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Adoption of AI-empowered Industrial Robots in Auto Component Manufacturing Companies

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Abstract

The usage of AI-empowered Industrial Robots (InRos) is booming in the Auto Component Manufacturing Companies (ACMCs) across the globe. Based on a model leveraging the Technology, Organisation, and Environment (TOE) framework, this work examines the adoption of InRos in ACMCs in the context of an emerging economy. This research scrutinizes the adoption intention and potential use of InRos in ACMCs through a survey of 460 senior managers and owners of ACMCs in India. The findings indicate that perceived compatibility, external pressure, perceived benefits and support from vendors are critical predictors of InRos adoption intention. Interestingly, the study also reveals that IT infrastructure and government support do not influence InRos adoption intention. Furthermore, the analysis suggests that perceived cost issues negatively moderate the relationship between the adoption intention and potential use of InRos in ACMCs. This study offers a theoretical contribution as it deploys the traditional TOE framework and discovers counter-intuitively that IT resources are not a major driver of technology adoption: as such, it suggests that a more comprehensive framework than the traditional RBV should be adopted. The work provides managerial recommendations for managers, shedding light on the antecedents of adoption intention and potential use of InRos at ACMCs in a country where the adoption of InRos is in a nascent stage.

Keywords: Industrial Robots, Auto Component Manufacturing, Adoption, Potential Use, TOE

Introduction

AI-empowered Industrial Robots (InRos) have significantly changed the face of the manufacturing industry across the globe. AI-empowered Industrial Robots are a particular set of automated handling devices, defined by ISO (Standard 8373:1994) as “an automatically controlled, re-programmable, multipurpose manipulator programmable in three or more axes” (Armbruster et al. 2005 p.7). In today’s era, AI-empowered InRos are driven by advanced technologies such as machine learning, Internet of Things, Artificial intelligence and deep learning (Pan 2016), which are helping to improve decision making and increase the production and productivity (Bibby and Dehe 2018; Dhawan et al. 2018; Duan et al. 2019; Dwivedi et al. 2019; Grover, Kar and Dwivedi 2020; Mariani and Borghi 2019; Tapiero 1990). InRos are utilised in industrial painting, welding, ironing, testing, pick and place, product inspection and assembly (Armbruster et al. 2005) applications.

Artificial intelligence (AI) technology is applied in the manufacturing industry to make InRos perform intelligent work (Li et al. 2017). In this work, we define AI as non-human intelligence programmed to perform particular activity or tasks (Dwivedi et al. 2019; Huang and Rust 2018). The common meaning and purpose of AI is "the increasing capability of machines to perform specific roles and tasks currently performed by humans within the workplace and society in general" (Dwivedi et al. 2019: p.2). Prior to the advent of AI technology, InRos were designed as mechanical devices that are multifunctional and performed a number of pre-programmed tasks in an organisation (Brady et al. 2012). AI is enabling InRos to automate the process in an enhanced way, as robots are increasingly able to acquire knowledge, learn, solve problems in almost real time and perform tasks with an enhanced level of accuracy (Dwivedi et al. 2019; Kaplan and Haenlein 2019; Pillai et al. 2020; Russell et al. 2016). This study focuses exactly on intelligent InRos that not only are automated, but can deal with tasks that also entail planning, controlling, communicating and optimizing the production (Kopacek 1999; Li et al. 2017; Mani 2018; Paryanto et al. 2015). Acccordingly, the object of our study is an advanced form of InRos that are AI-empowered. There will be 2.1 million number of AI-empwoered InRos installed across the world, with projections of an increase of 16% in Asia by 2021 (IFR 2018). The AI-powered InRos are enabling automation of press shops, weld shops, paint shops and cast shops which is lowering the cost of manufacturing in automobile companies (PWC 2019). InRos are extensively employed in the automotive industry (Cheng et al. 2019; IFR 2018). Cheng et al. (2019) argue that market conditions and governments are playing a crucial role in the adoption of robots across the industry in China. Worldwide, India has the largest manufacturing base of automobiles and auto components whose turnover is predicted to grow from USD 51.4 to 282.8 billion by 2026 (PWC 2019). The usage of AI-empowered Industrial Robots in ACMCs is increasing as it is helping companies to speed up the manufacturing process, improve productivity and make research of development activities more effective (Dhawan et al. 2018; PWC 2019). ACMCs are manufacturers of engine parts, chassis and body, electrical parts, suspension and braking parts, steering and drive transmission parts along with equipment for automobile companies (IBEF 2019). InRos help improve the flexibility in production and increase the return on investment. AI-empowered Industrial Robots' adoption is necessary for companies to be competitive in the marketplace. From a theoretical and empirical perspective, most of the research on advanced industrial manufacturing technologies (including InRos) is focused on the developed countries in the West rather than emerging economies such as India. However, different environmental settings and cultural contexts might affect differently the drivers and outcomes of InRos adoption. Contextual and institutional differences between developed and emerging economies such as India provided the authors with a crucial motivation to conduct this research. Hence, focusing on the Indian context is important to investigate the factors leading to the adoption of InRos from the perspective of firms (Mathews 2017; PWC 2018) that have to operate in emerging economies.

There are new recent technologies adoption studies from the Indian perspective with respect to cutting hedge digital technologies such as blockchain as well as smart manufacturing (Kamble et al. 2019; Mittal et al. 2019; Queiroz and Fosso Wamba 2019; Schuetz and Venkatesh 2019). However, there is a dearth of studies discussing the adoption of InRos from the firms' perspective in the Indian context (Mani 2018). Currently, the adoption of robots has been examined in different industries including the construction industry (Davila Delgado et al. 2019), home healthcare (Alaiad and Zhou 2014), hospitality, travel and tourism industries (Ivanov et al. 2018; Ivanov et al. 2019; Tung and Au 2018), manufacturing (Armbruster et al. 2005), FinTech (Belanche, Casaló, and Flavián 2019), other service industries (Borghi & Mariani 2020; Gursoy et al. 2019) and education and teaching (Park and Kwon 2016). Extant research discusses the impact of InRos on workers (Dauth et al. 2017). Turja and Oksanen

(2019) analysed various individual-level factors related to robot acceptance at work. Experimental research has been carried out to study the acceptance and attitude (Müller-abdelrazeq et al. 2019) and key concerns and expectations (Kildal et al. 2018) towards collaborative industrial robots. The Technology Acceptance Model (TAM) was deployed to apprehend the acceptance of collaborative industrial robots in production systems (Bröhl et al. 2016). These studies mainly discuss the workers' and users' perspectives on InRos adoption. Simoes et al. (2019) conducted a qualitative research in manufacturing companies to explore the drivers affecting collaborative robots adoption and found that ergonomics, operational efficiency, industrial innovation and human factors are the key drivers. So far, no studies have developed an adoption model of InRos by leveraging an organisational perspective. However, there is an increasing necessity to examine the factors affecting the adoption of InRos within an organisation's perspective (Turja and Oksanen 2019; Müller-abdelrazeq et al. 2019) as it is a rising concern for ACMCs to adopt InRos to survive the growing threats and stay competitive in the market. In India, the adoption of technologies such as AI in general and AI-empowered InRos, are still in the nascent stage (ACMA 2019). Mani (2018) found that though the usage of InRos is increasing in India, the country is still lagging behind compared to other Asian countries like Japan. There are barely a few multinational ACMCs who could afford the use of AI empowered InRos for manufacturing. Hence, this study aims to examine the adoption intention and potential usage of AI-empowered InRos in ACMCs. Therefore, this work's overarching research question is framed as follows:

RQ: What are the factors affecting the adoption and potential use of InRos in ACMCs?

To be clear, the aim of this work is not merely testing adoption intention of InRos, but rather to understand more subtly the drivers of adoption intention. This is consistent with the large body of literature that has tested the drivers of adoption of technologies (such as Big Data or RFID) once those technologies were already widely used and adopted in practice (Fosso

Wamba et al. 2016; Hossain et al. 2017; Sun et al. 2018) Accordingly, our work can be read as a both exploratory and explanatory study trying to disentangle the drivers of adoption and attempting to examine in a subtle way which of those drivers actually play a role in the adoption of InRos.

To uncover the adoption factors of InRos from an organisational perspective, the Technology, Organisation, and Environment (TOE) framework is chosen in this work. TOE has been mostly deployed in the information systems literature and broadly explains the implementation and adoption of innovation (Depietro et al. 1990; Dauth et al. 2017; Hassan et al. 2015; Jia et al. 2016; Kumar et al. 2016; Ramanathan et al. 2017; Sun et al. 2018; Wei et al. 2015; Yeh and Chen 2018). Therefore, TOE is appropriate to understand the adoption of innovative solutions embedding a user interface combined with hardware and software, such as InRos. The InRos adoption in ACMCs is a complex process and an organisational perspective needs to be taken (Müller-abdelrazeq et al. 2019; Turja and Oksanen 2019) his study is unique and helpful for senior management in ACMCs to understand the factors of adoption as InRos require a huge amount of investment in terms of time, money and efforts. This study is also beneficial to marketers and manufacturers of InRos for ACMCs. Accordingly, this research provides insights for scholars in production and planning by developing a conceptual model for InRos adoption. Furthermore, the proposed model is empirically validated. The outcome of this work will provide directions for ACMCs to develop suitable strategies for InRos adoption.

The remaining part of the paper is structured as follows: Section 2 reviews the relevant theory, including the TOE framework that is used to develop the key research hypotheses. Section 3 illustrates the research design and methodology, and the methods used to test the proposed model. In the fourth section, the work elucidates the results and discusses them. The fifth section describes managerial and theoretical implications. Finally, the last and concluding section discusses the limitations of the study and proposes a research agenda.

Theoretical Background

The Technology, Organisation and Environment (TOE) framework

In the Nineties Depietro et al. (1990) designed and proposed the TOE framework. The framework is a firm-level theory that discusses the adoption of innovative technologies by using three perspectives: technology, organisation and environment. The technological perspective highlights the distinctive features and characteristics of the technology; the organisational perspective emphasises the organisational adoption-related attributes; the environmental perspective revolves around the factors related to the surroundings (Baker 2011; Henderson et al. 2012). That said, this theoretical framework does not provide a particular set of factors for the analysed problem; rather it categorises the factors into the individual constructs where the technology adoption occurs (Wang, et al. 2010). The TOE framework has been also deployed to explore the adoption of augmented reality (Masood and Egger 2019), AI adoption in talent acquisition (Pillai and Sivathanu 2020), intelligent robots in manufacturing SMEs (Choi et al. 2018), software as a service (SaaS) (Oliveira et al. 2019), Industrial Internet of Things (Sivathanu 2019) and Industry 4.0 in the automotive industry in China (Lin et al. 2018). This paper intends to study the adoption of robots in manufacturing companies regardless of their size. A summary of the research stream related to the use of the TOE framework to explain the adoption of innovative advanced technologies such as SaaS, Industry 4.0, Industrial IoT, Business Intelligence System, 3D printing, RFID and e-procurement is shown in Table 1.

Table 1. TOE literature for Advanced Technology Adoption

Technology	Reference	Variables Examined
e-supply chain management	Lin (2014)	Perceived benefits*, perceived cost*, firm size, top management support*, absorptive capacity*, trading partner influence, competitive pressure*

Cloud computing	Oliveira et al. (2014)	Security concerns, cost saving*, relative advantage*, complexity*, compatibility*, technology readiness*, top management support*, firm size*, competitive pressure, regulatory support
RIFD	Wei et al. (2015)	Relative advantage, complexity, it infrastructure*, managerial capability*, absorptive capacity*, competition intensity, regulatory support, environmental uncertainty*
RFID	Wamba et al. (2016)	Relative advantage*, complexity, compatibility*, firm size, competitive pressure, firm's geographic location, industry sector, country of ownership*, manager's age, manager's gender, manager's education, (control variable: industry, sector, country)
Internet marketing	Shaltoni (2016)	Relative advantage*, complexity, compatibility*, innovativeness*, competitor pressure*, customer pressure*
ERP	Awa and Ojiabo (2016)	ICT infrastructure*, technical know-how*, perceived compatibility*, perceived values*, security*, size of the firm*, demographic composition*, scope of business operation*, subjective norms*, competitive pressure*, external support*, trading partner readiness*
ERP solution	Awa et al. (2016)	ICT infrastructure*, technical know-how*, perceived compatibility*, perceived values*, security*, scope of business operation*, demographic composition*, size of firm*, subjective norms*, external support*, competitive pressure*, trading partner readiness*
E-procurement	Hassan et al. (2017)	Relative advantage*, compatibility*, complexity, top management support, employee knowledge, external pressure*
RFID	Hossain et al. (2017)	Interoperability of components*, industry wide technology readiness*, organizational readiness*, market scope*, competitive market pressure*, data inconsistency*
Augmented reality	Masood and Egger (2019)	System configuration*, technology hardware readiness*, technology compatibility*, external support*, organization fit*, use barrier,
Industry 4.0	Lin et al. (2018)	IT Maturity*, technology incentives*, perceived benefits*, external pressure*, government policies*
Business intelligence system	Puklavec et al. (2018)	Relative advantages, cost*, bis part of erp*, rational decision making culture*, management support*, project champion*, organizational data environment*, organizational readiness*, external support, size and industry
Intelligent robot	Choi et al. (2018)	Direct usefulness*, indirect usefulness*, organizational support*, industry pressure*, governmental pressure*
3D printing (Factors Studied)	Yeh and Chen (2018)	Technology infrastructure, technology integration, relative advantage, organizational readiness, top management support, managerial obstacles, competitive pressure, expectations of market trends, trading partner, government policy, machine cost, labour cost, material cost
Industrial IoT	Sivathanu (2019)	IIoT infrastructure*, IIoT expertise*, relative advantage*, compatibility*, cost*, security and privacy*, top management support*, organizational readiness*, competitive pressure*, support from technology vendor*
SaaS	Oliveira et al. (2019)	Technology competence*, top management support*, coercive pressure*, normative pressure*, mimetic pressure*, (control variables) industry sector, firm size
*Denotes significant variables		

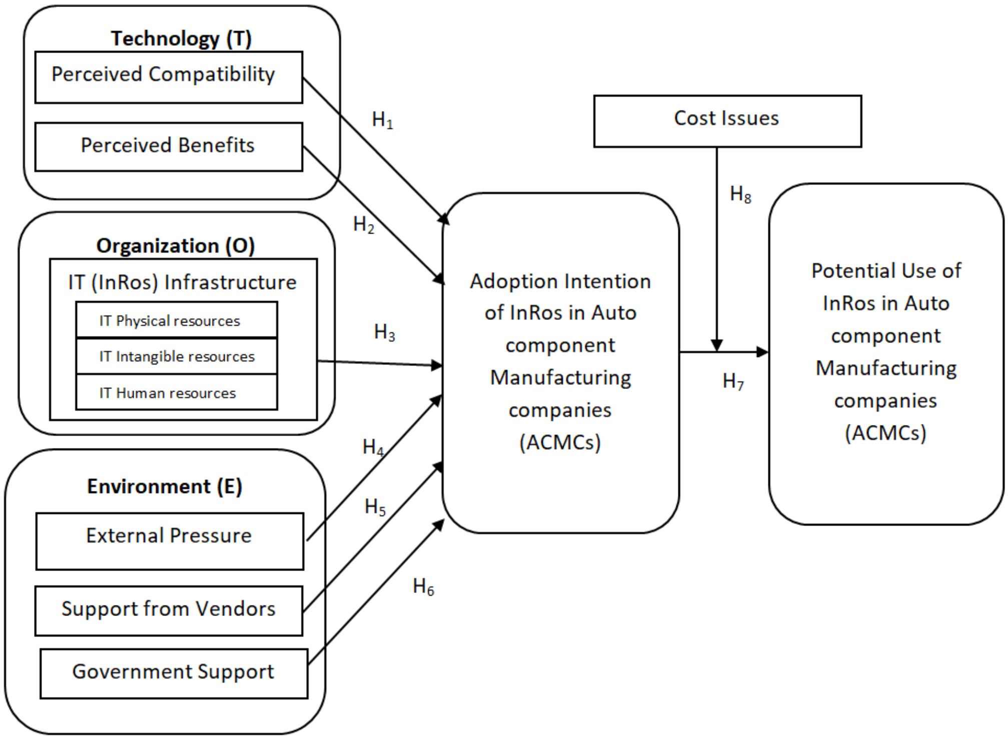
Research Model and Hypotheses

The model proposed and tested in this research is based on the TOE framework and is illustrated in Figure 1. It integrates three antecedents/drivers of InRos adoption 1) technological

2) organisational and 3) environmental. In the technological dimension, perceived compatibility (Awa and Ojiabo 2016; Masood and Egger 2019; Wamba et al. 2016) and perceived benefits (Lin 2014; Lin et al. 2018; Oliveira and Martins 2010) are considered. IT infrastructure (Wei et al. 2015) is considered as a major driver within the organisational perspective. Leveraging on previous studies within the environmental perspective, we consider external pressure (Aboelmaged 2014; Hassan et al. 2017; Guo et al. 2017; Lin 2014) support from vendors (Alshamaila et al. 2013; Ghobakhloo et al. 2011) and government support (Hwang et al. 2016; Lin et al. 2018; Osakwe et al. 2016) as key drivers and antecedents of InRos adoption.

This study intended to explore further the potential use of InRos as influenced by the adoption intention (Schmidt et al. 2015). As InRos require huge financial investment, this study explores the moderating effect of perceived cost issues between adoption intention and potential use of InRos, as cost is considered as a barrier for adoption (Maduku et al. 2016; Reyes et al. 2016).

Figure 1. Proposed Theoretical model



Source : Depietro et al. (1990)

Technology (T)

Perceived Compatibility

Perceived compatibility is our first antecedent and relates to "the degree to which an innovation is consistent with the existing business processes, practices and value systems" (Roger 1995: p.223). An innovation that is perceived as consistent with the existing business processes, practices and value system, is considered as compatible with the organisation (Roger 1995). Compatibility helps to lower the menace of possible innovation adopters and makes it easier for the organisation to achieve its goals and purposes (Grover 1993). In previous studies, perceived compatibility has been found to be a predictor of the adoption of innovative technologies such as ERP (Awa and Ojiabo 2016), RFID (Wamba et al. 2016), e-procurement (Hassan et al. 2017). Masood and Egger (2019) found that compatibility of technology affects the implementation of augmented reality (AR) in a number of industries including aerospace, automotive, chemical/pharmaceutical, commerce, construction, energy, electronics, FMCG, mining and transport. Research conducted on service enterprises in Nigeria found that compatibility negatively influences the adoption of technology (Awa et al. 2017). InRos are multi-purpose in function and are utilised for various production processes such as assembling, painting, welding, packaging, testing and inspection of production (Graetz and Michaels 2018). InRos require unique and customised programming as retrofitting is a challenge with AI-empowered Industrial Robots in ACMCs. The integration and fitting of InRos with current equipment in the manufacturing firms is a challenge (Teulieres et al. 2019). Hence, the above discussion leads to formulating the below hypothesis:

H_1: Perceived compatibility positively influences the adoption of InRos in ACMCs.

Perceived Benefits

Perceived benefits comprise both direct and indirect benefits. Direct benefits consist of "operational savings related to the internal efficiency of the organisation" (Iacovou et al. 1995: p.468). Indirect benefits instead relate to "the impact of technology on the business processes and relationships" (Iacovou et al. 1995: p.468). Perceived benefits pertain to the expected advantages that the adoption of innovative technology can offer to the organisation (Oliveira and Martins 2010). Managers' awareness of the benefits of the innovation might lead to an increase of the resources (i.e., financial, technological and managerial) required to adopt the focal innovation (Iacovou et al. 1995). Potential adopters evaluate the outcome of their adoption behaviour based on the perceived usefulness resulting from the new technology (Lin 2014; Venkatesh and Davis 2000). A study of strategic reactions to Industry 4.0 technologies of automotive manufacturing organisations in China found that perceived benefits increase the usage of advanced technology in manufacturing as they help improve smart manufacturing and supply chain performance (Lin et al. 2018). The study of innovative technology adoption confirms the positive effect of perceived benefits on the adoption of e-business (Oliveira and Martins 2010) and e-supply chain management (Lin 2014). Adopting InRos generates various benefits such as performing dangerous tasks in hostile conditions, improve product quality and increase productivity (Soffar 2019). Hence, the following relationship needs to be examined:

H_2: Perceived Benefits positively influence the adoption of InRos in ACMCs.

Organisation (O)

IT Infrastructure

IT infrastructure is a shared information delivery base, whose business functionality has been defined in terms of its reach and range (Keen 1991). In this research, in line with Grant (1991), IT infrastructure consists of three components: a) *IT Tangible Resources* that are made up by the IT components which are *physical* in nature; b) *IT Intangible Resources* that consist of *customer orientation, synergy* and *knowledge assets;* c) *IT Human Resources* that include IT skills, which are managerial and technical. The Resource Based View theory (Barney 1991, 2001) - while not being a major conceptual cornerstone of this work - discusses the importance of resources (Barney 1991, 2001; Bharadwaj 2011) a part of which for InRos are represented by IT infrastructure. Based on the RBV theory (Bharadwaj 2011), highly developed and integrated IT infrastructure enables the adoption of innovative IT applications in an organisation. Hence, tangible resources might affect InRos adoption. Human resources include managerial skills and IT technology-related skills as both these skillsets are required to trigger acceptance of InRos within the ACMCs context. As the adoption of InRos would require processes re-design and more co-ordination between the managers, HR is considered an important factor for InRos adoption. *Technical skills* are required for the design, analysis and implementation of new processes in business (Bharadwaj 2011). *Customer orientation* is an important element for innovation adoption. Customer-oriented organisations would look for innovations that would contribute to customer satisfaction (Wei et al. 2015). ACMCs would adopt InRos as they might help to speed up the production of auto components based on customers' needs and requirements. Hence, customer orientation is taken into account as a driver of InRos adoption in ACMCs. *Knowledge assets* are necessary to adopt InRos in ACMCs as employees should have strong skillsets and knowledge about the innovation associated with InRos. *Synergy* relates to resource sharing capabilities between the various divisions in an organisation (Bharadwaj 2011; Teece et al. 2007). Organisations that share information and knowledge among their various divisions are quick and agile in understanding customers' and markets' needs. InRos would require quick communication and enable companies to share the information between planning, purchase, production and warehousing divisions. Therefore, intangible resources such as synergy might positively affect InRos adoption. Wei et al. (2015) found that IT infrastructure influences the assimilation of RFID. Bharadwaj (2011) discusses that IT infrastructure provides the competitive advantage and is a major resource in any organisation. Hence, we formulate the following hypothesis in the context of InRos:

H_3: IT Infrastructure positively influences the adoption of InRos in ACMCs.

Environment (E)

External Pressure

In today's technology-driven manufacturing environment, ACMCs are facing pressure from competitors and customers for precise and faster production of auto-components by using InRos (Reyes et al. 2016; Lin et al. 2018) which, is considered as external pressure in this research. External pressure is an important antecedent of the adoption of innovative technology (Aboelmaged, 2014; Guo et al. 2017; Hassan et al. 2017; Lin, 2014). Manufacturing firms are facing pressure to accept advanced technology to be competitive (Huang et al. 2008) in the Indian market (Sangani 2019). Global automobile companies are coming up with new models of vehicles to face the competition. ACMCs have to provide new and customized products faster based on customers' requirements and InRos might help Indian ACMCs to fulfill the automotive companies' needs (OEMupdate, 2018). Hence, the following hypothesis is formulated:

H_4: The external pressure positively influences the adoption of InRos in ACMCs.

Support from vendors

Marketing activities of innovative technology along with the training and support provided by new technology vendors is defined as Technology vendor support (Maduku et al. 2016). The marketing strategies of technology vendors influence new technology adoption decisions (Alshamaila et al. 2013). The employees and the management are generally unaware of new technologies; hence, they need training from technology vendors and support from the vendors would affect the decision of adoption of the technology (Al-Qirim, 2007; Ghobakhloo et al. 2011). The present innovative technology literature confirms the influence of technology vendor support on adoption (Alshamaila et al. 2013; Ghobakhloo et al. 2011). In a mobile marketing adoption study, scholars found that if the employees have the capability to understand the technology, then the technology vendor support would not be a significant predictor of new technology adoption (Maduku et al. 2016). InRos is a new, highly sophisticated technology for ACMCs in India and would require vendor support. Therefore we formulate the following hypothesis:

H_5: Support from InRos' vendors positively influence the adoption of InRos in ACMCs.

Government support

It is the willingness of the government to promote and support new technology and provide suitable standards and policies to encourage adoption (Lin and Ho 2009; Zhu and Kraemer 2005). Government support encompasses initiatives taken by the government conducive to legislation, industrial standards, tax compliance and promotion through media (Chan and Chong 2012; Lin and Ho 2009) of the new technology. The literature of innovative technology confirms the effect of government support on adoption (Hwang et al. 2016; Lin et al. 2018;

Osakwe et al. 2016) . Under the “Make in India” scheme, the Indian government is providing incentives for research and development and tax benefits on research product outcomes in the automotive manufacturing sector (Chouhan et al. 2017). The Automotive Mission Plan 2016-26 (AMP 2026) formulates the collective governmental vision towards automotive sector growth, technological maturity, contribution to national development, institutional structure and global competitiveness (Chouhan et al. 2017). InRos Technology is in its emerging stage in the ACMCs in India (Sangani 2019). As the government is developing and promoting many initiatives that might affect the adoption of InRos positively, we formulate the ensuing hypothesis:

H_6: Government support for InRos positively affects the adoption of InRos in ACMCs.

Adoption intention and Potential use

Organisations are ready to invest in new technologies when they feel that the new technology is required for their business functions (Oliveira et al. 2019). Extant literature has dealt with various stages of adoption of new technologies (Chong and Chan 2012; Hossain et al. 2017b; Puklavec et al. 2018). In this study, the potential use of InRos means the perceived capability of the organisation (Schmidt et al. 2015) to implement the InRos for manufacturing. Though an ACMC may intend to adopt new technology such as InRos, it is not necessary that the ACMC has the capacity to implement the InRos for manufacturing. Therefore, we suggest that the relationship between adoption intention and potential use can be examined in the context of InRos for ACMCs as follows:

H_7: Adoption Intention of InRos positively affects the potential use of InRos in ACMCs.

Moderating effect of cost issues between adoption intention and potential use

InRos is a new technology that requires the related platforms, control systems, safety enclosures, mounting arrangements, all of which involve a high cost (Sangomla 2019). Installation and configuration of InRos also require a huge amount of investment from organisations (Steven 2019). Indian ACMCs have a deficiency of funds and low investment capacity to invest in InRos (Economic Times 2019). Perceived cost issues are understood as barriers and influence negatively the adoption of innovative technology (Maduku et al. 2016; Reyes et al. 2016). In this work, the authors intend to study the moderating effect of perceived cost issues on the relationship between adoption intention and potential use of InRos technology. Many ACMCs in India prefer to use human labor for manufacturing, which is more cost-effective than incurring the high implementation cost of InRos (Economic Times 2019). Though ACMC firms intend to adopt new technologies such as InRos for manufacturing, this might affect their potential use due to perceived cost issues. Therefore, the below hypothesis is formulated:

H_8: Perceived cost issues moderate the relation between the Adoption Intention and the potential use of InRos in ACMCs.

Research Methodology

This study leveraged quantitative methods. In-person face-to-face, online and telephone survey methods were deployed as they helped researchers save time and also overcome the geographic distance limitations (and related budget demands). Research instrument design, sampling and data collection were developed and performed to investigate the relationships between the variables in the proposed research model. The key dependent variables to be tested in the proposed model are InRos Adoption Intention (ADN) and ultimately Potential Use of InRos (PTU).

Research Instrument Design

The existing literature of TOE was utilised to design the research instrument to examine the InRos adoption in ACMCs. The measurement scale was adapted from existing literature in the TOE area and innovative technology adoption (Abramowicz 2015; Al-Qirim 2006; Awa et al. 2017; Ghobakhloo et al. 2011; Grant 1991; Lin 2014; Lin and Ho 2009; Lin et al. 2018; Maduku et al. 2016; Oliveira and Martins 2010; Reyes et al. 2016; Sackey and Bester 2016; Wei et al. 2015). The validity of the constructs and reliability of the scale (Fornell and Larcker 1981) was verified for all the constructs.

Five subject matter experts were identified from the Auto Component Manufacturing Association of India (ACMA) and senior officials from the 'Make in India' Scheme. Before the collection of data, the scope and objectives of the research were explained and discussed with them. The face validity was confirmed by considering and incorporating the suggestions of the subject matter experts and subsequently, the pre-test questionnaire was prepared. The constructs were measured using a five-point Likert scale.

The list of ACMCs was taken from the ACMA database, including more than 800 firms in India. The ACMCs where advanced technology similar to InRos such as Industrial IoT, Computer vision, Blockchain, Artificial Intelligence, Augmented reality, was used for the manufacturing process were chosen randomly for this research. The pre-test survey was conducted by interviewing 30 managers, technology officers and owners of ACMCs using the preliminary questionnaire. A few minor revisions in the questionnaire were made considering the feedback from the respondents; the Cronbach's alpha was utilised to check the internal consistency and reliability. Pilot tests were conducted among 110 respondents and the analysis of data was completed using PLS-SEM. The collection of main data was completed after satisfactory results were derived from the pilot test. Table 2 shows the constructs operationalised.

Table 2: Operationalization of Constructs

Main Construct	Type	Factor Loading	Indicators / items	Reference
Technology				
Perceived Compatibility (PCM) AVE = 0.741 CR = 0.903 α = 0.802	Reflective	0.887	InRos would be appropriate for the current technology in our organisation.	(Awa et al. 2017; Al-Qirim 2006)
		0.877	InRos would be suitable for our work processes and practices in the organisation.	
		0.874	InRos would be appropriate for our work culture.	
		0.882	InRoswould be based on our norms, values, systems and philosophies at our organisation.	
Perceived Benefits (PBT) AVE = 0.708 CR = 0.860 α = 0.829		0.821	InRos improve sales' revenue.	(Lin 2014; Oliveira and Martins 2010)
		0.857	InRos improve the overall productivity of the manufacturing process.	
		0.829	InRos provides more speed in production.	
		0.889	InRos allows to achieve a competitive advantage.	
		0.890	InRos could provide a defect-free and accurate product manufacturing.	
Organisation				
IT Infrastructure (INF) AVE = 0.711 CR = 0.893 α = 0.809	Reflective	0.837	I feel that the necessary physical IT infrastructure is available in our organisation for InRos.	(Grant 1991; Wei et al. 2015)
		0.828	I feel that the staff would be equipped with the managerial and technical skills required for InRos.	
		0.840	In our organisation, experience and skills of human resources are rooted in policies, repositories of information and processes.	
		0.846	I feel that across the various departments of the organisation, we would be capable of sharing resources of InRos.	
		0.835	Our organisation can foresee the customer needs in this technology-driven manufacturing market.	
Environment				
External Pressure (EPR) AVE = 0.759 CR = 0.902 α = 0.799	Reflective	0.882	We have to improve productivity, as customers demand it.	(Reyes et al. 2016; Lin et al. 2018)
		0.828	We have pressure from customers to provide accurate and defect-free products.	
		0.827	We have pressure from customers to speed up the production and delivery of products.	
		0.819	We have to always compete with competitors with new technology such as InRos.	
Support from InRos Vendors (SPV) AVE = 0.706 CR = 0.851 α = 0.804	Reflective	0.813	InRos vendors would technically support the ACMC companies.	(Ghobakhloo et al. 2011; Maduku et al. 2016)
		0.806	InRos vendors would provide the necessary training of InRos operations for ACMCs	
		0.802	InRos vendors give free trainings for marketing InRos.	
		0.812	InRosmarketing is actively done by InRos vendors.	
Government support (GSP) AVE = 0.738 CR = 0.879	Reflective	0.848	The government financially supports the InRos technology.	(Lin and Ho 2009; Lin et al. 2018)
		0.812	The government encourages companies to suggest and apply InRos projects for funding	

α = 0.851		0.897	The government provides training for InRos related skills.	
		0.804	InRos norms are supported by Government.	
Adoption Intention (ADN) AVE = 0.744 CR = 0.897 α = 0.806	Reflective	0.876	Organisation is ready to invest in resources to adopt InRos.	(Oliveira et al. 2019)
		0.831	Business activities in ACMCs require InRos.	
		0.854	InRos is required for different tasks at our organisation.	
Potential Use of InRos (PTU) AVE = 0.752 CR = 0.884 α = 0.821	Reflective	0.873	We propose to implement InRos in the near future.	(Abramowic 2015; Sackey and Bester 2016; Lin et al. 2018)
		0.876	We are inclined to increase use of advanced technology such as InRos.	
		0.848	We have capacity to use and implement InRos in our organisation.	
Perceived Cost Issues (COI) AVE = 0.701 CR = 0.902 α = 0.834	Reflective	0.850	Configuration cost of InRos is high.	(Reyes et al. 2016)
		0.875	InRos has high cost of installation.	
		0.879	The platform, control systems safety enclosure and mounting arrangement require huge investment for InRos.	

Sampling and Data Collection

To determine the suitable sample size, the traditional rule of thumb was considered and adopted (Gefen et al. 2000). The largest construct in this model was identified and we derived the right sample size as being ten times the number of items considered. Therefore, 50 is the required sample size for this research. The primary data was collected by administering the final survey questionnaire shown in Table 2. The survey was carried out on the list of ACMCs taken from the ACMA database. The ACMCs were chosen where some kind of advanced technology similar to InRos was used for the manufacturing process. The automobile hubs in the states of Maharashtra, Tamil Nadu, Gujarat, Madhya Pradesh and the National Capital region were considered for data sampling. The random sampling method was used to collect the data from 480 ACMCs from the corresponding automobile hubs.

Along with online surveys, telephonic permission was asked prior to the company visit and then ACMCs were personally visited to conduct the survey. In these companies, technology managers, owners and production managers were surveyed. On completion of the survey, a total of 460 questionnaires were suitable for data analysis out of 720 questionnaires with a response rate of 63.8%. The total data collection process took 14 months as data was collected from various automobile hubs and clusters in India. The data collection was done from the states of Maharashtra (24%), Tamil Nadu (20%), Gujarat (18%), Madhya Pradesh (17%) and the National Capital Region (21%) in India constituting a total of 480 ACMCs that were surveyed.

Out of total ACMCs surveyed, 9% have used AI-empowered InRos for more than six months and 7% for less than six months. Moreover, 84% ACMCs have been using mechanical industrial robots for more than a year along with some type of advanced manufacturing technology. The breakup of the sample is as follows: 29% are production managers, 35% Technology Heads/Managers, and 36% owners and proprietors. 68% of the companies are using advanced technologies and 32% are using automation technologies similar to InRos for other manufacturing functions.

Non-response Bias

A t-test was calculated to analyse the difference in the response between the early wave (270) and late wave (190) groups (Armstrong and Overton 1977; Tsou and Hsu 2015). The result ($p=0.36$) proved that non-response bias is not present. The total number of complete responses were 460.

Data Analysis

Common method bias and endogeneity

The single factor Harman test (Abdallah et al. 2017; Podsakoff et al. 2003; Podsakoff and Organ 1986; Wang et al 2018) was performed to scrutinize common method bias presence. The variance explained by a single factor was 28.62%, which is less than 50% indicating common method bias is not a concern in this research. Hence, the reliability and validity of the measures were assessed. Additionally, Recursivity in the structural model may cause endogeneity (Dubey et al. 2018; Lai et al. 2018). The variance in an exogenous variable may be endogenous to the model (Guide and Ketokivi 2015) as the cross-sectional data may result in a mis-specified model. Hence, a Ramsey regression equation error test was employed (Lai et al. 2018) and established that the endogeneity was not in the proposed model. Hence, the validity and reliability of the measures were established.

PLS-SEM

PLS-SEM is a variance-based path modeling method that has the capability to symbolize variables with multiple indicators in the study. PLS-SEM makes limited distributional assumptions of OLS regression (Chin, Peterson, and Brown 2008). PLS-SEM is employed to test conceptual models and causal relationships between the latent constructs and their indicators (Gudergan et al. 2008). Compared to the maximum likelihood method, PLS-SEM is a flexible method preferred to model constructs (Henseler and Chin 2010). PLS-SEM is employed in studies when the research purpose is the extension of the present theory (Hair et al. 2011). PLS-SEM has also been employed in innovative technology adoption studies (Akter et al. 2017; Almuraqab 2017; Cao et al. 2019; Delic and Eyers 2020; Jasimuddin et al. 2017; Rampasso et al. 2019). Hence, the data analysis was performed employing Smart PLS 2.0 (Ringle et al. 2005).

Measurement model

PLS-SEM was utilised for the analysis of the conceptual model. PLS-SEM is generally used in social science studies as it is appropriate for non-normal data and supports small as well as large sample sizes (Hair et al. 2014; Hair et al. 2017). The SmartPLS 2.0 software (Ringle et al. 2005) was applied for primary data analysis. The measurement properties in the final model were calculated for the latent constructs, reflective in nature, and having multiple indicators.

The high internal consistency of all the constructs is confirmed as the value of Cronbach alpha was above 0.7 (Nunnally 1978). Based on Table 2, CR values confirm the high level of reliability and internal consistency of all the constructs as the outer loading for all the items were higher than the minimum beginning value of 0.6. The AVE values are greater than the minimum beginning value of 0.5, so the convergent validity for all the constructs is proved (Guadagnoli and Velicer 1988; Hair et al. 2017; Wang, et al. 2013).

The comparison of the inter-correlations of the constructs with the AVE off-diagonal values as revealed in Table 3 proves the discriminant validity. Discriminant validity between the constructs is supported (Fornell and Larcker 1981), as the squared variance values were lower than the corresponding AVE.

Table 3. Discriminant Validity

Research Construct	**PCM**	**PBT**	**INF**	**EPR**	**SPV**	**GSP**	**ADN**	**PTU**	**COI**
PCM	**.860**								
PBT	.677	**.841**							
INF	.520	.679	**.843**						
EPR	.404	.501	.497	**.871**					
SPV	.389	.483	.477	.580	**.840**				
GSP	.357	.406	.507	.524	.414	**.859**			
ADN	.308	.357	.378	.405	.367	.516	**.862**		
PTU	.298	.321	.420	.388	.397	.408	.209	**.867**	
COI	.267	.287	.224	.287	.271	.347	.228	.284	**.837**

Structural Model

The validity and reliability of the measurement model was established and then the path analysis was estimated using the structural equation model. The path coefficients and their significance level are illustrated in Table 4 and Figure 2.

Figure 2. Structural model

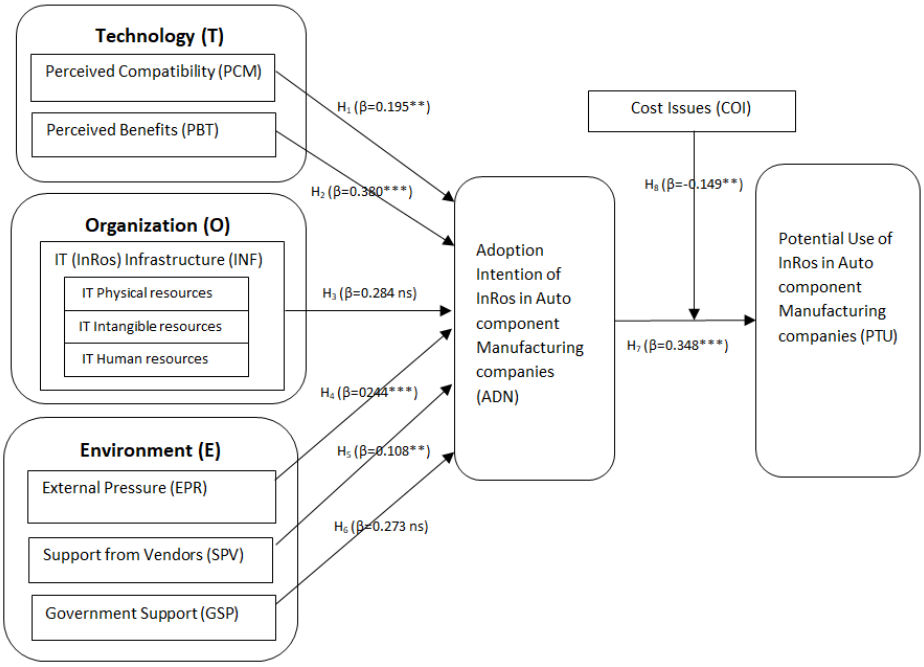


Table 4. Path Coefficient

Hypothesis	Path	β	T Statistics
H_1	PCM→ ADN	0.195	2.033 **
H_2	PBT → ADN	0.380	3.688***
H_3	INF → ADN	0.284	1.616 ns
H_4	EPR → ADN	0.244	3.565***
H_5	SPV → ADN	0.108	2.077**
H_6	GSP →ADN	0.273	1.292 ns
H_7	ADN → PTU	0.348	3.322***
H_8	ADN x COI →PTU	-0.105	3.291***
a. t-values for two-tailed test : *** t-value 2.58 (Sig. level = 1%) , **1.96 (sig. level = 5%) and *t=value 1.65 (sig. level=10%). Hair et al. 2011			

Results

The findings reveal that PCM (β= 0.195, $p < 0.05$) influences positively the and, which is in line with part of the previous literature (Awa and Ojiabo 2016) but contradicts a study of technology adoption in Nigeria (Awa et al. 2017). The PBT (β=0.380, $p<0.01$) affects positively the ADN which is in line with present studies (Lin 2014; Oliveira and Martins 2010), as there are many benefits associated with the adoption of InRos in ACMCs. It is found that INF (β=0.284, n.s.) has a non-significant relation with ADN which is not consistent with previous findings of an RFID-related study (Wei et al. 2015). As there are various types of new technologies deployed in ACMCs for manufacturing automation in addittion to InRos, organisations might not give much importance to IT physical infrastructure (Chau et al. 1991). Accordindly, it may well be that ACMCs are giving more importance to the benefits and compatibility of InRos technology than the requirement of skilled people, synergy among various departments and physical infrastructure. EPR (β=0.244, $p<0.01$) is strongly and positively influencing the ADN (Aboelmaged 2014; Guo et al. 2017; Hassan et al. 2017; Lin 2014) as ACMCs are facing stiff competition from global competitors and need to serve the global customers. The SPV (β=0.108, $p<0.05$) influences positively the ADN: this finding contradicts the study of mobile marketing adoption study (Maduku et al. 2016). InRos is an innovative and complex technology and ACMCs require assistance from vendors. GSP (β= 0.273, n.s.) was found to be non-significant towards ADN of InRos (Oliveira et al. 2014). This finding contradicts most of the present literature (Hwang et al. 2016; Lin et al. 2018; Osakwe et al. 2016). A plausible explanation for this contrasting finding might be that while schemes such as “Make in India” allow promoting manufacturing technology, there is scarce awareness of InRos among ACMC managers and strict government regulations make the relationship more complex and multifaceted, so that it is not possible to predict ex-ante if government support will enhance by itself the intention to adopt the focal technology (Chiu et al 2017; Hsu and Yeh 2017; Troshani et al. 2010). Though government has policies to promote InRo however due to political issues and the fear of loosing a number of jobs in ACMCs is not much promoting InRo schemes. As govnerment will have pressure of labour welfare of workers who will loose jobs due to adoption of InRo in ACMCs. Government needs to ensure the transition in assoctation with industry and reskilling workers (Dhakkapa 2017; Dhritiman 2018; Menifestias 2020). There is a lack of econsystem, high import duties imparted by government are impediments (Dhritiman 2018). Government regulations as not much advanced technology friendly (Dhritiman 2018)

ADN (β=0.348, $p<0.01$) is the predictor of PTU of InRos in ACMCs. It is also found that the relationship between ADN and PTU is moderated by COI (β=-0.105, $p<0.01$) and COI negatively influences the relationship of ADN and PTU.

Discussion

In this research, we examined the predictors of adoption intention and potential use of InRos in ACMCs. In today's competitive environment, ACMCs have to adopt new technologies to survive in the marketplace. The respondents feel that their organisations have appropriate work culture, processes, practices, values and systems to adopt InRos. They also mention the appropriateness of InRos in line with the current technologies utilised in their organisations. InRos require unique and customized programming due to the features that the products of the ACMCs need to display and are utilised for various production processes such as assembling, painting, welding, packaging, testing and inspection of production (Graetz and Michaels 2018). PCM explains the integration and fitting of InRos with current equipment in the manufacturing ACMCs.

We found that PCM is a good predictor of the adoption of InRos in ACMCs. There are many benefits pertaining to the adoption of InRos such as improved production, improved sales revenue, reduced manpower cost, accurate and defect-free products, and higher likelihood to achieve a sustained competitive advantage for ACMCs active in the market (Soffar 2019). Therefore, managers perceive that InRos are beneficial to ACMC organisations and they would adopt them. IT infrastructure in this research discusses the physical IT infrastructure, employee/staff technical and managerial skillsets, current repositories of information and processes, co-ordination between the departments and foresightedness of managers towards the customer needs.

We found that INF is not a significant predictor of ADN. This suggests that ACMCs need to upgrade with the physical IT infrastructure as the latter is not up to the mark. InRos is a new technology in India; hence, there is not much skilled manpower available in the ACMCs. Even many of the ACMCs in India still prefer to use traditional labour-based manufacturing workforce rather than InRos technology (Economic Times 2019), which shows the dearth of managerial skillsets that suggest that apparently, managers do not totally understand InRos technology for production and manufacturing of auto-components. The current information repositories and processes would also need an upgrade as InRos is an advanced and sophisticated technology.

External pressure is faced by the ACMCs due to the globalization of the Indian automobile sector. In India, many global customers exist and they expect the usage of advanced technology in manufacturing for accurate and fast production. ACMCs face pressure not just from the competitors but also from customers' demand for quick delivery of the auto components and products. To be competitive in the market, ACMC organisations need to adopt advanced technologies (Sangani 2019). External pressure influences the InRos adoption which is in line with present research (Aboelmaged 2014; Guo et al. 2017; Hassan et al. 2017; Lin 2014).

In this technology-driven manufacturing environment, InRos vendors are strongly marketing InRos to ACMCs. Managers feel that training and continuous support from InRos vendors are required for better adoption of InRos. Hence, SPV influences the InRos adoption by ACMCs. Contrarily to the expected results, government support (GSP) was not found to be statistically significant towards ADN of InRos in ACMCs, although the government is providing many incentives through the "Make in India" program and AMP 2026. The explanation of this phenomenon could stem from the diminishing enthusiasm of the ACMCs to comply with the governmental norms due to the obstacles and hindrances faced in the audit and compliance, with strict government regulations. The government could help ACMCs to adopt InRos by taking more initiatives to provide incentives and reduction of import duties of InRos, or promote InRos indigenous manufacturing in India.

This study found that ADN is a predictor of potential use of InRos in ACMCs. Organisations' readiness to invest in InRos influences the capability of implementation and increases potential usage of InRos. However, there are perceived cost issues that moderate the relationship between the ADN and PTU significantly. As the cost of installation and configuration of InRos is very high and the safety systems, enclosures and mounting arrangements for InRos require huge investment, COI moderates negatively the relationship between ADN and PTU. This study uniquely finds that the potential use of InRos will be lessened due to the high cost of InRos IT physical infrastructure, installation and configuration costs.

Theoretical implications

From a theoretical perspective, this work makes several contributions. the majority of the research related to advanced industrial manufacturing technologies such as InRos is focused on developed countries in the West rather than emerging economies such as India. However, different environmental settings and cultural contexts may generate different results.

Second, this research makes a distinctive contribution to the body of literature on the innovation of new advanced technologies and InRos adoption in the production settings. This work explores the factors affecting the adoption intention and potential use of InRos leveraging the TOE framework. The TOE does not provide by itself the factors useful to analyse the problem at hand, and it categorizes the factors into the respective constructs where the adoption of the technology actually happens (Puklavec, Oliveira, and Popovič 2018). Third, and related to the previous point, this study offers a novel academic contribution to the research stream revolving around the application of TOE in adoption studies, as it shows that some resources – especially IT infrastructure– are not sufficient to explain the new technology adoption. Accordingly, we believe that the traditional TOE framework should be extended by incorporating other metrics that might proxy the value of resources such as the total assets and the number of employees. Therefore, future research focusing on technology adoption should reflect in their model specification a wider appreciation of resources by leveraging on the Resource-Based View theory of the firm (Barney 1991; 2001; Peteraf 1993). Future studies might also understand if InRos can represent a set of valuable, rare, difficult to imitate and non-substitutable resources in today's competitive auto component manufacturing industry, potentially capable of making those ACMCs endowed with them to attain a sustained competitive advantage due to the heterogeneity of their resources compared to those owned, controlled and leveraged by their competitors (Penrose 1958; Rumelt 1984; Wernerfelt 1984).

Fourth, governmental support was found to be non-significant towards ADN of InRos (Oliveira et al. 2014) and it contradicts the present studies (Hwang et al. 2016; Lin et al. 2018; Osakwe et al. 2016). GSP is not a signficant contributor as most of the ACMCs are not aware of the government schemes and even government taxation has created slowdown in the automation industry. Currently, the increased rate of Goods and Services Tax (GST) imposed by Government of India (GoI) and the automobile market slowdown is a major challenge for ACMCs. Though GoI has initiated the ‘Skill India’ program to train the workforce, still there is a dearth of skilled workforce for InRos adoption and its potential usage (Dhakkapa 2017; Dhritiman 2018; Menifestias 2020). There is a lack of incentives provided by GoI for research and development activities at ACMCs (ACMA 2019). Associations such as “All India Council for Robotics and Automation” (aicra.ac.in) and ACMA are helping ACMCs for automation by delivering government schemes and training the workforce.

Fifth, this work attempts to fill the research gap of InRos adoption literature (Müller-abdelrazeq et al. 2019; Turja and Oksanen 2019) by identifying InRos-related contextual factors in the TOE framework with an organisation’s viewpoint. Moreover, this study empirically validated the theoretical model anchored in the TOE Framework incorporating the resource-based view theory. We also discuss the potential use of InRos in ACMCs which was not given much importance in earlier studies (Schmidt et al. 2015) as shown in Table 1.

Sixth, this research takes further steps to study the influence of adoption intention on the potential use of InRos. It also empirically validates the moderation effect of perceived cost issues between ADN and PTU, which is a unique contribution as it was found that perceived cost issues negatively moderate the relation between ADN and PTU of InRos. This study contributes to the existing literature on the adoption of advanced IT manufacturing technology–InRos adoption in ACMCs. Building on TOE, the proposed research model helps to understand how TOE related constructs influence the adoption intention and potential use of InRos in ACMCs. The high explanatory power of the proposed validated model with independent variables explaining InRos ADN of 68.9% (R^2=.689) and PTU of 62.2% (R^2=.622) represents a valuable contribution to the existing body of InRos literature.

Managerial Implications

This work highlights the factors affecting the adoption of InRos and subsequently its potential use which can be considered by B-2-B marketers to formulate marketing strategies for InRos in ACMCs. The findings of this work confirm that perceived compatibility, perceived benefits, external pressure, support from vendors are significant predictors of InRos adoption intention. The study also revealed that IT infrastructure and government support do not influence InRos adoption intention. Furthermore, it was found that perceived cost issues negatively moderate the relationship between the adoption intention and potential use of InRos.

The designers, manufacturers and marketers of InRos can understand the factors affecting the adoption intention of InRos and define suitable strategies to manufacture and market InRos. The designers and manufacturers should consider the compatibility of InRos with current manufacturing processes and systems in the organisation. This shall be useful for aligning InRos with the current production systems.Marketers and manufacturers should ensure continuous training and support to ACMCs as InRos is a new technology and employees are not much well versed with it. Even marketers should provide free training and demonstrations to understand the InRos benefits as perceived benefits are an important antecedent of InRos' adoption. The InRos marketers should also provide the testimonials of existing customers that successfully adopted InRos to promote them and built good perception about vendor support among ACMC managers. The marketers can highlight the InRos adoption benefits to ACMCs such as lower workforce cost, seamless production planning along with improved and accurate production by minimizing the defects.

Managers of ACMCs would understand the factors of adoption from this research. The IT infrastructure was not found significant which confirms that the IT infrastructure is not up to the mark in these ACMCs. The InRos is an advanced technology which requires new skillsets and IT infrastructure which ACMCs must embrace to facilitate the InRos Adoption.

Government support was found not significant, although the government is providing many incentives through the "Make in India" program and AMP 2026. The GoI and policymakers need to investigate the awareness among the ACMCs about these schemes and benefits provided by the government for InRos. If the government takes more initiatives towards providing incentives and reduction of import duties of InRos or promote InRos indigenous manufacturing in India it would help ACMCs to adopt InRos. A skilled workforce and better InRos infrastructure would help in accurate, low-cost and efficient production.

The adoption intention influences the potential use of InRos. However, the perceived cost issues negatively moderate the relationship between adoption intention and Potential use of InRos. The perceived cost issues faced by ACMCs are due to the high cost of infrastructure, maintenance of InRos infrastructure and high import duty for InRos purchase from other countries. Perceived cost issues are limiting the InRos potential use in ACMCs. The government can play a vital role in reducing the cost of InRos by promoting indigenous manufacturing of InRos in India or reducing the import duties.

Policymakers need to devise policies that would promote the InRos adoption as InRos has many benefits that would improve the faster and accurate production at ACMCs. More specifically, Indian policymakers are encouraged to frame policies and regulatory frameworks that might provide incentives to ACMCs to increasingly adopt InRos which might generate positive effects on industrial production planning, productivity and national GDP.

Conclusion

InRos is an advanced technology that can be utilised for manufacturing in ACMCs. InRos boost the productivity by automation of various activities in the manufacturing process. It also improves the return on investment. It is imperative for ACMCs to adopt InRos to be competitive in this technology-driven manufacturing era. The research sought to examine the antecedents of InRos adoption intention and potential use of InRos in ACMCs. The model was developed incorporating the resource-based view in the traditional TOE framework by surveying 460 valid respondents of ACMCs. Perceived compatibility, perceived benefits, external pressure, support from vendors were found to be significant predictors of InRos adoption intention. It was also revealed that IT infrastructure and government support do not influence the InRos adoption intention. Further, it was found that perceived cost issues negatively moderate the relationship between the adoption intention and potential use of InRos in ACMCs.

Limitations and Further Research

This study displays a few limitations. First, as the empirical setting is a specific country (i.e., India), the implications of this work are mainly related to the observed emerging economy. However, the drivers of adoption of InRos may vary across different geographic regions or counties. Second, the research model might be enriched by embedding more constructs and variables such as anthropomorphism, trust, organisational fit, security, perceived values and additional control variables such as firm size and type of industry. Third, further investigations can be conducted to examine the adoption of InRos in various sectors and industries, for instance by examining how they are being embedded into service sectors (Mariani and Borghi 2019). Also, future studies can be carried out on the assimilation, implementation and actual usage along with the issues related to actual usage of InRos. Last, future scholars might embrace the most recent versions of the RBV theory of the firms, including those that focus on dynamic capabilities (Teece et al. 1997) to shed more light on how the adoption of InRos might be affected by a well-developed set of firm's dynamic capabilities allowing the manufacturing firms not only to boost their efficiency, effectiveness and performance but also to sense and seize business opportunities and to maintain competitiveness by reconfiguring existing resources.

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