TM strategies, they have primarily focused on traditional approaches, overlooking the transformative potential of emerging technologies.

This research empirically integrates AI-driven TM with RBV and DCV perspectives, offering a novel theoretical contribution by demonstrating how technological trust conditions impact these relationships in the FMCG context. This implies that integrating AI in TM practices is a powerful catalyst for enhancing efficiency and precision. As organizations become more employee-centric, AI-driven systems accelerate decision-making, foster employee engagement, boost productivity, and contribute to improved enterprise performance by creating a positive work environment. These observations are supported by previous studies of Arora & Mittal (2025), Pillai & Sivathanu (2020), Rožman et al. (2022), & Tusquellas et al. (2024), which emphasize the importance of implementing AI-driven TM to optimize talent management processes in the future.

It also verifies the effect of AI-driven TM on OR; thus, H2 is supported. This implies that AI-TM practices that reflect talent attraction, development, and retention were significant in fostering the organization's required capabilities to prepare for, manage, and adapt to changes or crises, thereby achieving sustained CA. These results highlight the importance of effectively managing human resources in response to dynamic and disruptive environmental changes. This corresponds with prior investigations of Bouaziz & Smaoui Hachicha (2018); Bouteraa & Bouaziz (2023); Di Prima et al. (2024); Harsch & Festing (2020), who discovered that strategic HRM and TM practices enhance resilience by strengthening organizational agility, integrity, and robustness through recognizing and cultivating top talents who enhance the organizational ability to navigate challenges and maintain competitive performance.

Moreover, the sectoral context might influence the robustness of the observed relationships. Compared to more stable sectors, the FMCG sector is marked by significant environmental changes, intensified market shifts, and workforce volatility. This intensifies the strategic significance of AI-driven TM practices for detecting, reallocating, and reconfiguring human capital in real time. Thus, building OR through AI-driven TM practices is likely to be more significant in the FMCG context, where agility and continuity are essential for maintaining long-term competitive advantage.

By positioning AI-driven TM as a facilitator of resilience, this study enriches theoretical debates by showing how technology-enabled TM serves as both a resource (RBV) and a reconfiguration mechanism (DCV), offering a more comprehensive explanation of organizational adaptability. This implies that using AI-driven TM can substantially augment OR by enhancing agility, adaptability, and decision-making capabilities. AI can assist organizations in properly identifying top talent, predicting workforce requirements, and optimizing recruitment and retention strategies. This results in a more skilled and engaged workforce better equipped to manage disruptions. Moreover, AI-powered HR analytics can track and monitor employee performance, recommend personalized training programs, and improve workforce planning, ensuring that organizations possess the right capabilities during crises, thereby reinforcing employee engagement and cohesion.

Integrating AI into TM enhances organizational proactivity, data-driven decision-making, and efficiency, hence increasing resilience capacity in the face of uncertainty and change, which is consistent with Bouaziz & Smaoui Hachicha (2018); Bouteraa & Bouaziz (2023). This study also discovered a positive impact of OR on SCA, supporting H3. Several researchers have argued that OR serves as a source of SCA for organizations, including Chen et al. (2021); Eichholz et al. (2024); Liu & Zhang (2024); YahiaMarzouk & Jin (2022). This confirms the argument of Wang et al. (2022), who highlight that organizations with high resilience can internalize human capital, allowing them to emerge from crises, respond proactively, and develop creative measures to foster growth despite challenges, ultimately gaining sustained CA. The present study further validates the role of OR on SCA within the domain of the FMCG sector, offering new insights into the existing studies.

Accordingly, this study capitalizes on the DCV, in which AI-driven TM not only directly affects the organization's sustained CA but can also influence SCA through OR as a dynamic capability, as supported by Wang et al. (2022), who highlighted the positive effect of dynamic capabilities on CA in a dynamic environment. Therefore, OR partially mediates the relationship between AI-driven TM and SCA, meaning that AI-TM has both a direct and an indirect effect on SCA through OR, supporting H4. This dual-theory application demonstrates that while RBV explains AI-driven TM as a valuable, rare, and hard-to-imitate resource, DCV extends the argument by showing that resilience functions as an adaptive capability enabling firms to reconfigure these resources in turbulent environments. These findings suggest that organizations can achieve a CA not only by leveraging their AI-driven TM strategies but also by fostering resilience to adapt, recover, and maintain superior performance. This indicates that investing in AI-driven Talent acquisition, development, and retention not only cultivates a robust workforce but also fortifies an organizational capacity to endure challenges, ultimately creating SCA. The rise of organizational resilience as a mediator underscores its vital role in facilitating AI-driven practices to drive FMCG competitiveness.

Furthermore, the research findings demonstrate the influence of AI-driven TM on SCA through OR, contingent upon the degree of AI-Tech Trust (AIT) supporting H5. This implies that when AIT is low, the positive effect of AI-TM on SCA through OR reduces. Even if an organization cultivates robust resilience through effective AI-TM, a lack of trust in AI-driven technologies can undermine the translation of that resilience into SCA. This is supported by previous studies of Arora & Mittal (2025), Lukyanenko et al. (2022), & Montag et al. (2023), which have established that trust in AI technology is essential for its successful adoption and integration across various HR practices. This may be attributed to various potential explanations. Initially, when trust in AI-Tech is low, employees may exhibit skepticism towards using AI technology in TM processes, resulting in decreased engagement and hesitation in utilizing AI-supported HR tools for decision-making. This creates barriers to agility and adaptability, key elements of both OR and SCA, as evidenced by Arora & Mittal (2025); Malik et al. (2023). This reluctance may restrict the effectiveness of AI-driven TM in strengthening OR and, subsequently, in its capacity to drive SCA.

Previous studies confirmed that trust in AI is affected by various factors, such as perceived fairness of AI tools in terms of bias mitigation and ensuring equitable treatment of employees to strengthen their acceptance and psychological safety (Langer et al., 2021). Second, transparency in AI-enabled TM decisions, by offering a clear understanding of algorithmic suggestions and complementing the role of AI with human judgment, is supposed to diminish confusion and perceived inconsistency (Glikson & Woolley, 2020). Third, clear governance frameworks that guide accountability, ethical standards, and human interventions for AI-driven insights (Glikson & Woolley, 2020). When these trust-building conditions are inadequate, employees may limit the effective use of AI-enabled TM practices, thus restricting organizational agility and hindering the transformation of OR into SCA. On the other hand, when AI technologies are governed in a transparent, fair, and ethical way, trust enhances employees' acceptance, adaptability, and learning, thus multiplying the AI-driven TM effect on building OR.

6. Implications and further research

This research extends the existing knowledge of CA from the RBV perspective by exploring how TM strategies contribute to building the foundational organizational resources necessary for sustaining CA. While some research has explored how AI strengthens TM capabilities via complementary and substitution effects (Raisch & Krakowski, 2021), there is still limited research on how AI-driven TM influences talent identification, development, and retention, enabling organizations to gain SCA. This, in turn, strengthens an organization's competitive position, particularly in the FMCG sector, where research on HR professionals' adoption of AI-driven TM remains scarce. By addressing this gap, the study provides valuable insights into the role of AI in TM practices, thereby promoting organizational competitiveness.

Second, this research adds to the literature on AI-driven TM and SCA by examining the mediating role of OR, including organizational agility, integrity, and robustness, building on the idea of making organizations more resilient by attracting and motivating human resources, as well as through ability-enhancing and opportunity-grabbing activities that ensure long-term organizational success. Despite the growing interest in AI-driven TM, limited research has explored how it can be integrated with other dynamic capabilities, such as OR, to create unique resources that sustain CA (Bouaziz & Smaoui Hachicha, 2018; Bouteraa & Bouaziz, 2023; Wang et al., 2022). Drawing on DCV and RBV theory, this study extends existing knowledge by investigating the mechanisms through which AI-driven TM contributes to SCA and verifying the mediating effect of OR. By doing so, it provides a more comprehensive understanding of how AI-driven TM enhances the organization's long-term competitiveness through greater resilience.

Third, this study is among the first studies to operationalize the AI-driven TM framework developed by Rožman et al. (2022) within the Egyptian context. Initially designed for the Slovenian enterprise context. However, adopting it in this study has enabled its re-validation in a different setting, confirming its reliability and validity. This measure provided empirical insights into the relationships between AI-driven TM practices, OR, and SCA, thereby strengthening the theoretical and practical understanding of these dynamics. Fourth, this study advances the research model by incorporating AI-tech trust as a moderating variable. Incorporating AIT into explaining how AI-driven TM can affect OR and CA has not been examined before. This study fills this gap by demonstrating that AIT plays distinct moderating roles in the correlation between AI-driven TM and SCA, mediated by OR, thereby deepening our understanding of how AI-driven TM interacts with perceived OR and SCA and offering new insights into the strategic implications of AI adoption in TM.

This research provides valuable insights for organizations incorporating AI technology into TM. They can enhance employee experience and increase their competitiveness. AI can help organizations move beyond a standardized, one-size-fits-all HR approach by fostering a more human-centric work environment (Di Prima et al., 2024). Talents need to feel that they are not just parts of the organizational machine but rather unique individuals with distinct capabilities, goals, and ambitions. AI-powered TM practices can support this by better identifying individual competencies, assessing training and development needs, creating customized learning paths, retaining talent, predicting potential attrition, and identifying future skill requirements. This could benefit organizations and employees by streamlining and automating numerous processes, allowing them to allocate more time and focus on strategic initiatives.

Additionally, this study's results show that AI-driven TM practices positively affect CA through OR. These practices seem to constitute a cohesive set. They can be utilized to develop TM strategies to enhance resilience, especially in situations marked by various crises. A better understanding of TM's function in fostering resilience capacity provides a novel explanation for why some firms outperform others. AI-driven TM enhances integrity, robustness, and agility, hence strengthening organizational competitiveness. If organizations want to enhance their resilience capacity and survive in a volatile environment, HR practitioners are advised to leverage AI within their HR departments to aid in deploying TM processes.

Besides exploring the benefits of AI applications, HR professionals must also navigate several challenges associated with AI adoption in TM, including information deficiencies, data management anxiety, distrust, and job instability (Arora & Mittal, 2025). Consequently, trust significantly influences HR professionals' attitudes toward integrating AI. As HR practitioners develop trust in the accuracy, dependability, and fairness of AI algorithms, they become more willing to utilize AI in HR tasks. To foster this trust, organizations should encourage transparent communication within the HR department about AI adoption. They might proactively educate HR professionals about AI's capabilities and potential uses in TM to enhance their understanding of its benefits.

Finally, in today's rapidly changing digital environment, organizations require competent employees to develop, oversee, and deploy intelligent technology to enhance sustainable performance. Possessing AI knowledge and the capability to use it is essential for organizational development and growth (Odugbesan et al., 2023). Consequently, to enhance HR employees' capabilities and skills, organizations ought to invest in training programs focused on data analysis and AI-driven solutions used across diverse TM practices. These initiatives will assist HR practitioners in accurately interpreting complex information generated by deep learning (DL) and machine learning (ML) models, thereby enabling more informed, strategic TM decisions that enhance long-term competitiveness.

To enable this, organizations should encourage collaboration between HR professionals and AI experts to deepen their comprehension and optimize the utilization of AI technologies across various TM functions. Thus, employee engagement, training, and effective communication are crucial for cultivating a favorable change in HR practitioners' perception of this technology, facilitating its successful integration into various TM processes. By taking these steps, firms can successfully deploy AI while minimizing risks and promoting positive employee outcomes, ultimately strengthening their CA and long-term sustainability.

This research has several limitations. First, it focused on three AI-driven TM dimensions (talent acquisition, development, and retention). Whereas further research could examine additional practices, such as talent engagement and performance management, in fostering SCA. Second, while the study examined the overall relationship between AI-driven TM and CA, it did not disentangle the relative contribution of each TM practice on SCA. Third, the cross-sectional survey design, while helpful in capturing perceptions at a single point in time, limits the ability to infer causality or track changes over time. Reliance on self-reported data from HR practitioners may also introduce social desirability bias and common-method bias, despite the use of reverse-coded items and assurances of confidentiality.

To overcome these shortcomings, future research may consider triangulating data sources, employing mixed methods that incorporates interviews or case studies, thereby allowing for richer contextual understanding. In addition, longitudinal, multi-source research design such as panel studies that track the implementation of AI-driven TM over time and include insights from line managers, HR practitioners, and employees, would be effective in elucidating the evolution of AI adoption trust and OR in volatile environments.

Fourth, because the data were drawn from employees in the FMCG sector, generalizability is limited. Hence, comparative cross-sector studies could clarify how AI-TM is applied across different industries. Fifth, although the sample size of 290 was adequate for statistical analysis, it still limits the robustness of the findings. Moreover, the snowball sampling, initiated with purposive contacts, may have introduced selection bias, as respondents were likely to share similar characteristics or networks. Larger, more diverse samples and probability-based sampling would enhance representativeness.

Sixth, this research controlled for age, gender, tenure and Job title but did not account for other organizational or technological factors that may shape AI adoption, such as organizational size, level of digital maturity, access to AI tools or resources, and training received on AI systems. Future research should consider these variables to provide a more nuanced understanding. Furthermore, while AI-driven TM influenced SCA through OR, this study did not test the effect of each OR dimension. Future research could assess the mediating role of individual OR dimensions on this relationship. Finally, the study focused only on HR practitioners, whose perspectives may differ from those of line managers or employees affected by AI-enabled TM practices. Expanding the respondent base to include multiple stakeholders could help capture perception gaps and provide a more holistic view.

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