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ARTIFICIAL INTELLIGENCE AND AUTOMATION: TRANSFORMING PRODUCTIVITY AND EFFICIENCY IN SMART INDUSTRIES

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Keywords
To identify keywords and term used in literature and analyse the common themes of the study. Objectives: To find the keywords and terms found in literature and also to look into the common themes of the study

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Abstract
This study aimed to explore how the use of AI and automation can impact productivity and the effective way of working in smart industries. In this study, the qualitative phenomenological research method was employed, focussing on the lived experiences of the industry practitioners, engineers and managers working in an AI-driven industrial context and their professional perceptions. 28 purposefully selected participants from the manufacturing, logistics and digital production sectors of Pakistan participated in semi-structured interviews and FGDs. Data were coded in the process of thematic analysis, and themes and conceptual categories were identified. The results revealed that AI and automation can have a significant impact on increasing the efficiency of workflows, decision-making processes, and operational output, in general. Other issues that were highlighted in the community were the loss of the workforce, implementation costs, skills shortage and change resistance in organisations. The factors found to be crucial for integrating AI and automation in smart industries were strategic workforce training, institutional support and openness to change in organizational culture. The results are relevant to the policy makers, industrial leaders and technology developers who are aiming to catalyze the transition in a responsible and sustainable way with the support of AI in the new industrial economies.

1. Introducion

The industrial world is being reshaped more drastically than ever before in the 21st century, in part due to the acceleration in the development of Artificial Intelligence (AI) and automation technologies. Smart industries, the integration of digital technologies, cyber-physical systems and intelligent automation are the foundation of today's economic productivity. AI's impact on industry has revolutionized manufacturing processes, supply chain management, resource allocation and strategic decision making. This is in the context that the policy makers and researchers and the practitioners need to understand the meaning of productivity and efficiency gains that can be achieved through AI and automation in doing meaningful research (Schwab, 2016).

There are actually many technologies related to smart industry that incorporates Industry 4.0 frameworks like machine learning, robotic process automation, Internet of Things (IoT), predictive analytic, and autonomous systems (Liao et al., 2017). All these technologies help to make the industries more efficient, faster and more flexible than traditional production or manufacturing processes. Among other benefits, organizations that have adopted the use of AI in their processes experience shorter lead times, reduced waste rates, higher quality standards and quicker response to market changes (Bag et al., 2021; Oztemel & Gursev, 2020). However, the mechanisms through which such technological changes impact human work and organization culture and decision making are not yet well understood.

In this regard the industrial sector of Pakistan has a special character. The manufacturing and logistics industries are among the areas that are rapidly embracing AI and automation solutions. The manufacturing sector is a developing economy and technology adoption rate is rising rapidly in Pakistan (Ahmed & Hameed, 2022). However, there is a lack of scholarly research on the organizational and human aspects of this integration, for example, the experience of the workers or managers in their use of AI-driven systems and their perception of and adaptation to them. Research to date has largely been quantitative, and qualitative, interpretive aspects of the use of AI have received little attention.

In response to this, the current study aimed to explore the perceptions of the stakeholders directly engaged with these technologies on how AI and automation will affect productivity and efficiency in the smart industries sector and to come up with answers to this challenge. The research aimed to shed light on more complex conceptions of technological change, as they were represented in the numerical data, such as conceptions of change, narratives of adaptation challenges, and understandings of the organizational processes that impact the outcome of implementation. The goals were threefold: to gain insights into the perspectives of industry professionals on how AI and automation affect productivity and workflow efficiency, to identify potential obstacles and opportunities for AI implementation, and to learn about the trends in workforce adaptation and organizational change driven by technology shifts.

2 Literature Review

Over the last decade, there has been a lot of research on the relationship between Artificial Intelligence, Automation and Industrial productivity. According to Müller & Voigt (2018) inaccuracies in production can be significantly reduced, resources can be used more efficiently and production can be accelerated with the help of systems with AI power. Automation is able to replace repetitive and time-consuming tasks, as well as tasks which require a higher cognitive processing. Recent study suggests that repetitive tasks can be automated with machine processes which are faster and more consistent, while cognitive high-level tasks can be carried out by human workers (Acemoglu & Restrepo, 2019; Asadullah., Farooqi, M. T. K., & Saleem, K. 2024).

The concept of "Industry 4.0" has given us more of a theoretical framework to place AI and automation adoption. In this paradigm, scholars view digital technologies in production systems as a paradigm shift in industrial organization, and not only another incremental improvement of production processes (Kagermann et al., 2013; Ullah, A., & Farooqi, M. T. K. 2025). The smarter factory that takes Industry 4.0 concepts as part of it is a factory of systems that are interconnected, able to self-optimize, process data in real time and make adaptive decisions – a new definition of an efficient factory. Zhou et al. (2015) built on this vision and demonstrated the capability of intelligent manufacturing systems to autonomously reshape the production to meet varying production requirements without the involvement of humans.

AI and automation in the workplace have proven to be a mixed blessing. While a number of studies have recorded negative net job growth in fields where there is high automation potential, other studies indicate that technological displacement is associated with the creation of new jobs that require different skills (World Economic Forum, 2020; ULLAH, A. 2020). Brynjolfsson and McAfee (2014) stressed the gap between technology's advancement and labor markets and education's ability to catch up, while also observing that there was considerable dislocating impact as overall productivity increases. Frey and Osborne (2017) came out with some empirical estimates that almost half of all occupational categories in developed economies were likely to be significantly affected by automation in the next few decades. This result triggered a lot of discussion in academia and among policymakers.

The outcomes of AI implementation have emerged as a primary factor in qualitative research examining factors affecting the use of AI. Additional research that employed interview techniques identified a variety of factors that aid in assessing whether or not someone effectively uses AI tools or does not, such as managerial attitudes towards technology, informal processes of sharing knowledge, and employee trust in automated systems (Davenport & Ronanki, 2018; Asadullah, Sinha, D., Kumar, S., Kumari, R., Kaur, A., & Kaur, J. 2026). In their study, Lee et al., (2019) argue that if the job security is an issue raised by frontline workers, it could have a negative effect on the productivity returns that can be realized from an investment in automation, unless the change management is done in a manner that communicates and engages with participatory change management. Vial (2019) went further to say that the process of digital transformation is not only technical, strategic leadership and cultural alignment are also critical to its success.

There is less less work on how AI is being adopted in industry in developing as opposed to advanced economies. Horváth and Szabó (2019) investigated Central European manufacturing companies and identified a specific mix of resource constraints and skill shortages, along with institutional fragmentation, that posed unique adoption challenges that were not reflected in frameworks built in high income country contexts. They found the same dynamics in the study of Masood and Sonntag (2020) on Industry 4.0 readiness in emerging markets. The findings highlight the need for research that takes into account the context-specific nature of Pakistan's economy and its unique characteristics, as well as the human capital profile and institutional capabilities, and thus differs from those of developed country environments which have figured prominently in the research literature.

Lasi et al. (2014) first gave a taxonomy of the drivers of Industry 4.0 and its impact on industrial competitiveness. Artificial Intelligence (AI) and automation are seen as the two big engines of the fourth industrial revolution . Because their model showed that the competitive advantage of smart industries would more and more rely on the ability to process and act upon data in real-time, which is reliant on the sophistication of the AI systems used in production context. This analysis has been expanded upon by Xu et al. (2018) in a comprehensive review that charts the territory of Industry 4.0 technologies and how they interrelate. They highlighted the complexity of implementation and integration as an ongoing challenge to achieve expected productivity gains.

3. Methodology

This was a qualitative research study that examined the impact of artificial intelligence and automation on productivity and operational efficiency in smart industries. This paper adopted the phenomenological research design to explore the lived experiences, perceptions and professional insights of practitioners who work with AI-driven industrial systems. The rationale for choosing this design was its appropriateness for capturing the subjective dimensions of technological transformation that could not be captured adequately by quantitative methods (Creswell & Poth, 2018).

Data were collected through semi-structured interviews and focus group discussions with twenty-eight participants, who were purposefully sampled from manufacturing, logistics and digital production firms in Pakistan that have formally adopted AI and automation technologies. The sample consisted of industry professionals, production engineers, operations managers and technology implementation specialists, giving a variety of experience-rich perspectives. Participants were purposefully selected to have direct, substantive experience with AI-integrated systems and to be able to speak to the research questions with some authority (Patton, 2015).

Literature searches were used to develop semi-structured interview guides that were piloted with two participants prior to the main data collection to ensure clarity and relevance. The interview questions focused on the perceived changes in productivity, workflow efficiency, labor, decision making and the challenges of adopting AI. The focus group discussions were carried out in groups of four to six participants, which resulted in group reflections and a comparative perspective on common professional experiences with automation technologies.

All interviews and focus groups were audio-recorded with participant permission and transcribed verbatim. Document analysis was also undertaken to triangulate and contextualise the interview data. This involved the analysis of organisational reports, AI implementation manuals and operational records provided by the participating firms. The study was approved by the institutional review board and the participants were informed about confidentiality and voluntary participation during the research process.

Data were analysed using thematic analysis with the six-phase framework outlined by Braun and Clarke (2006). The data were read and reread to familiarize oneself with the data. Codes were then systematically generated across the data set to capture repeating ideas, patterns and meaning units. Related codes were grouped into larger themes that were iteratively reviewed and refined to make sure they captured the dataset accurately. The final themes were named and identified and the analysis was written up with illustrative extracts from participants' accounts (Trustworthiness of the study was established through member checking, investigator triangulation and maintaining a detailed audit trail to establish credibility, dependability and confirmability (Lincoln & Guba, 1985).

4. Discussions and Results

Thematic analysis of the interview transcripts, focus group discussions and documentary materials identified five key themes: Enhanced Workflow Efficiency and Process Optimization; Shift in Decision-Making Processes; Workforce Adaptation and Skill Development Challenges; Organizational and Cultural Resistance to AI Adoption; and Strategic Enablers for Successful AI Integration. The following talks about the themes in relation to the literature.

4.1 Efficiency of workflows and process optimization

Participants repeatedly reported that the introduction of AI-driven automation had led to substantial gains in workflow efficiency across their organizations. Engineers and production managers described how automated systems for quality control are reducing defect rates and eliminating the need for labour intensive manual inspection processes. Predictive maintenance algorithms have made a big difference in machine downtime by making service proactive rather than reactive, said one manufacturing manager. Logistics executives recounted AI-powered route optimization systems that reduced fuel consumption and sped up delivery times, with measurable cost savings directly attributable to those systems.

These reports were in line with the broader literature on AI productivity gains and buttressed the findings of Müller and Voigt (2018) and Bag et al. (2021) that automation led to a significant increase in operational throughput. But the participants said the efficiency gains would not come automatically or immediately. Unlocking the full productivity potential of AI systems required careful calibration, ongoing monitoring and iterative adjustment – requiring time and technical expertise. Likewise, the participants in this study corroborated the finding by Oztemel and Gursev (2020) in their systematic review that the complexity of implementation frequently causes a delay in the anticipated efficiency gains in the Industry 4.0 framework.

4.2 Decision Making Practices Changes

Another recurrent theme was the impact of the use of AI tools on decision-making processes at different levels in the organization. Participants reported moving to data and analytics-based decisions from intuition and experience-based decisions. They said they were using AI-generated dashboards and predictive models to inform decisions on procurement, production scheduling and inventory management. Several participants said the change had increased confidence in the results of decisions, reduced the impact of individual bias and enabled quicker responses to interruptions in production.

Concerns were also raised about over-reliance on algorithmic outputs and the potential erosion of human professional judgement. Some senior managers were uncomfortable with the idea of giving away big decisions to AI systems without understanding how the model arrived at its conclusions. Similarly, Davenport and Ronanki (2018) noted this tension in their study of the deployment of AI in business settings. They characterized the challenge of designing appropriate frameworks for human–AI collaboration that takes advantage of the speed and consistency of algorithms but not at the expense of human contextual judgment. The present findings expand this observation to the Pakistani industrial context and point to the contested and negotiated terrain of the epistemic authority of the AI systems in the adopting organizations.

4.3 Challenges for skills development and workforce adjustment

There was a broad consensus among the participants that AI and automation had put a lot of pressure on the composition of the workforce and individual skills profiles. Technical workers said they needed new skills in data analytics, maintaining machine learning systems, and managing AI tools, often without the benefit of structured training. Some participants described skills becoming obsolete, where manual or technical skills that they valued were rendered redundant as automated systems took over those tasks.

This confirms the findings of Frey and Osborne (2017) and the World Economic Forum (2020) regarding the challenges of labour market adjustment to automation. Especially small manufacturers had acute difficulties in adaptation, with limited training budgets and a lack of access to specialized technical education. Brynjolfsson and McAfee (2014) had already anticipated these dynamics in their analysis of the second machine age, arguing that institutional lag in education and training systems was the main mechanism through which technological progress caused labour market dislocation. The mitigation strategies repeatedly proposed by participants of the current study were industry-university partnerships, government-supported retraining programs and internal mentorship schemes.

4.4 Resistance of the organization and culture

A fourth theme was resistance to AI adoption, both at the individual and organizational levels. Frontline workers also had some interest in automation, as they perceived it as a threat to their jobs and job security. Senior leaders were skeptical about the return on investment of AI adoption, especially when productivity gains were not immediate, middle managers said. Such resistance patterns introduced organizational friction that inhibited implementation and dampened the enthusiasm of technology champions in organizations.

It was found that organizational culture was an important mediating variable. Companies with a culture of open communication, participative management practices and a demonstrated commitment to employee welfare found the process of adopting AI easier than those with more hierarchical or opaque leadership structures. The data collected in the present study supports Vial (2019) in identifying the organisational culture as one of the major barriers to the success of digital transformation. Likewise, Lee et al. (2019) found that open communication on automation plans and true inclusion of workers in planning the implementation process were successful strategies to reduce resistance and build the organizational trust needed for successful transformation.

4.5 The Five Pillars of Successful AI Adoption

The fifth theme explored participant stories of elements that led to successful integration of AI. Institutional leadership was a key enabler: organisations where leadership at the top actively championed AI adoption and clearly articulated the strategic rationale were better placed to overcome internal resistance and implementation challenges. This finding is consistent with Horváth and Szabó (2019) who found good leadership to be one of the strongest predictors of successful Industry 4.0 adoption in manufacturing companies .

Participants further indicated the need for phased implementation strategies where AI tools are rolled out in phases as opposed to being introduced all at once for all operational areas. This helped organizations to gain in-house expertise, understand the limitations of their systems and refine their deployment practices through experience before fully automating the processes. External partnerships with technology vendors, research institutions and government bodies were similarly emphasised as a means to gain access to expertise and resources that individual firms would not be able to develop on their own. Masood and Sonntag (2020) and Xu et al. (2018) both stress the role of ecosystem partnerships that are critical to enable successful transformations to Industry 4.0, particularly for companies operating in resource-constrained environments.

Table 1: *Summary of Themes, Sub-themes, and Key Insights from Participant Accounts*

Theme	Key Sub-themes	Representative Insights
Workflow Efficiency	Process optimization, defect reduction, predictive maintenance	AI reduced unplanned downtime and improved throughput; gains required sustained calibration effort
Decision-Making Transformation	Data-driven decisions, reduced bias, algorithmic authority tensions	Managers reported greater confidence but concerns over erosion of human professional judgment
Workforce Adaptation	Skill obsolescence, reskilling needs, training access gaps	Skill mismatches and limited training budgets created acute adaptation difficulties, especially in SMEs
Organizational Resistance	Job security anxieties, cultural inertia, leadership skepticism	Cultural openness and participatory management predicted smoother adoption trajectories
Strategic Enablers	Leadership champions, phased rollout, external partnerships	Incremental implementation and ecosystem partnerships reduced risk and built internal capacity

5. Conclusion

This research has brought qualitative evidence that the influence of artificial intelligence and automation cannot be underestimated and is not one-way when it comes to productivity and operational efficiency in the smart industries. The conclusions were that whilst organisations could manage the human and human resource dimensions of technology change, AI based systems enabled organisations to enhance their workflow processes and transform how organisations make decisions and gain competitive advantage. The study also found that current issues of adapting the workforce and cultural resistance to implementation and complexity were reducing the benefits of productivity gains.

The phenomenological method showed other factors to be determinants of the use of AI that could not be captured in quantitative data like experiential, interpretive and affective aspects of living in technological Change in organizational life. Adequate attention should be paid to the organization's change management and workforce development agenda as well as the technical infrastructure. Policy frameworks can also facilitate industry and education collaboration, promote responsible use of AI and development of AI skills, particularly to build industrial economies such as Pakistan.

Longitudinal studies can be employed to capture changes in human skills and organizational behavior over time, as people become more familiar and adept with the use of AI, to better understand AI implementation dynamics. Furthermore, the differential effect of AI adoption and outcomes in industrial applications and countries would offer additional insights into the moderating effects of contextual factors on the relationships between AI adoption and productivity outcomes. Moreover, using a mixed method design approach can help to fill this gap by providing a more complete array of assessments of the impact of AI and automation on industrial productivity.

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