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Artificial intelligence strategy, creativity-oriented HRM and knowledge-sharing quality: Empirical analysis of individual and organisational performance of AI-powered businesses

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Abstract

Purpose – To investigate the relationship between artificial intelligence strategy (AIS), creativity-oriented HRM (CHRM), and knowledge-sharing quality (KSQ). At individual and organisational levels, this paper measures also the innovative work behaviour (IIWB) and effective performance (OEP) of international organisations conducting AI-powered business practices in Egypt.

Design/methodology/approach – The authors presented a multilevel-model, after reviewing the relevant literature, and tested it through employing mixed-methods approach. Data were collected from 168 questionnaires answered by AI-experts at IT departments of 20 international AI-powered organisations in Egypt in addition to 25 depth interviews, AI-based focus group and international forum.

Findings – Following PLS-SEM approach, results revealed that AIS affects positively and significantly KSQ and CHRM. CHRM affects positively and significantly KSQ and IIWB. KSQ affects positively and significantly OEP and IIWB. The significant positive direct AIS-OEP relationship was not supported yet the significant positive indirect relationship via KSQ was supported.

Originality/value – Empirically, it is the first research that assessed AIS-CHRM-KSQ relationship and its effect on IIWB and OEP of AI-powered businesses from 7 sectors of an emerging economy. Conceptually, the authors adopted an interdisciplinary approach while reflecting on the literature that studied AIS implementation in different business functions (production, operations and supply-chain management, human resources management, strategic management and marketing).

Practical implications – Strategic leaders and managers of different functional areas can benefit from the empirical findings of this study as well as from the examples of best AI-enhanced practices drawn from the literature.

Keywords – Artificial intelligence strategy, AI-powered business functions, Creativity-oriented HRM, Knowledge-sharing quality, Organisational effective performance, Innovative work behaviour, Operations management, Strategic management, Expert system, Machine learning, Forecasting.

Track – e-Business and e-Government

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1. Introduction

The artificial intelligence (AI) field was founded academically in the 1950s, yet it did not receive practically the deserved interest until the big data revolution and the post-digital era (Fountaine *et al*., 2019; Haenlein and Kaplan, 2019). Despite its importance, many organisations to date do not realise the ability of AI systems and machines in simulating human intelligence while interpreting input data (e.g., text, numbers, figures/images and sound) and undertaking different processes to produce outputs in the form of decisions/solutions (Akerkar, 2018; Von Krogh, 2018; Fountaine *et al*., 2019; Haenlein and Kaplan, 2019). Furthermore, most of the institutions that recognised its importance and are applying it to its business operations are only implementing it in one single function/process/practice (Fountaine *et al*., 2019). Thus, only few of them can be considered as AI-powered organisations, which have artificial intelligence strategy (AIS) formulated and executed by a cross-functional team assigned for developing different AI-enhanced business functions/practices across these organisations' value chains (Fountaine *et al*., 2019; Kreutzer and Sirrenberg, 2020). Even in the literature, researchers studied AI either *conceptually* (e.g., Burggräf *et al*., 2018; Von Krogh, 2018; Baryannis *et al*., 2019) or *empirically but in terms of a single business practice/function* (e.g., Yu, 2011; Stalidis *et al*., 2015; Abdou *et al*., 2017). For all these reasons, the authors were motivated to carry out this *empirical research* in this promising and rising AI-field. Also conceptually, the authors adopted an *interdisciplinary approach* while reflecting on the previous literature that studied AIS implementation in different business functions (*production, operations and supply-chain management, human resources management, strategic management and marketing*) to consolidate it in one paper. Since human-AI relationship was described in the literature as being collaborative and complementary rather than substitutionary and competitive, the human factor is crucial to maximise the output value (Von Krogh, 2018; Wilson and Daugherty, 2018). As a result, creativity-oriented HRM (CHRM) was particularly chosen as a construct by the authors due to the importance of investigating the significant role of HRM in reinforcing the creativity of its employees (Song *et al*., 2019) that will be reflected on promoting the individual innovative behaviour and organisational effective performance. In spite of AI importance towards leveraging knowledge sharing that was discussed in the literature, there is still scant empirical research analysing that relationship (Liebowitz, 2001) especially in terms of quality of shared knowledge. Besides, there is a lack of studies that measured empirically AI-performance direct relationship. Further, the relationships between AI, knowledge and performance were mostly discussed in the literature either conceptually or indirectly via other mediating constructs, which encouraged the authors to assess empirically direct/indirect AIS-KSQ-OEP relationships. Hence, this paper can be regarded as the first empirical study that examined AIS-CHRM-KSQ relationship and its effect on IIWB and OEP of AI-powered businesses from 7 sectors of an emerging economy.

Many reasons incentivised the authors to select AI-powered organisations in Egypt as the main context for the empirical work. *First*, according to the American Chamber of Commerce in Egypt (Wood, 2018), investment in AI is expected to boost the economic development of Egypt and the Countries of the Gulf Cooperation Council (GCC) by $320 billion throughout the coming years. *Second*, the different positive steps that were taken by the Egyptian government towards facilitating the implementation of AI in the public and private organisations show the external institutional support for its application. For example, the Egyptian Cabinet created a national AI-council that developed an AIS, which will be executed at the national level for the beneficial employment of AI across the different Egyptian sectors (Egypt Today, 2019). Moreover, the Egyptian government conducted the 2019 World Youth Forum (WYF) in Egypt starting with an AI-session that was moderated by *Sophia the robot* (manufactured by Hanson Robotics using AI) and attended by many international AI-experts from different countries to discuss many successful practical examples of AI-implementation and fields of application. This AI-based international forum was attended by the authors and added to the value of this study by the qualitative interviews that were undertaken there with AI-experts. Further, the Ministry of Communications and Information Technology (MCIT) in

Egypt (2019) declared that it formulated for the African union an African AIS that exploits the advantages of each African country, identifies their developmental areas, utilises the national/regional/international opportunities and faces the challenges related to AI-employment in Africa. Regarding Egypt's advantages in terms of AI-implementation, it has skilled HR and IT-experts in addition to its large population that represents an attractive market for businesses to use and test AI-application in its different sectors (Wood, 2018) as well as for the authors of this paper.

2. Literature Review

2.1. Using artificial intelligence strategy for AI-powered business functions

AI was conceptualised in the literature as the ability of AI systems/machines to simulate human intelligence in interpreting input data (e.g., text, numbers, figures/images and sound) and undertaking different processes in order to produce outputs in the form of decisions/solutions (Müller and Bostrom, 2016; Akerkar, 2018; Von Krogh, 2018; Fountaine *et al*., 2019; Haenlein and Kaplan, 2019). Wilson and Daugherty (2018) elaborated on how AI enhances/complements rather than substitutes human knowledge, skills and abilities. They discussed how AI can: (a) reinforce human decision-making and analytical skills via supplying us with the required information effectively/efficiently; (b) communicate/interact with customers and employees while performing planned tasks; and (c) be embedded within a robot to be used in manufacturing or as a co-worker to augment our physical capabilities (Wilson and Daugherty, 2018). All these AI-capabilities can be done through symbolic and numeric computational techniques via using expert systems (in which computerised programmes are being developed to solve problems based on rules/procedures stated by human experts) and machine learning approaches (by which a model is created for problem-solving and decision-making based on historical data about previous decisions) (Donald *et al*., 1992; Ben-David and Frank, 2009).

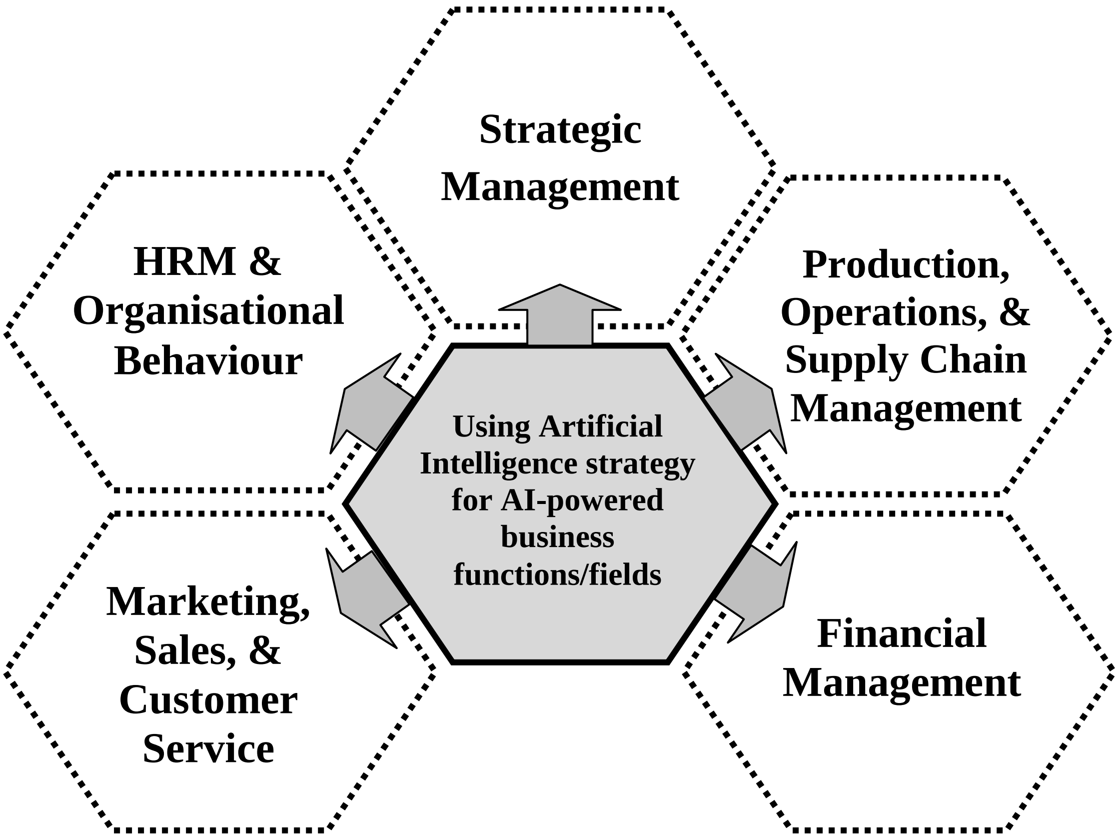

Fig. 1. Using artificial intelligence strategy in different AI-powered business functions and areas of application
Source: The authors

Table I. Artificial intelligence strategy applied in different AI-enhanced business functions and areas of application

AI-powered business function and area of application	AI-enhanced practices	Source/Citation
Human resources management and organisational behaviour	– Automated recruitment using classification-based techniques – Turnover prediction – Candidate search and data acquisition from résumés – Performance management and career planning – Workforce planning – AI-based emerging jobs (e.g., machine relations manager) – Shifting from management of human resources (HR) to management of human-AI resources (HAIR)	Shukla (2009), Strohmeier and Piazza (2015), Buzko *et al*. (2016), Agrawal *et al*. (2017), Wilson *et al*. (2017), Huang and Rust (2018), Ojanperä *et al*. (2018), Plastino and Purdy (2018), Upadhyay and Khandelwal (2018), Brown *et al*. (2019), Li *et al*. (2019), Kreutzer and Sirrenberg (2020)
Production, operations and supply chain management	– Forecasting using machine-learning techniques – AI-based scheduling – Supply chain management using expert-systems and machine-learning techniques – AI-supported production planning and control – Inventory management – Capacity planning – Facility layout – Product and process design – AI-enhanced robots in manufacturing	Metaxiotis *et al*. (2002), Chaudhry and Luo (2005), Crone *et al*. (2006), Ławrynowicz (2007, 2008), Benyoucef and Jain (2009), Min (2010), Tsadikovich *et al*. (2010), Yu (2011), Hadavandi *et al*. (2012), Gunasekaran and Ngai (2014), Pérez-Romero *et al*. (2015), Abbasi and El Hanandeh (2016), Morabito (2016), Kumar (2017), Zor *et al*. (2017), Burggräf *et al*. (2018), Baryannis *et al*. (2019), Hagemann *et al*. (2019), Kreutzer and Sirrenberg (2020)
Strategic management	– Strategic decision making with expert-systems – All levels of organisational decision-making (tactical, operational and strategic) using machine-learning – AI-Human collaborative strategic planning and strategy formulation – Digital business strategy	Knoppe (2000), Rosso (2004), Li and Li (2009), Morabito (2016), Jarrahi (2018), Kuncoro *et al*. (2018), Duan *et al*. (2019), Nieto *et al*. (2019)
Marketing, sales and customer service	– Social media analysis – Market knowledge generated from big data in B2B marketing – Automated market-basket analysis for cross-selling and up-selling marketing using association rule – Recommendation/recommender system within e-commerce – Forecasting customers' buying behaviour – Predicting customer's lifetime value – Estimating the priorities/size of target markets	Cavique (2005), Zhang and Qian (2012), Martínez-López and Casillas (2013), Stalidis *et al*. (2015), Akerkar (2018), Syam and Sharma (2018), Paschen *et al*. (2019), Capatina *et al*. (2020), Kreutzer and Sirrenberg (2020)
Financial management	– Financial forecasting in the stock market – Credit risk assessment/evaluation using classification-based techniques – Prediction of bankruptcy for banks/companies via machine-learning – Financial security and detection of fraud	Butler (2009), Ghodselahi and Amirmadhi (2011), Fletcher (2012), Abdou *et al*. (2017), Corea (2019), Kreutzer and Sirrenberg (2020)

As consolidated in Table I and depicted in Figure 1, applying an effective AI strategy with its different techniques (e.g., machine-learning and expert-systems) to several business functions (production, operations and supply-chain management, human resources management, strategic management, finance and marketing) can promote the collaborative AI-human decision making process in each function. Specifically, it can support the development of AI-enhanced business practices across these different functions (e.g., capacity planning, scheduling, inventory management, recruitment, workforce planning, performance management, marketing research, as well as forecasting of demand, customers' buying behaviour, and financial performance) (as illustrated in Table I).

For example, concerning applying AIS in the business area of ***production, operations and supply-chain management***, prior studies reported successful AI research attempts in that context. *First*, machine-learning techniques were employed in organisations for effective/efficient forecasting of demand or any variable of interest (Crone *et al*., 2006; Hadavandi *et al*., 2012; Abbasi and El Hanandeh, 2016; Zor *et al*., 2017). *Second*, expert-systems were used in automating process planning and developing a sequence for operations as well as AI-enhanced robots were deployed in smart manufacturing (Kumar, 2017; Hagemann *et al*., 2019; Kreutzer and Sirrenberg, 2020). *Third*, expert-systems that imitate experts' decision-making and problem-solving skills are utilised to support capacity management, production planning and scheduling in developing then choosing from alternative plans according to resource constraints in dynamic environment (Metaxiotis *et al*., 2002; Ławrynowicz, 2007, 2008; Pérez-Romero *et al*., 2015; Burggräf *et al*., 2018). *Fourth*, AI-based classification methods enabled managers to categorise numerous inventory items effectively/efficiently (Yu, 2011). *Fifth*, both expert-systems and machine-learning techniques were exploited in overcoming the bullwhip effect while managing global hierarchical supply-chains via sharing real-time information and taking complex decisions across distant numerous nodes (Benyoucef and Jain, 2009; Min, 2010; Tsadikovich *et al*., 2010; Gunasekaran and Ngai, 2014; Baryannis *et al*., 2019). *Sixth*, AI was employed to set better arrangements that solve facility layout problems and facilitate more effective/efficient product and process design especially in case of applying customisation and mass-customisation techniques with interactive modular systems (Chaudhry and Luo, 2005; Kreutzer and Sirrenberg, 2020).

With respect to AIS execution in ***strategic management***, some studies (Knoppe, 2000; Rosso, 2004; Duan *et al*., 2019; Nieto *et al*., 2019) promoted the importance of using AI to support all levels of organisational decision-making (tactical and operational as well as strategic decisions) using machine-learning and expert-systems. These techniques can boost the speed and quality of AI-human collaborative strategic planning and strategy formulation process through analysing vast amount of data, setting relationships among many variables, and selecting the required actions among alternative plans to sustain the organisational competitive advantages (Rosso, 2004; Li and Li, 2009; Jarrahi, 2018; Kuncoro *et al*., 2018).

2.2. Artificial intelligence strategy, knowledge-sharing quality, and organisational effective performance

AI as a strategy enables organisations to sustain their competitive advantages especially in the big-data era, which needs an effective functional strategy that utilises the opportunity of continuous emergence of novel technologies (David and David, 2017; Makridakis, 2017). Despite the challenges of AI-revolution represented in the fear that humans might lose their jobs, Makridakis (2017) concluded that the advantages of implementing AIS exceed its threats. In addition, AI-human collaboration will boost the value of performed tasks rather than causing unemployment to workers (Wilson and Daugherty, 2018). This can be done by effective and efficient knowledge sharing (KS) among relevant stakeholders. On the other hand, knowledge management (KM) is considered in the literature as a strategic asset (Greasley, 2013) that needs technological support of AI (Tsui *et al*., 2002). Hence, prior studies investigated the relationship between AI and Knowledge in different contexts. For example, Liebowitz (2001) addressed conceptually how AI enhances KM through boosting the ability of organisations to share knowledge among interested internal/external stakeholders. From a technology-oriented perspective, Tsui *et al*. (2002) pinpointed that AI can add a technical dimension to KM strategy (i.e., knowledge-engineering) that is related to the searching and knowledge processing aspects. Nemati *et al*. (2002) proposed an AI-platform that can leverage the outcome of each phase of KM-process (socialisation, articulation/externalisation, integration/combination, and understanding/internalisation). Practically, Abubakar *et al*. (2019) used AI-technique in forecasting knowledge-hiding, instead of knowledge-sharing, behaviour in banks. Regarding the relationship between KM and performance, it was examined differently in the literature using different research methodologies with different constructs. For example, Gold *et al*. (2001) reported the significant effects of knowledge infrastructure (in terms of structure, culture, technology) and process capabilities, as two independent factors, on organisational effective performance. The authors followed the scale used in this study for assessing OEP. Chen and Huang (2009) measured KM capacity in terms of acquisition, sharing and application and asserted its significant mediation effect between strategic HRM and organisational performance (OP) (in terms of managerial and technical innovation). In addition, the indirect relationship between KM (as one factor without sub-dimensions) and OP (sales growth, profitability, and customer satisfaction) while using innovation as a mediator was tested and found to be significant by Noruzy *et al*. (2013). Also, KM strategy (people-oriented and technology-oriented) was reported by Ling (2013) to be a significant moderator of the relationship between intellectual capital and OP (with financial, innovation, and agility aspects). Concerning KSQ, Waheed and Kaur (2016) and De Zubielqui *et al*. (2019) revealed that there is inadequate empirical research that assessed knowledge quality (KQ) in specific. Thus, De Zubielqui *et al*. (2019) investigated the indirect relationship between KQ and OP via using innovativeness as a mediator. As for this paper, the authors followed Chiu *et al*. (2006) and Ganguly *et al*. (2019) in operationalising KSQ. In spite of the aforementioned importance of AI towards leveraging KS that was discussed in the literature, there is still scant empirical research analysing that relationship (Liebowitz, 2001) especially in terms of quality of KS. Besides, there is a lack of studies that measured empirically AI-OP direct relationship. Further, AI-KS-OP relationships were mostly discussed in the literature conceptually or indirectly through other mediating constructs, which encouraged the authors to assess empirically the direct and indirect AIS-KSQ-OEP relationships. Consequently, this research developed the following hypotheses related to these three constructs (as depicted in Figure 3). In ***H1*, *AIS affects KSQ positively and significantly***. As for ***H3*, *KSQ affects OEP positively and significantly***. Regarding the direct AIS-OEP relationship represented by ***H5*, *AIS affects OEP positively and significantly***. Concerning the mediation effect tested by ***H8*, *KSQ mediates positively and significantly the relationship between AIS and OEP***.

2.3. Artificial intelligence strategy and Creativity-oriented HRM

Despite the various valuable benefits drawn from using AI (e.g., supporting decision-making at corporate, business and functional levels) (Wilson and Daugherty, 2018), there are challenges associated with AIS implementation (Hughes *et al*., 2019). Scholars emphasised that humans and machines are complementary rather than substitutionary (Ernst *et al*., 2018; Von Krogh, 2018; Wilson and Daugherty, 2018). For instance, machines can perform effective/efficient forecasts while humans should undertake the judgment process and then select the final decision (Agrawal *et al*., 2017; Kreutzer and Sirrenberg, 2020). So far, there is scant empirical evidence on how AI positively influences performance (Von Krogh, 2018). Researchers discussed the relationship between ***AI and HRM within two main research lines***: (a) how AI augments employees' knowledge, skills, abilities and others (KSAOs), and (b) how AI influences HR system/practices. Figure 2 was depicted by the authors to summarise the collaborative human-AI enhanced KSAOs based on the reviewed prior literature (Kolbjørnsrud *et al*., 2016; 2017; Agrawal *et al*., 2017; Wilson *et al*., 2017; Bughin *et al*., 2018; Ernst *et al*., 2018; Jarrahi, 2018; Ojanperä *et al*., 2018;

Plastino and Purdy, 2018; Wilson and Daugherty, 2018; Hughes *et al*., 2019; LaPrade *et al*., 2019). AI strategy needs employees to adapt and acquire new skills (Ernst *et al*., 2018) as well as enhanced-knowledge and abilities. According to Wilson and Daugherty (2018), employees should know how to: (i) train machines to estimate any variable of interest and set the procedures for any task, (ii) interpret the machines' outputs, then (c) assure that safety/ethical procedures are being followed. Furthermore, managers should teach/train employees how to collaborate/engage safely and comfortably with machines/robots in order to ensure organisational fairness (Wilson and Daugherty, 2018). With respect to its significant impact on HR system/practices, AI not only resulted in the creation of new jobs (Ernst *et al*., 2018; Hughes *et al*., 2019) but also altered the nature of jobs as well as the mechanism of doing it (Ojanperä *et al*., 2018). Hence, job design and workforce planning were influenced. In order to cope with post-digital era, organisations should implement AIS to facilitate their operations and adapt their current competencies/structures accordingly (LaPrade *et al*., 2019). On the one hand, AI affects HRM through conducting AI-enabled HR functions/practices (Chelliah, 2017). It can reinforce innovation (Plastino and Purdy, 2018; Vocke *et al*., 2019) and boost quality of decision-making (Chelliah, 2017; Jarrahi, 2018). On the other hand, HR system should be aligned with the requirements of AIS implementation to ensure its success (Chelliah, 2017). By this means, HRM contributes to the adaptation process by two ways. First, HR system should operate creatively (e.g., using extensive training programmes) in order to support the acquisition of new complementary human-based KSAOs (e.g., creative problem-solving and critical thinking skills) (Kolbjørnsrud *et al*., 2016; Bughin *et al*., 2018; Plastino and Purdy, 2018). Second, it should restructure the work in a manner that guarantees successful human-AI collaboration (Kolbjørnsrud *et al*., 2016; Jarrahi, 2018). For example, AI-powered robots can undertake basic cognitive tasks (Bughin *et.al.* 2018; Wilson and Daugherty, 2018). Thus, HRM should support the creative inputs of humans, which encompass sensemaking ability, while dealing with tricky/complex situations (Kolbjørnsrud *et al*., 2016; Jarrahi, 2018; Wirtz, 2019).

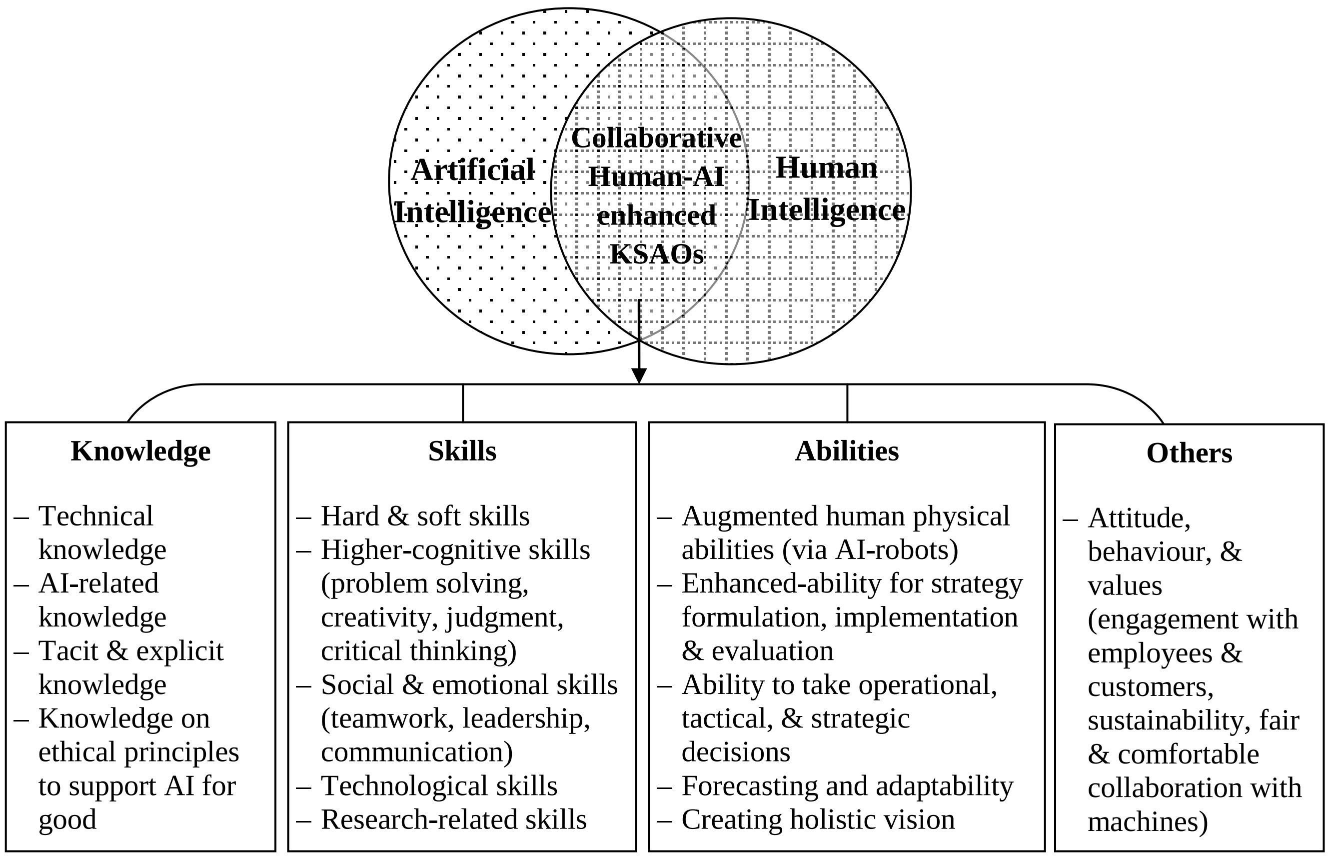

Fig. 2. Collaborative human-AI enhanced KSAOs
Source: The authors

Consequently, creativity-oriented HR practices should be directed towards developing high-skilled workers/employees to be more creative with the aid and positive effect of innovation and creativity supporting capabilities provided by a well established AIS (Agrawal *et al*., 2017; Plastino and Purdy, 2018; Wilson and Daugherty, 2018; Vocke *et al*., 2019). Based on the above discussion, the authors assume that depending only on AI is inadequate for heightening innovative behaviour. Accordingly, creativity-oriented HRM should be complementary to and supported by effective AI strategy in order to guarantee AI success. That is why ***H7 states that AIS positively and significantly affects CHRM***.

2.4. Creativity-oriented HRM, knowledge-sharing quality and individual innovative work behaviour

The significant role of HR practices in acquiring new knowledge through attracting talented candidates and managing current knowledge within organisations was intensively studied in the literature (Shih and Chiang, 2005; Younis and Hammad, 2020). Particularly, HR practices (e.g., training, work design, staffing, performance appraisal and compensation) work on supporting and encouraging KS behaviour (Cabrera and Cabrera, 2005; Fong *et al*., 2011; Kim and Ko, 2014). Yet, the need to understand quality of KS calls for more empirical research (Chiu *et al*., 2006; Waheed and Kaur; 2016; De Zubielqui *et al*., 2019). KSQ is a multidimensional construct (Yoo *et al*., 2011; Yoo, 2014), which assesses whether quality of KS across the relevant stakeholders is characterised by being accurate, timely, comprehensive, reliable and understandable or not (Ganguly *et al*., 2019). It was pointed out in the literature that evaluating KSQ, which represents an organisational challenge, can be beneficial in understanding how knowledge impacts performance within multilevel perspectives (Yoo, 2014; De Zubielqui *et al*., 2019). Different reasons can lie behind being an organisational challenge. For example, KSQ can be affected by non-traditional factors related to the nature of knowledge and realising the importance of KS (Stenius *et al*., 2016), and whether the participating members are having shared vision and interactive networking (Chiu *et al*., 2006; Chang and Chuang, 2011; Yoo *et al*., 2011). However, there is still a paucity of studies that tackled revisiting HRM practices to be aligned with KSQ requirements. Creative HRM practices are needed not only to incentivise employees to share knowledge with an acceptable quality level, but also to deal with their worries and hopes through effective HR executives. Thus, organisations should reshape its HR systems through adopting creativity-oriented HRM practices. CHRM was conceptualised as a set of HRM practices that promote creativity via motivating employees to generate and exchange work-related novel ideas that are beneficial for the business (Song *et al*., 2019). Prior studies (Chang and Chuang, 2011; Yoo *et al*., 2011) pinpointed that people-oriented HRM practices, which pay considerable attention to interactive collaboration, social interactions, diversity and encouragement can motivate employees to elevate KSQ. Thus, the authors suggest that CHRM can foster the quality of KS among organisational members. As presented in Figure 3 by ***H2, CHRM positively and significantly affects KSQ***.

Although prior literature (Yoo *et al*., 2011; Yoo, 2014) have reported the positive impact of KS on innovativeness, its effect on the individual innovative behaviour is still under-researched (Radaelli *et al*., 2014). Mura *et al*. (2013) promoted that innovative behaviour can be affected by the context of KS while Madrid *et al*. (2014) added the influence of personality. It was also concluded that knowledge generated from collaborations amplifies individual creativity (Younis, 2019) as well as boosts IIWB (Atitumpong and Badir, 2018; Schuh *et al*., 2018). Besides, Ganguly *et al*. (2019) indicated that having accurate, timely, comprehensive, reliable and understandable KS can improve innovative work behaviour. Based on the aforementioned discussion, the authors hypothesised ***H4*** that assumes ***KSQ positively and significantly affects IIWB***.

Despite the availability of studies that contended on the significant role of HRM practices in promoting IIWB (Prieto and Pérez-Santana, 2014; Noopur and Dhar, 2019), only few of them that investigated the mediating role of KS in that relationship (Lopez-Cabrales *et al*., 2009). HRM was regarded as a crucial enabler for sustaining innovativeness via knowledge (Theriou and Chatzoglou, 2008; Chen and Huang, 2009) and KS behaviour (Lopez-Cabrales *et al*., 2009). Creative-thinking based on sufficient, valuable and timely knowledge is vital for maximising IIWB (Lopez-Cabrales *et al*., 2009). At the individual level, HR practices are responsible for developing and sharing knowledge (Younis, 2018), ensuring its effective/efficient exchange among organisational members, and facilitating innovation. For instance, interactive collaboration/engagement supported practices can improve employees' creative capabilities through seamless KS between members (Younis, 2019). Further, Cabrera and Cabrera (2005) clarified that constructive performance evaluation associated with compensation system that reflects KS behaviour can support KS within organisations. Additionally, extensive training programmes can be directed towards stimulating IIWB through lessening KS obstacles and promoting learning (Fong *et al*., 2011). Particularly, diversity-based training programmes can be designed for constructing diverse pool of KSAs that are crucial for creativity (Younis, 2019). As a result, ***H6* and *H9* were formulated to assume that *CHRM positively and significantly affects IIWB*** as well as ***KSQ mediates positively and significantly CHRM-IIWB relationship***.

3. Research Methodology

The purpose of this study was to investigate the relationship between AIS, CHRM, KSQ, IIWB and OEP of international organisations conducting AI-powered business practices in Egypt. Accordingly, the authors presented a multilevel-model (as illustrated in Figure 3), after reviewing the relevant literature, and tested it through employing mixed-methods approach (as demonstrated in Figure 4). Quantitative data were collected from 168 questionnaires answered with a five-point Likert-scale by AI-experts at IT departments of 20 international AI-powered organisations in Egypt.

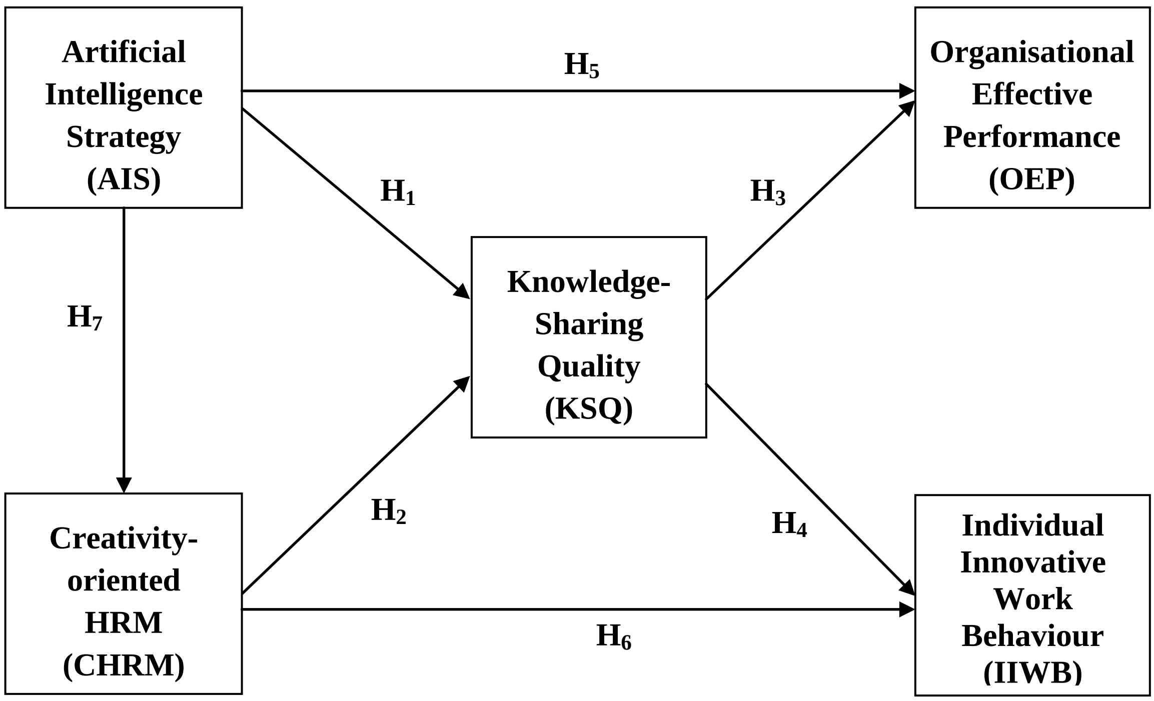

Fig. 3. Conceptual framework showing the relationship between AIS, CHRM, KSQ, IIWB and OEP

Source: The authors

Concerning the questionnaire's items used in assessing the research constructs, the authors adopted/adapted the scales developed by previous studies (as shown in Table II). The AIS, first independent variable, was assessed through a scale adapted from Duft *et al*. (2019). The CHRM, second independent variable, was operationalised via relying on the items adopted from Song *et al*.

(2019). The authors adapted the measures constructed by Chiu *et al*. (2006) and used by Ganguly *et al*. (2019) to evaluate KSQ (i.e., mediator). Regarding the dependent variables, the IIWB was measured with a scale adopted from De Jong and Den Hartog (2010) and the OEP was assessed via measurement-items adopted from Gold *et al*. (2001).

Table II. The scale sources of the measurement items

Factor	Number of Measurement Items	Scale Source
Artificial Intelligence Strategy (AIS)	12	Adapted from Duft *et al*. (2019)
Creativity-oriented HRM (CHRM)	11	Adopted from Song *et al*. (2019)
Knowledge-Sharing Quality (KSQ)	6	Adapted from Chiu *et al*. (2006) and Ganguly *et al*. (2019)
Individual Innovative Work Behaviour (IIWB)	10	Adopted from De Jong and Den Hartog (2010)
Organisational Effective Performance (OEP)	14	Adopted from Gold *et al*. (2001)

As for our research population, this study targeted the AI-powered organisations in Egypt. Fountaine *et al*. (2019) discussed that an AI-powered organisation is the one that has an AIS formulated and applied by a cross-functional team assigned for developing different AI-enhanced business functions/practices/processes at this organisation. The authors followed Goodman (2011) and Cooper and Schindler (2014), who advocated the *snowball sampling-technique* for the hard-to-reach population and when the researchers are not being able to develop defined sampling-frame for it. Consequently, the authors started with selecting and visiting the technology companies that develop AI software-packages in Egypt (as revealed in Table III). The AI-experts at these technology companies recommended other institutions (academic/non-academic organisations) that are teaching AI academic courses or carrying out AI-supported business practices. Then, for exploratory purposes, the authors undertook 15 depth individual interviews with the AI-experts that are practicing/teaching AI at these recommended institutions in order to (a) build profound understanding about the AI-enhanced business processes in Egypt, and (b) confirm the *content/face validity* of the questionnaire's measurement-items (as advised by Cooper and Schindler, 2014). Furthermore, as a result of these interviews, a total of 20 organisations were pointed out by the interviewees as AI-powered organisations (working across 7 sectors in Egypt as stated in Table III) that formed our respondent-driven sample. Afterwards, the authors visited these AI-enabled organisations and filled a total of 168 questionnaires answered by 168 AI-experts that were delegated to represent these 20 organisations.

Table III. Sample characteristics

	Industry	No. of Companies	Frequency (No. of Respondents)	%
1	*Telecommunications* (mobile network operators, and internet service providers)	5	55	32.7%
2	*Telecommunications Equipment*	2	17	10.1%
3	*Automation* (construction, healthcare, and energy)	2	10	6%
4	*Technology* (computer hardware/software, search engine, cloud computing and electronics)	4	48	28.5%
5	*Banking*	4	7	4.2%
6	*Semiconductors Manufacturing*	2	24	14.3%
7	*Automotive Supplier of Technology*	1	7	4.2%
	Total	20	168	100%

The mixed methods approach, which merges/combines quantitative and qualitative methods together, was chosen by the authors for this paper as commended by Cooper and Schindler (2014) for business research in order to acquire comprehensive understanding especially for new research topics. Qualitatively, as depicted in Figure 4, before collecting the 168 questionnaires the authors undertook *15 depth individual qualitative interviews* for exploratory purposes. Afterwards, the authors –in order to explain the research quantitative findings– conducted *10 more interviews* with AI-experts after attending: (1) a focus group that was moderated by the Business Development Manager who is working at the United Nations Strategic Engagement Division, International Telecommunication Union (ITU) and participating in applying the UN initiative for using AI as a power/force for good (International Telecommunication Union, 2018; 2019); and (2) the AI session of 2019 World Youth Forum (WYF) in Egypt that was moderated by *Sophia the robot* (manufactured by Hanson Robotics using AI). Malik *et al*. (2019) and Kreutzer and Sirrenberg (2020) mentioned that Sophia is an AI-supported robot that can interact and communicate with humans with different facial expressions. ***Sophia the AI-robot stated at this WYF's AI-session about AI-humans relationship: "AI-enabled robots and humans are complementing each other rather than competing together".*** This annual WYF is one of the important events organised by the Egyptian government through which many national strategies are declared by the government and discussed by the international experts. For example, strategies related to sustainability (Adel and Mahrous, 2018), internationalisation of higher education (Adel *et al*., 2018), reinforcing creative product designs and innovation climate to industrial entrepreneurs (Adel and Younis, 2019), and interactive entrepreneurial marketing strategies (Adel *et al*., 2020).

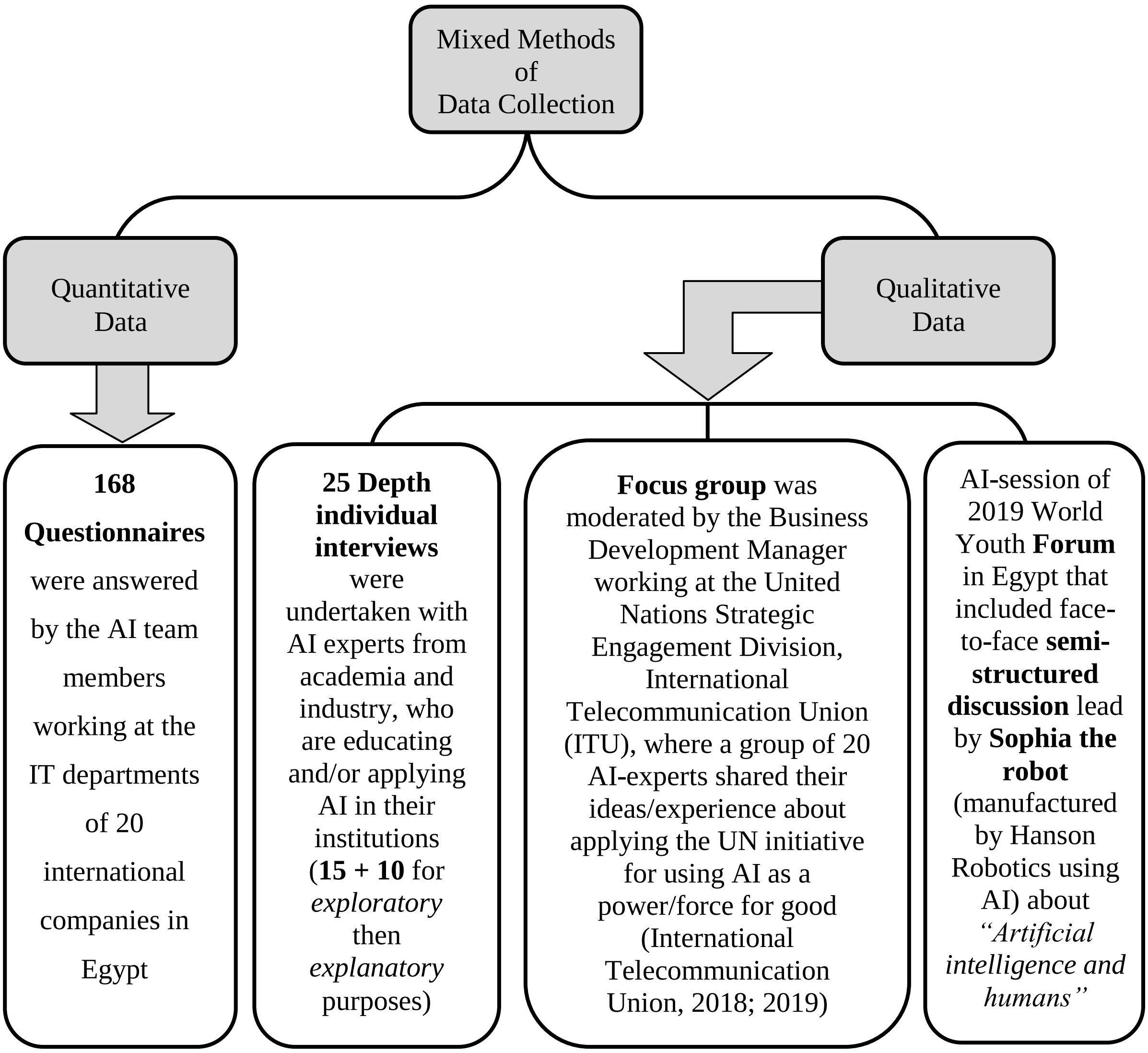

Fig. 4. Mixed methods approach of data collection used for this research
Source: The authors

4. Data analysis and findings

As for analysing the suggested model, the following steps were undertaken. First, the authors demonstrated the descriptive statistics of the main variables and conducted exploratory factor analysis (EFA) using SPSS (v.24) to check whether there is a common method bias. Afterwards, a correlation analysis was carried out to test the direction/significance of the suggested relationships as well as the multicollinearity issue between the variables. Further, the authors used partial least squares-structural equation modeling (PLS-SEM) via Smart-PLS (v.3.2.9) (Ringle *et al*., 2015) to examine the suggested conceptual-model (Figure 3). Table IV clarifies the descriptive statistics of every research construct. Based on a five-point Likert-scale that ranges from 1/strongly disagree to 5/strongly agree, the highest mean of the five variables was found to be 4.12 and the lowest mean was 3.91 out of 5. This indicates that the sample almost agreed on the five main research constructs. Moreover, the Skewness and Kurtosis coefficients were found to be not equal to zero; thus, the normality assumption was violated. Yet, that violation was observed to be within the suggested range for the studies of social sciences (from -3 to +3 for skewness and from -10 to +10 for kurtosis) as recommended by Pallant (2011) and Kline (2015).

Table IV. Descriptive statistics of the main variables

Variables	N	Minimum	Maximum	Mean	Skewness	Kurtosis
AIS	168	2.25	5.00	3.91	-.77	.60
CHRM	168	1.45	5.00	3.99	-1.58	2.47
KSQ	168	2.17	5.00	4.12	-1.34	1.86
IIWB	168	2.20	4.80	3.95	-1.03	.17
OEP	168	1.57	4.93	4.01	-1.38	1.93

Moreover, Table V reveals the sample mean for each variable across the seven sectors. The highest mean for AIS, CHRM, KSQ, and IIWB were observed to be in the companies working in two sectors (automotive supplier of technology as well as computer hardware, software, search engine, cloud computing and electronics). On the other hand, the lowest mean for AIS was found to be in the banking sector whereas for the rest of the five constructs it was noticed to be in the automation companies operating in the industries of construction, healthcare, and energy. With regards to OEP, the technology and semiconductors manufacturing companies responded with the highest mean.

Table V. The sample mean for each variable across the seven sectors

Variables	Semiconductors Manufacturing	Telecommunications Equipment	Telecommunications	Automation	Technology	Banking	Automotive Supplier of Technology	Total
AIS	4.01	3.71	3.88	3.38	4.10	3.36	4.25	3.91
CHRM	4.14	3.84	3.96	3.25	4.20	3.35	4.21	3.99
KSQ	4.23	4.00	4.15	3.45	4.26	3.62	4.31	4.12
IIWB	4.08	3.58	3.92	3.44	4.15	3.63	4.21	3.94
OEP	4.12	3.55	4.03	3.23	4.23	4.07	4.11	4.01

Before examining the hypotheses of our suggested model, EFA was conducted for all measurement-items through SPSS to check whether there is a common method bias (Podsakoff *et al*., 2003; Jordan and Troth, 2020). As illustrated in Table VI., the eigenvalues of 18 items exceed 1.

Accordingly, these items can explain 75.56% of the total variance whereas the first item can explain 26.21% only of the total variance. Hence, according to Harman's single-factor test, common method bias cannot be considered as an issue for this study.

Table VI. Part from EFA results*

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.889	26.206	26.206	13.889	26.206	26.206
2	3.479	6.563	32.770	3.479	6.563	32.770
3	2.683	5.062	37.831	2.683	5.062	37.831
4	2.444	4.611	42.442	2.444	4.611	42.442
5	1.978	3.732	46.174	1.978	3.732	46.174
6	1.850	3.490	49.664	1.850	3.490	49.664
7	1.651	3.115	52.779	1.651	3.115	52.779
8	1.532	2.891	55.670	1.532	2.891	55.670
9	1.429	2.696	58.367	1.429	2.696	58.367
10	1.291	2.436	60.802	1.291	2.436	60.802
11	1.159	2.188	62.990	1.159	2.188	62.990
12	1.109	2.092	65.082	1.109	2.092	65.082
13	1.086	2.050	67.132	1.086	2.050	67.132
14	.970	1.829	68.961			
15	.923	1.741	70.702			
16	.884	1.667	72.369			
17	.871	1.644	74.013			
18	.819	1.546	75.559			
-	-	-	-			
-	-	-	-			
53	.161	.425	100.000			

* Kaiser-Meyer-Olkin (measure of the sampling adequacy) = 0.851; Bartlett's Test of Sphericity: Approx. Chi-Square = 4684.04; *df* = 1378; Sig. = 0.000.

The following correlation analysis was carried out by the authors to test the direction/significance of the suggested relationships in addition to the multicollinearity issue between the variables. Table VII points out that the correlation coefficients among the research variables are significantly positive. Besides, the relationship among every pair of independent variables lies between 0.504 and 0.626 (i.e., less than 0.7). According to Field (2009) and Pallant (2011), multicollinearity is not a problem for this study.

Table VII. Pearson correlation test

Variables	AIS	CHRM	KSQ	IIWB	OEP
AIS	1				
CHRM	***.517***	1			
KSQ	***.504***	***.626***	1		
IIWB	.476**	.623**	.586**	1	
OEP	.503**	.660**	.699**	.749**	1

** Correlation is significant at 0.01 (1-tailed).
Italic and **Bold** numbers indicate the relationships among possible independent variables

The authors adopted PLS-SEM approach to discover and test new relationships that contribute to the prior AI-literature and the latent scores of the examined variables will be employed in further analyses (Hair *et al.*, 2014; 2019). In addition, confirmatory composite analysis (CCA) in SEM was used as it was reported for being more useful than confirmatory factor analysis (CFA) (Hair *et al.*, 2020). Thereby, PLS-SEM attracted great attention in the business research related to many functions such as ***operations management*** (Peng and Lai, 2012), ***strategic management*** (Hair *et al.*, 2012), ***human resources management*** (Ringle *et al.*, 2018), and ***supply-chain management*** (Kaufmann and Gaeckler, 2015). As for building the SEM, the authors pursued the systematic two-stage method. At the first stage, the measurement model was tested and CCA steps were carried out (Hair *et al*., 2020). Afterwards, the suggested relationships of the structural model were assessed (Hair *et al*., 2011; 2014; 2016). All research variables were assessed on reflective lower-order constructs measurement level (Sarstedt *et al*., 2019). After verifying the face validity as mentioned earlier, the measurement model was tested using multi-criteria (e.g., convergent and discriminant validity as well as construct reliability) (Hair *et al*., 2010). The authors relied on the average variance extracted (AVE) to confirm the convergent validity of all five constructs (Hair *et al*., 2010), and on the HTMT criterion to check the discriminant validity (Henseler *et al*., 2015). In addition, the construct reliability was evaluated using composite reliability and Cronbach's alpha. Table VIII summarises the assessment of our measurement model using multi-criteria.

Table VIII. Assessment of the measurement model

Constructs	Construct Reliability		Construct validity					
	Cronbach's alpha	Construct reliability	Convergent validity	$HTMT_{0.85}$				
		CR	AVE	AIS	CHRM	IIWB	KSQ	OEP
AIS	0.688	0.809	0.515					
CHRM	0.818	0.870	0.533	0.651				
IIWB	0.812	0.869	0.571	0.491	0.780			
KSQ	0.725	0.829	0.550	0.711	0.800	0.683		
OEP	0.853	0.888	0.532	0.514	0.784	0.828	0.780	

As shown in Table VIII, AVE coefficients are greater than 0.5 (i.e., ranging from 0.515 to 0.571). Thereby, the convergent validity of every construct is verified. Additionally, the discriminant validity was also confirmed as the HTMT criterion between every two constructs is less than 0.85. The minimum values of the Cronbach's alpha and CR are 0.688 and 0.809 respectively (i.e., > 0.6), which verify our constructs' reliability. Afterwards, the structural model was tested through relying on multi-criteria (Hair *et al*., 2014). The multicollinearity test was carried out among the independent/exogenous variables via obtaining the variance inflation factor (VIF). Then, the suggested direct relationships were examined with the beta coefficient and the indirect ones were tested by further conducting the mediation analysis. Table IX and Figure 5 display the structural model and its hypotheses.

Table IX. Structural model and testing of direct relationships

Path		VIF	Beta	T value	P Values	Result
H7	AIS -> CHRM	NA	0.484	6.930	0.000	Supported***
H1	AIS -> KSQ	1.306	0.286	4.109	0.000	Supported***
H5	AIS -> OEP	1.377	0.118	1.439	0.075	Not supported
H6	CHRM -> IIWB	1.655	0.527	6.089	0.000	Supported***
H2	CHRM -> KSQ	1.306	0.491	6.926	0.000	Supported***
H4	KSQ -> IIWB	1.655	0.212	2.385	0.009	Supported**
H3	KSQ -> OEP	1.377	0.561	7.333	0.000	Supported***

***Significant at confidence level 99.9%. **Significant at confidence level 99%.

The VIF values (displayed in Table IX) that lie between 1.306 and 1.655 are within the acceptable range (from 0.2 to 3), which act as another evidence for the absence of multicollinearity after the correlation matrix (Table VII) (Hair *et al*., 2020). Moreover, the path coefficient of every hypothesis was assessed to check its significance at confidence level 95% while using bootstrapping method of 5000 subsamples and 300 iterations. Accordingly, AIS was found to have positive significant effect on KSQ by 28.6% (99.9% confidence level). So, H1 was supported. CHRM affected positively and significantly KSQ by 49.1% (99.9% confidence level). Thus, H2 was supported. KSQ affected positively and significantly OEP by 56.1% (99.9% confidence level). Therefore, H3 was supported.

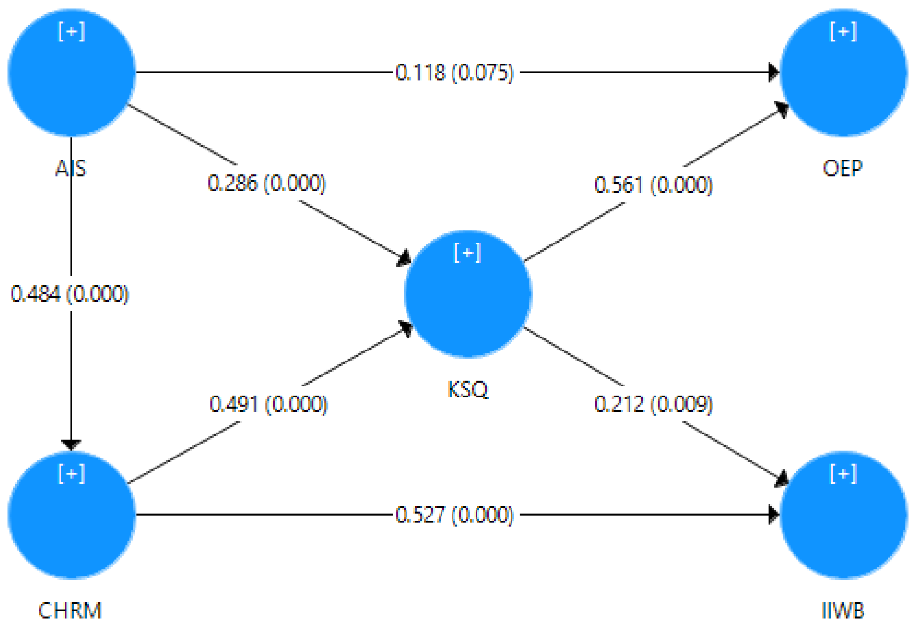

Fig. 5. Structural model developed using Smart-PLS 3.2.9
Source: The authors

Also, KSQ had significant positive impact on IIWB by 21.2% (99% confidence level). Thereby, H4 was supported. However, AIS had an insignificant positive effect on OEP by 11.8% (95% confidence level). Consequently, H5 was not supported. CHRM affected positively/significantly IIWB by 52.7% (99.9% confidence level). As a result, H6 was supported. Furthermore, AIS affected positively/significantly CHRM by 48.8% (99.9% confidence level). Hence, H7 was supported. Concerning the mediation analysis, the authors followed Zhao *et al*. (2010) approach as commended by Nitzl *et al*. (2016) and Carrión *et al*. (2017). Table X reports the results of mediation analysis.

Table X. Mediation analysis

H	Hypothesis	Indirect effect	Direct effect	Result
8	AIS -> KSQ -> OEP	0.160 $^{(0.000)}$	0.118 $^{(0.075)}$	Full mediation
9	CHRM -> KSQ -> IIWB	0.104 $^{(0.009)}$	0.527 $^{(0.000)}$	Partial complementary mediation

As presented in Table X, the direct relationship between AIS and OEP was found to be positive yet insignificant by 11.8% (95% confidence level). However, the significant positive indirect relationship between both constructs via KSQ was supported by 16% (99.9% confidence level). Therefore, a full mediation role of KSQ in AIS-OEP relationship can be verified (99.9% confidence level). For that reason, H8 was supported. Additionally, the direct CHRM-IIWB relationship was found to be significantly positive by 52.7% (99.9% confidence level) as well as the indirect relationship between both constructs was also found to be significantly positive by 10.4% (99% confidence level). Accordingly, a complementary partial mediation role of KSQ in CHRM-IIWB relationship can be confirmed with 99% confidence level. Thus, H9 was supported.

5. Conclusions, discussion, managerial implications and limitations

This empirical study investigated the direct/indirect relationships between AIS, CHRM, KSQ, IIWB and OEP of international organisations conducting AI-powered business practices in Egypt. The authors presented a multilevel model, after reviewing the relevant literature, and tested it through employing mixed-methods approach (168 questionnaires, 25 depth interviews for exploratory then explanatory purposes, AI-based focus group and international forum). In order to examine the research hypotheses, quantitative data were collected from 168 questionnaires answered by AI-experts, who were assigned by their 20 international AI-powered organisations in Egypt to participate as respondents. Following PLS-SEM approach, results revealed that AIS affects positively/significantly KSQ, which in turn affects positively/significantly OEP. The significant positive direct AIS-OEP relationship was not supported yet the significant positive indirect relationship via KSQ was supported. This indicates the importance of using KSQ to mediate the AIS-OEP relationship and improve the organisational performance effectively. In spite of the abovementioned importance of AI towards leveraging KS that was discussed in the literature, there is still scant empirical research analysing that relationship (Liebowitz, 2001) especially in terms of KSQ. Besides, there is a lack of studies that measured empirically AI-OP direct relationship. Further, AI-KS-OP relationships were mostly discussed in the literature either conceptually or indirectly through other mediating constructs (not in terms of quality), which makes this paper the first empirical one that examined the direct/indirect AIS-KSQ-OEP relationships. Yet, our findings contributes to Gold *et al*. (2001) that reported the significant effects of knowledge infrastructure (in terms of structure, culture, technology) and process capabilities, as two independent factors, on OEP. Moreover, AIS affects positively/significantly CHRM, which in turn affects positively/significantly KSQ and IIWB. This asserts the need for creativity-oriented HRM to be directed towards developing high-skilled individuals to be more creative with the aid and positive effect of innovation and creativity supporting capabilities provided by a well established AIS (Agrawal *et al*., 2017; Plastino and Purdy, 2018; Wilson and Daugherty, 2018; Vocke *et al*., 2019). From another side, it reveals that depending only on AI is inadequate for heightening IIWB. Thus, creativity-oriented HRM should be complementary to and supported by effective AIS in order to guarantee AI success and enhanced IIWB. Hence, our results are consistent with the findings of prior literature (Chang and Chuang, 2011; Yoo *et al*., 2011; Noopur and Dhar, 2019). Further, KSQ affects positively/significantly IIWB. In addition, the significant mediation role of KSQ in CHRM-IIWB relationship was supported. Our findings were found to be also consistent with prior KM studies that reported KS to be crucial factor for reinforcing innovation (Radaelli *et al*., 2014). As well, these results are consistent with studies that regarded HRM as vital enabler for sustaining innovativeness via knowledge (Theriou and Chatzoglou, 2008; Chen and Huang, 2009) and KS behaviour (Lopez-Cabrales *et al*., 2009).

Based on the empirical findings of this study, qualitative depth interviews with international AI-experts, semi-structured discussions/presentations throughout the AI-based international forum and focus group in addition to the relevant literature review, strategic leaders and managers of different functional areas can benefit from the following implications:

(1) An AI-strategy that is well formulated, implemented and evaluated along with the leadership commitment to its execution by supporting it with skilled human resources and suitable technological infrastructure will enhance knowledge-sharing quality and creativity-oriented HRM in an AI-powered organisation.

(2) Creativity-oriented HRM that empower employees to suggest and share innovative ideas among their peers/leaders, engage them in the decision making process, develop their innovative performance and reward them on their creative ideas will boost knowledge-sharing quality across the organisation and their individual innovative work behaviour.

(3) The quality of knowledge shared across the relevant stakeholders, which is characterised by being accurate, timely, comprehensive, reliable and understandable, can develop organisational effective performance and individual innovative work behaviour.

(4) An effective AI-strategy can maximise OEP, through using enhanced knowledge-sharing quality, in terms of being able to provide new innovative products/services/processes and exploit emerging business opportunities/markets in the digital era.

(5) Applying an effective AI-strategy with its different techniques (e.g., machine-learning and expert-systems) to several business functions (***production, operations and supply-chain management, human resources management, strategic management, finance and marketing***) can promote the collaborative AI-human decision making process. Additionally, it can support the development of AI-enhanced business practices across these different functions (e.g., capacity planning, scheduling, inventory management, recruitment, workforce planning, performance management, marketing research, as well as forecasting of demand, customers' buying behaviour, and financial performance).

The unequal sizes of respondents in each sector from the 7 Egyptian sectors that possess AI-powered organisations represent one of the limitations of this research. This can be justified by the recent introduction yet promising and rising application of the AIS in the Egyptian emerging economy. However, as was discussed in the AI-session of the 2019 World Youth Forum in Egypt, many Egyptian public and private organisations from several sectors are now aware of the AI importance and its numerous applications in the field of business and management (World Youth Forum, 2019). Thus, further comparative studies are needed to investigate the differences between these sectors and among other developing/developed countries in applying the AIS. Additionally, the AIS was assessed through using 12 measurement-items as one construct. Therefore, it is recommended for other empirical studies to investigate this construct in terms of different dimensions representing the AI-enhanced functional areas in the AI-powered organisations.

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Appendix

Table AI. Questionnaire's measurement-items

Factor	Description
Factor (1). AIS (adapted from Duft *et al*., 2019)	
AIS_1	We have a clear strategy for artificial intelligence in our organisation
AIS_2	We have leaders' ownership of and commitment to artificial intelligence
AIS_3	We have suitable technological infrastructure to support artificial intelligence
AIS_4	The availability of talent with appropriate skill sets for artificial intelligence work
AIS_5	We have functional integration that enables end-to-end artificial intelligence solutions
AIS_6	We have enough resources to be used for implementing artificial intelligence strategy
AIS_7	The availability of useful data collected for further processing
AIS_8	We generate relevant insights from artificial intelligence
AIS_9	We use artificial intelligence-based decision making
AIS_{10}	We have high expectations for return on artificial intelligence investments
AIS_{11}	We implement changes to relevant processes after artificial intelligence's adoption
AIS_{12}	We have clear measures for evaluating our artificial intelligence strategy
Factor (2). CHRM (adopted from Song *et al*., 2019)	
$CHRM_1$	We provide opportunities for employees to communicate and cooperate
$CHRM_2$	We encourage employees to suggest creative ideas
$CHRM_3$	We provide opportunities for employees to participate in decision making
$CHRM_4$	We provide opportunities for employees to express voice
$CHRM_5$	We implement both individual and team performance evaluation
$CHRM_6$	We provide for employees both constructive feedback and developmental feedback
$CHRM_7$	We implement both process-oriented and result-oriented evaluation regarding employee knowledge and skills
$CHRM_8$	We reward employees when adopting their creative ideas
$CHRM_9$	We enable employees to acquire diverse skills through job rotation
$CHRM_{10}$	We find out what job areas or content that employees are skilled in through job rotation
$CHRM_{11}$	We pay attention to diverse knowledge and skills training for employees
Factor (3). KSQ (adapted from Chiu *et al*., 2006; Ganguly *et al*., 2019)	
KSQ_1	The knowledge shared among the stakeholders of my organisation is timely
KSQ_2	The knowledge shared among the stakeholders of my organisation is complete and clear
KSQ_3	The knowledge shared among the stakeholders of my organisation is mostly accurate
KSQ_4	The knowledge shared among the stakeholders of my organisation is easy to understand
KSQ_5	The knowledge shared among the stakeholders of my organisation is relevant to the topics pertaining to the business operations of my organisation
KSQ_6	The knowledge shared among the stakeholders of my organisation is reliable
Factor (4). IIWB (adopted from De Jong and Den Hartog, 2010)	
$IIWB_1$	Our employees pay attention to issues that are not part of his daily work
$IIWB_2$	Our employees wonder how things can be improved
$IIWB_3$	Our employees search out new working methods, techniques or instruments
$IIWB_4$	Our employees generate original solutions for problems
$IIWB_5$	Our employees find new approaches to execute tasks
$IIWB_6$	Our employees systematically introduce innovative ideas into work practices
$IIWB_7$	Our employees attempt to convince people to support an innovative idea
$IIWB_8$	Our employees make important organisational members enthusiastic for innovative ideas
$IIWB_9$	Our employees contribute to the implementation of new ideas
$IIWB_{10}$	Our employees put effort in the development of new things
Factor (5). OEP (adopted from Gold *et al*., 2001)	
OEP_1	My organisation has improved its ability to innovate new products/services
OEP_2	My organisation has improved its ability to identify new business opportunities
OEP_3	My organisation has improved its ability to anticipate potential market opportunities for new products/services
OEP_4	My organisation has improved its ability to rapidly commercialise new innovations
OEP_5	My organisation has improved its ability to adapt quickly to unanticipated changes
OEP_6	My organisation has improved its ability to anticipate surprises and crises
OEP_7	My organisation has improved its ability to coordinate the development efforts of different units
OEP_8	My organisation has improved its ability to quickly adapt its goals and objectives to industry/market changes
OEP_9	My organisation has improved its ability to decrease market response times

OEP_{10}	My organisation has improved its ability to react to new information about the industry or market
OEP_{11}	My organisation has improved its ability to be responsive to new market demands
OEP_{12}	My organisation has improved its ability to avoid overlapping development of corporate initiatives
OEP_{13}	My organisation has improved its ability to streamline its internal processes
OEP_{14}	My organisation has improved its ability to reduce redundancy of information and knowledge