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SHAPING THE HUMAN CAPITAL ABSORPTIVE CAPACITY: ROLE OF ARTIFICIAL INTELLIGENCE

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Abstract
In Pakistan, engineering industries are far behind in manufacturing products as compared to other industries across the world. One of the major reasons behind this failure is the dearth of specific human capital skills to effectively operate artificial intelligence technology. This research aims to investigate the impact of artificial intelligence on human capital and identify significant skills that increase innovation and productivity. The population of this study was the manufacturing industry, specifically the automobile industry of Pakistan. Data were collected through closed-ended questionnaires from those employees who were engaged with artificial intelligence-related projects. Results indicate that artificial intelligence has a positive impact on human capital. The computer, mathematics, and robotic-mechanical associated skills are essential for the effective utilization of this technology towards improving the innovation and productivity of firms. This research is useful for manufacturing organizations to understand the significant relationship between artificial intelligence and human capital. Further, it provides HR Managers with a list of indispensable skills to train their employees to effectively and efficiently deal with artificial technology to increase innovation and productivity in their firms. Moreover, the model of this study opens new avenues for researchers to expand their research work to identify others' human capital skills to increase the performance of the organizations. This is one of the few research studies that have been conducted in the context of Pakistan. It will help to improve human capital skills according to the necessity of the business environment.
Keywords: Artificial Intelligence; Human Capital; Absorptive Capacity; Innovation; Productivity.

1. INTRODUCTION

This is the age of Industry Revolution 4.0, where robots (i.e. Machines) are rapidly replacing the major labor force of the manufacturing sector including the automobile industry to perform repetitive and perilous jobs with the assistance of artificial intelligence. However, running these machines is not an easy job (Charlwood & Guenole, 2022), wherein highly skilled professionals are required to operate these machines to achieve sustainable results. Subsequently, in the near future, human capital will be considered as the only leading asset of the organizations, whereas artificial intelligence will be used as the only refined technology to run business operations across the world. The combination of both will be considered the most effective strategy for a competitive edge to remain dominant in the market (Das, 2023; Samarasinghe & Medis, 2020). Many research studies have also highlighted that the adoption of robot technology will change the demand for skill sets which ultimately impact the jobs of white and blue collar in firms (Baldwin, 2019). Thus, today, companies do not need a workforce at the workplace, but they need highly skilled individuals with core competencies to run business operations (Anastasiu et al., 2020). As artificial intelligence has changed the understanding of jobs and forced organizations to align the skills of their human resource with this technology to get a competitive edge (Marlapudi & Lenka, 2024).

According to Chowdhury et al. (2023), artificial intelligence technology has geared up the contemporary developments of automation and digitalization in machines by many folds. Artificial intelligence performs a major role in boosting the economy of many countries and is considered a significant instrument in the accomplishment of leading companies across the world (Wisskirchen et al., 2017). Owing to the importance of artificial

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intelligence, many leading international firms are continuously spending a substantial chunk of their budgets on artificial intelligence research and development. (Lu et al., 2017). Further, the Netherlands, the USA, Switzerland, Qatar, and Singapore are fully equipped with technology to embrace the fourth industrial revolution. These countries are seriously encouraged to develop their human capital duly equipped with the in-depth knowledge and skills of artificial intelligence. For instance, nowadays, the Netherlands is more focused on training their new generation in skilled programs that are directly connected with artificial intelligence technology instead of traditional educational degrees, which are outdated in the marketplace and have no connection with technology of artificial intelligence (Wisskirchen et al., 2017). However, in developing countries, the maximum number of states still have not made any serious efforts to transform the human capital on the paradigms of artificial intelligence and other essential contemporary technologies. In many cases, the educational programs of these countries are not only outdated in the market but also do not have any link with artificial intelligence technologies (Mubarik, 2015). Keeping the pace and importance of artificial intelligence, it is becoming indispensable for firms of less developing countries to adopt this technology at the workplace and equip their employees with related essential skills (Kastelli et al., 2024; Rasiah, et al., 2016; Ransbotham, et al., 2017).

In the case of Pakistan, the majority of industries are far behind in manufacturing products according to the world's standards. One of the major reasons behind this failure is the dearth of human capital skills to effectively operate artificial intelligence technology (PIAIC, 2018). Human capital is the most significant source of performance of organizations (Badghish & Soomro, 2024) because it is rare, valuable, and hard to replace (Anastasiu et al., 2020). Against this backdrop, this study examines the impact of artificial intelligence technologies on the effectiveness of human capital, measured as skills. Likewise, the study also examines the role of absorptive capacity in the relationship between artificial intelligence and human capital development by taking the case of Pakistan. In doing so, this study contributes in many ways. This research supports manufacturing firms specifically automobile organizations to understand the significant relationship between artificial intelligence and human capital. Further, it provides HR Managers with a list of indispensable skills to train their employees to effectively and efficiently deal with artificial technology to increase innovation and productivity in their firms. Moreover, the model of this study opens new avenues for researchers to expand their research work to identify others' human capital skills to increase the performance of the manufacturing sector including the automobile industry.

2. LITERATURE REVIEW

2.1. Artificial intelligence and human capital

Artificial intelligence is recognized as the intelligence of a machine, and it executes works as human intelligence (Budhwar et al., 2023), despite different novelties in artificial intelligence, still this intelligence has certain boundaries as compared to the human brain. The human has the knowledge, skills, and ability to perform any given task beyond the functions of artificial intelligence (Al Naqbi et al., 2024). Although artificial intelligence has a profound influence on all three facets of human capital, its impact on skill is profound (Mubarik, 2015; Bontis, 2019). Usually, the word skill narrates an employee 's characteristics, but in business, it has great importance and is considered as a larger scale to having an individual great understanding and grip to resolve a complex problem that cannot be resolved by every employee (Prochno, 2001). The concept of human capital skill took great importance in the 1980s due to advancements in technology, organizational development, and changes in economic factors. Human capital skill development was treated as a strategic tool and took great importance in an environment of business competition (Nyhan, 1998). Moreover, Akerman, et al. (2015) argued that today, the economic scenario has rapidly changed from mass production to customized production, where human capital having extraordinary skills has taken great importance due to a specific focus on customers' needs wherein innovation is most important. It creates a complex condition for manufacturing firms to integrate their workforce and artificial intelligence into one system to increase the quality of their products (Melo & Machado, 2018). This technology amplifies individuals' skills to achieve new productivity targets with the support of machines, which was never possible before (Gould, 2018). However, it has been found that many firms invest huge money in the installment of robot machines but fail to deliver the results due to ignoring the importance of the required human capital skills set to effectively operate this latest technology (Martínez-Caro et al., 2018).

The rapid expansion of artificial intelligence technology has created a demand for computer experts, mathematicians, and certain fields of science in the labor market; besides this, employees having critical, creative, and problem-solving approaches get more important in changing business dynamics (Wisskirchen, et al., 2017). There is a need for organizations to reskill their existing labor force with artificial intelligence technology (Bankins et al., 2024). Nevertheless, the main problem of re-skilling employees is based on the mindset of employees who don't accept the reality and importance of artificial intelligence in an organization, and they are not ready to learn new skills and want to remain in their comfort zone, in this perspective human resource professionals are required to identify the new skills pertain to artificial intelligence by keeping in view the organizational strategic goals and change the mindset of their employees so that they should learn new skills, even they themselves must grip on new software such as learn and implement ERP to handle this matter more

professionally (Pariss-Brassens, 2017). Artificial intelligence has a constructive impact on the performance of an organization (Marlapudi & Lenka, 2024). Hence, the following hypotheses are assumed.

H_1: AI has a constructive effect on HC.

H_2: AI has a constructive effect on HC leading to innovation.

H_3: AI has a constructive effect on HC leading to productivity.

2.2. Mediating role of absorptive capacity

Absorptive capacity has an effective mediating role between AI technology assimilation and human capital leading to organizational performance (Martínez-Caro et al., 2018). The absorptive capacity improves the internal knowledge, skills, and ability of human capital through external knowledge for effectively operating the AI technology. It updates human capital to handle the latest technology leading to innovation and productivity of firms (Darakeh & Zoubi, 2024; Pradana et al., 2020). Absorptive Capacity is a firm's capability to admit the worth of advanced knowledge which derives through external elements, then integrate it and utilize it for commercial objectives (Allen, 1983). The core function of a firm's absorptive capacity is to transform the competencies of those workers who are capable and willing to accept new procedures toward innovation and production (Tsai, 2001). Transfiguration brings re-codification and interaction in the absorptive progression wherein the worker integrates new knowledge and skills with prior knowledge and skills to deal with computer-based technology (Jiménez-Barrionuevo et al., 2011). Furthermore, absorptive capacity is influenced by firm progress through novelty; it denotes an organization or worker having the talent to admit novel knowledge, understand, interpret, and implement the same leading to the organization's production, it is a competitive edge in dynamics conditions (Da-Costa, et al., 2018). The following hypotheses are assumed.

H_4: AC has a positive intermediating role in the relationship between AI and HC

H_5: AC has a positive intermediating role in the relationship between AI and HC leading to innovation.

H_6: AC has a positive intermediating role in the relationship between AI and HC leading to productivity.

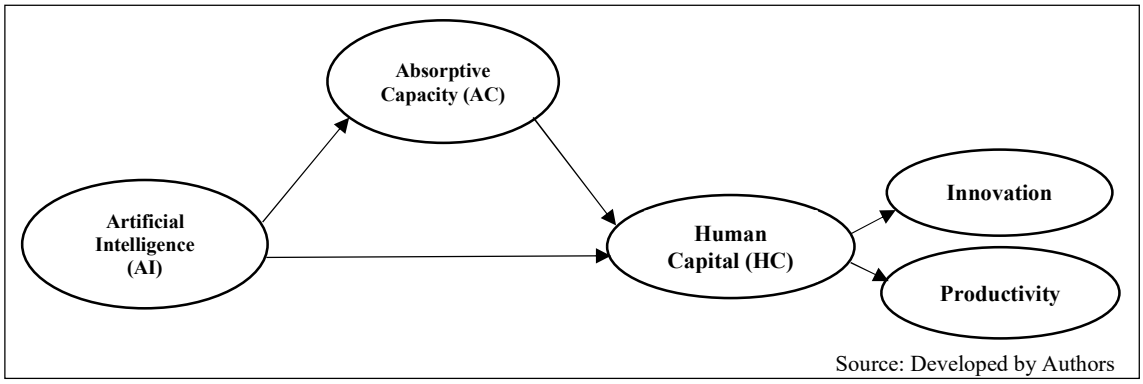
2.3. Theoretical exposition

The Technology Acceptance Model (TAM) theory strongly supports this model. According to Davis (1989), having technology is not guaranteed to increase the performance of the firms unless they change the behavior of employees to accept the tehnology. Once an organization changes employees' behavior then it is easy for them to improve their necessary skills of employees to lead in the competition. Further, handling robots (i.e. artificial intelligence) is not an easy job where specialized skills are required for employees to operate these automatic machines. Therefore, the human capital theory strongly also supports this study, which focuses on a firm's need to invest in their employees, which backs them to deliver their duties effectively and efficiently (Becker, 1993). Further, human capital theory defines that investment in employees is productive and economically beneficial for firms (Sweetland, 1996).

2.4. Conceptual framework

The framework of this research work was designed according to the nature of the topic "Shaping the Human Capital Absorptive Capacity: Role of Artificial Intelligence" wherein the researcher will investigate the impact of artificial intelligence (independent variable) on human capital and identify significant skills that increase innovation (dependent variable) and productivity (dependent variable). Further, examines the mediating role of absorptive capacity in the relationship between artificial intelligence and human capital as illustrated in figure 2.1.

Figure 2.1. Conceptual framework AI-HC



3. METHODOLOGY

This is a quantitative study wherein positivism philosophy was used with a deductive approach. The population of this research encompassed all employees who were working only in the large-scale firms of the

automobile industry of Pakistan because the major operational activities of these companies are performed through artificial intelligence technology. The sample size of this study was limited to 230. According to Hair et al., (2010) a minimum sample size of 100 was required for having five constructs while applying the CB-SEM technique for data analysis, however, this research collected data from 230 participants to cover maximum large-scale automobile industries. Further, the purposive sampling technique was used to collect data from only those employees who were directly engaged with artificial intelligence technology.

Primary data were required from a large sample size by conducting the survey, therefore, a close-ended questionnaire was designed to collect data from employees of the automobile mobile industry as the close-ended questionnaire is the most suitable research tool to collect the primary data wherein a five Likert scale was used. This questionnaire consists of five constructs (i.e. artificial intelligence, human capital, innovation and productivity, and absorptive capacity) wherein constructs of artificial intelligence and human capital were developed by applying EFA and CFA techniques whereas constructs of absorptive capacity (Flatten et al., 2011), innovation and productivity (Mubarik, 2015) were adopted. The Covariance- Structural Equation Modeling (CB-SEM) technique was performed to analyze the data due to the complexities of association among variables and the exceptionality of the model. CB-SEM is supportive of evaluating the goodness of fit that reduces the inconsistencies among observed variables and predictable covariance matrix (Hair et al., 2010).

4. RESULTS AND DISCUSSION

4.1 Reliability and validity of the model

Firstly, collected data were used to examine the reliability and validity of the model. For this, different statistical tests were applied to confirm the internal reliability, indicator reliability, and convergent validity of the relationship between artificial intelligence (AI) and human capital (HC). These were examined through factor loading (FL), composite reliability (CR), and average variance extracted (AVE) The results of the tests are shown in Table 4.1.

Table 4.1. Reliability and validity tests

Construct	Items	FL	CR	AVE
Artificial Intelligence	AI1	0.78	0.81	0.53
	AI2	0.87		
	AI3	0.68		
	AI4	0.73		
	AI4	0.77		
	AI6	0.71		
	AI7	0.67		
	AI8	0.69		
	AI9	0.70		
	AI10	0.66		
Human Capital (Skills)	HC1	0.88	0.77	0.51
	HC2	0.79		
	HC3	0.69		
	HC4	0.65		
	HC5	0.61		
	HC6	0.66		
	HC7	0.76		
	HC8	0.77		
	HC9	0.80		
	HC10	0.82		
Productivity	P1	0.75	0.75	0.51
	P2	0.78		
	P3	0.71		
	P4	0.88		
	P5	0.69		

Innovation	INN	0.75	0.73	0.52
	INN2	0.77		
	INN3	0.71		
	INN4	0.69		
	INN5	0.88		
	INN6	0.72		
	INN7	0.65		
Absorptive Capacity	Ab.C1	0.67	0.71	0.50
	Ab.C2	0.69		
	Ab.C3	0.68		
	Ab.C4	0.66		
	Ab.C5	0.88		
	Ab.C6	0.71		
	Ab.C7	0.88		
	Ab.C8	0.69		
	Ab.C9	0.75		
	Ab.C10	0.77		
	Ab.C11	0.71		
	Ab.C12	0.69		
	Ab.C13	0.69		
	Ab.C14	0.75		

Table 4.1 exhibits the value of CR drifts between 0.71 to 0.81, which is indicating the internal reliability of the model is good. Whereas factor loading values float between 0.61 to 0.88 and maximum loadings are greater than 0.70 which explains that items are sound loaded related to their corresponding constructs and having reliable indicators. Moreover, AVE values are equal to or higher than 0.50 of all constructs in results which ascertaining the convergent validity of the model.

4.2. The Goodness of Fit Test

Different goodness of fit indices are available to test model fitness, however, the most recognized and satisfactory indices are applied to examine the research model fitness, and its fitness with sample data, for instance, Absolute fit indices are observed through Chi-square, RMSEA, and CFI statistical tests, Incremental fit indices are investigated through NFI, and CFI tests and Parsimony fit indices are scrutinized through PGFI test. Examine outcomes are demonstrated in Table 4.2.

Table 4.2. Goodness of Fit test

	Absolute fit indices			**Incremental fit indices**		**Parsimony fit indices**
	Chi-square	RMSEA	GFI	NFI	CFI	PGFI
Artificial Intelligence (AI)	5.1	0.082	0.89	0.94	0.92	0.90
Human Capital (HC)	5.6	0.079	0.91	0.95	0.93	0.89
Productivity (Prod)	5.4	0.055	0.92	0.93	0.95	0.92
Innovation (INN)	4.95	0.067	0.94	0.95	0.91	0.93
Absorptive Capacity (Ab.C)	6.75	0.089	0.88	0.89	0.89	0.88

4.2.1 Absolute fit indices (Table 4.2)

Chi-square test results in Table 4.2 indicate that INN has a 4.95 statistics value whereas Ab. C has a statistics score of 6.75. Further, the statistical value of AI is 5.1 whereas HC statistical score is 5.6, however, the Prod value is 5.4. RMSEA test results displayed in Table 4.2 elaborate that HC, Prod, and INN have a statistical score is lower than 0.08, for instance, 0.079 is the statistical value of HC, 0.055 is the statistical value of Prod, and 0.067 is the statistical value of INN. It specifies a good fit however statistical outcome of Ab. C and AI has a fair fit with a score of 0.089 and 0.082 correspondingly. Furthermore, the GFI outcome score in Table 4.2 shows the INN has the uppermost statistical score of 0.94 and Ab. C has the lowermost score value of 0.88 while HC, Prod, and AI have score values of 0.91, 0.92, and 0.89, correspondingly. HC, Prod, and INN have statistical scores

above 0.90 that are appropriate. To sum up, the absolute fit indices statistical outcome specifies complete model fitness is decent. It was measured by using the recognized assessments like Chi-Square, RMSEA, and GFI statistical tests. Further, it is portrayed, the statistical score of all indices specifying model fitness is well above the threshold score defined by Hair et al., (2016).

4.2.2. Incremental fit indices (Table 4.2)

NFI statistical score in Table 4.2 specifies that mostly all constructs have statistical scores greater than 0.90, for instance, AI (0.94), HC (0.95), INN (0.95) and Prod (0.93) however Ab. C (0.89) score is close to 0.90. Further, the CFI statistical score in Table 4.2 specifies that mostly all constructs having a score greater than 0.90, for instance, AI (0.92), HC (0.93), INN (0.91) and Prod (0.95), while AI (0.89) score is close to 0.90. Further, the Incremental fit indices are so perfect that mean it easy to make alterations in the model of research. Furthermore, the Instrumental fit indices are assessed by using two acceptable tests as Normed-fit-index (NFI) as well as Comparative-fit-index (CFI). According to the threshold score value defined by Hair et. al, (2016), all outcomes of statistical tests these indices are meet threshold score.

4.2.3. Parsimony fit indices (Table 4.2)

The results of the Parsimony fit index float between 0.88 and 0.93, and the majority of constructs are equal to or greater than 0.90, whereas the values remaining are also above the threshold, which explains that the model is fit as the results of indices are positive.

4.3 Hypothesis Testing

For validation of the hypotheses, different statistical tests were used on data to examine the results of the Coefficient as well as the T-value to ensure whether the results accept or reject the research hypotheses of this study. The statistical results are displayed in Table 4.3.

Table 4.3. Hypotheses testing

Hypothesis	Co-efficient	T-value	Decision
Artificial Intelligence→Human Capital	0.47	7.52	Accepted
Artificial Intelligence→Human Capital→Innovation	0.11	4.20	Accepted
Artificial Intelligence→Human Capital→Productivity	0.12	4.10	Accepted
Artificial Intelligence→Absorptive Capacity→Human Capital	0.13	9.45	Accepted
Artificial Intelligence→Absorptive Capacity→Human Capital→Innovation	0.09	0.98	Rejected
Artificial Intelligence→Absorptive Capacity→Human Capital→Productivity	0.07	2.11	Accepted

Table 4.3 shows that Hypothesis-1: AI has a constructive impact on HC specifying the co-efficient statistical score is 0.47 however the T-value statistical score is 7.52 which indicates the hypothesis is accepted. Further, Hypothesis-2: AI has a constructive impact on HC leading to Innovation by specifying the co-efficient statistical score is 0.11 whereas the T-value score value is 4.20 which indicates the hypothesis is supported and AI has a greater impact on HC to achieve the innovation. Hypothesis-3: AI has a constructive impact on HC leading to Productivity specifying the co-efficient statistical score value is 0.12 however the T-value statistical score is 4.10, which indicates that the hypothesis is supported and accepted. Hypothesis 4 examines the mediating role of the Absorptive Capacity. Results indicate that Absorptive Capacity has a positive role in the relationship between AI and HC by specifying the co-efficient statistical score as 0.13, however, the T-value statistical score is 9.45, which indicates that the hypothesis is supported and accepted. However, Hypothesis-5: about the Absorptive Capacity mediating role in the relationship of AI and HC leading to Innovation is rejected with having a co-efficient statistical score of 0.09 and a T-value statistical score of 0.98. Hypothesis-6: Absorptive Capacity has a positive mediating role in the relationship between AI and HC leading to Productivity specifying the co-efficient statistical score as 0.07 however the T-value statistical score is 2.11 which indicates that the hypothesis is supported. To sum up, the results of the Co-efficient statistical score and the T-value statistical score explain that five hypotheses (i.e. 1, 2,3,4, and 6) are accepted whereas one hypothesis (i.e. 5) is rejected.

5. DISCUSSION

Results of the study explained that AI technology has a positive impact on HC leading to the performance of organizations in contexts of innovation and productivity. This study consisted of 6 hypotheses against the research questions. Out of 6 hypotheses, 5 were accepted. The results of hypothesis 1 signify that there is a positive impact of AI on HC, this means AI technology has an imperative role in innovation and productivity wherein organizations cannot operate this technology effectively without aligning the skills of their employees in three fields: computer skills (i.e. program developers, software engineers, data scientists, network engineer, data designers, cyber security engineer, and hardware engineers), mathematician (i.e. mathematics specialists need to develop the algorithm and logic of program wherein their machines will operate accordingly) and robot mechanics (i.e. effectively control and handle the robot machines and confirm that robots machines must ready to operate

round the clock so that steadiness of operation process may not agonize at the point because a minor error can trouble the whole operation). This indicates that the manufacturing sector, further, it is indispensable for the automobile industry of Pakistan to develop and align the skills of their production side employees in three technical fields of computer, mathematics, and robot mechanics to sustain in competition otherwise foreign automobile companies will take full control of Pakistan's market. The results of hypothesis 1 are also supported by the previous research work of (i.e., Rasiah et al., 2016; Ransbotham et al., 2017; Mubarik, 2015; Bontis, 2019; Melo & Machado, 2018).

Moreover, the results of hypothesis 2 demonstrate that due to the application of AI, the HC skills have changed melodramatically which significantly impacts innovation. Whereas results of hypothesis 3 indicate that due to the adoption of AI, there is a constructive effect on productivity with the help of change in HC skills. This demonstrates that automobile companies of Pakistan must invest in the training and development of their human capital skills in three domains of computer, mathematics, and robot mechanics so that their employees can effectively use AI technology to bring innovation in the vehicles to compete with international competitors and increase the productivity to meet the huge demand of the local market. This will strongly support the economy of Pakistan by reducing the importing of vehicles which is consistently increasing as currently Pakistan's automobile manufacturers are not fulfilling the expectation of local customers. Results of the hypotheses 2 and 3 are supported by previous research studies of Gould, (2018); Mubarik (2015). However, the results of hypothesis 4 explain that absorptive capacity has a constructive role in the relationship of AI and HC therefore, there is a necessity that companies must confirm that their employees have sufficient absorptive capacity before adopting AI. For this automobile firms acquire external knowledge, skills, and techniques to incorporate in organizations to effectively utilization of their employees to get maximum output of AI technology to lead in the market. Moreover, the results of hypothesis 6 define that there is a robust requirement for absorptive capacity to transform the HC skills that lead to productivity. It means that absorptive capacity has a very important role in increasing productivity. Results of both hypotheses are supported by the studies of (i.e., Martinez Caro et al., 2018; Prandana et al., 2020).

6. CONCLUSION

Artificial intelligence is a progressive and fast-growing technology that has performed the dominant role in changing business dynamics across the world. In the automobile industry, this technology has dramatically uplifted the performance of firms toward achieving the targets of innovation and productivity. This technology needs specific human capital skills to operate effectively to bring innovation in their products and get the maximum output to meet the demand of the customer. This study empirically proved the significant relationship between artificial intelligence and human capital by developing skills of their employees in the field of computer (i.e. software engineers, program developers, network engineers, data scientists, data designers, hardware engineers, and cyber security engineers), mathematician (i.e. mathematics experts need to draw the algorithm and logic of program on which machines will work) and robot mechanics (i.e. control the heavy robot machines and ensure that robots machines work round the clock so that continuity of operation may not suffer at the stage because a small error can stop the entire operation). Further, this research work demonstrates that artificial intelligence has a constructive impact on human capital leading to innovation and production in the automobile industry wherein human capital skills in the fields of computer, mathematics, and robotic-mechanical are indispensable to functioning artificial intelligence machines. Moreover, this study also explains that the absorptive capacity has an instrumental mediating role in developing new skills toward productivity which elaborates that the automobile companies of Pakistan need to focus on acquiring and adopting the external knowledge in their organizations for effective use of AI technology. These skills can be learned through competency training programs which provide employees with depth knowledge and skills in particular fields dealing with AI technology. Once employees are trained in specific fields then the organization provides coaching as on-the-job guidance to effectively utilizations their knowledge and skills to avoid any error. Later, organizations engage in their independent projects to get a full grip on specific fields of AI technology towards innovation and productivity.

7. IMPLICATIONS

There is a great need for the automobile industry and other manufacturing firms, specifically underdeveloped countries like Pakistan, to make substantial invest in the infrastructure of artificial intelligence technology and development of essential human capital skills (i.e. computer, mathematics, and robotic-mechanical) on a priority basis to advance their products in footings of economical, attractiveness, quantity and quality to hold their local customers else they will chase by international manufacturers. This research supports manufacturing organizations to understand the significant relationship between artificial intelligence and human capital. Further, it provides HR Managers with a list of indispensable skills to train their employees to effectively and efficiently deal with artificial technology to increase innovation and productivity in their firms. Moreover, the model of this study opens new avenues for researchers to expand their research work to identify others' human

capital skills to increase the performance of the manufacturing sector. Further, scholars can also examine the impact of human capital skills on the improvement of the quality of products of manufacturing firms.

8. LIMITATIONS AND FURTHER AREAS OF RESEARCH

This study was limited to identifying the essential human capital skills for effective utilization of artificial intelligence technology in the automobile industry, but there is a need to conduct a research study on how these skills can be developed not only in the automobile industry but also in the overall manufacturing and service sectors. Further, this study was conducted in the context of Pakistan, there is a need to conduct this study South Asia region as these other countries of this region have similar problems in the automobile industry. Moreover, this study was cross-sectional therefore there is a need to conduct a longitudinal study to further strengthen the results of this study.

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